

CHANGING COURSE: THE INFLUENCE OF SOCIAL POSITION AND SOCIAL
NETWORKS ON COLLEGE FACULTY'S ADOPTION OF EDUCATIONAL
INNOVATIONS

by
Michael Joseph Reese, Jr.

A dissertation submitted to Johns Hopkins University in conformity with the
requirements for the degree of Doctor of Philosophy

Baltimore, MD
October 2014

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Abstract

Problem: In an era of rising tuition costs and accountability movements, colleges and their faculty find themselves under increasing pressure to adopt evidence-based teaching best practices. The science-of-learning field demonstrates the positive impact of research-based teaching practices and educational resources on student learning, but faces challenges in diffusing these strategies broadly. Research on diffusion of innovations can inform dissemination initiatives; previous studies predominantly focused on business and healthcare domains but not higher-education systems. This study contributes to our understanding of how the spread of educational innovations in higher education are associated with college instructors' social positions and the information networks they consult.

Methods: I conducted surveys of faculty members at U.S. colleges who became aware of three broadly diffused educational innovations: Calibrated Peer Review, Peer-led Team Learning, and the Student Assessment of Learning Gains. Survey data were combined with user logs and registration data. The analyses explore the likelihood that instructors aware of an innovation will adopt (or not) and the likelihood that adopters will become a change agent (or not) using survival analysis, Poisson and negative binomial regression, multinomial logit regression, and qualitative analysis.

Results: Overall, instructors who consult social-exchange networks are more likely to adopt than faculty who consult anonymous-search networks. This association was

sometimes affected by the social position of the potential adopter, but more often influenced by innovation characteristics. Tenured faculty and instructors from research universities who adopt are more likely to become change agents for an innovation than adopters who are not tenured or not from research universities. Findings also suggest the potential adopters filter information based on the change agent's social position. Potential adopters use the change agents' position as a proxy for credibility and compatibility in deciding to adopt or not and then to secure approval or resources from senior administrators during implementation.

Conclusions: Social position and information networks are associated with faculty adoption patterns, but the findings suggest that innovation characteristics must also be considered. These characteristics include not only innovation attributes but also the structure of communities that develop to support the innovation's use and dissemination.

Dissertation Advisors:

Dr. Stephen Plank, first reader

Dr. Lingxin Hao, second reader

Acknowledgements

I am drawn to endurance challenges. The dissertation is no less a team effort than any other sport, although, it is the only marathon I have participated in where I have more respect for the process now that it is done. I would have abandoned the course years ago if it had not been for my coaches.

I did not allow myself to think about finishing until recently. During the dark fogs that clouded my faith and confidence in completing the project, I did not think about the diploma, the fancy cap and gown, or the time I would get back. I imagined writing this – a thank you letter to so many people.

Thank you, Steve Plank, for meeting with me at Café Q in 2003. Your openness to the idea of pursuing a Ph.D. while working gave me hope that I could achieve one of my life's major goals. I appreciate the countless hours of your time and spontaneously scribbled 2 X 2 cross-tabs you generously gave me. You were also a great motivator. There were many times I thought about quitting as the demands of working and school overwhelmed me. I never complained or admitted that to you, but you somehow knew and delivered encouragement just when I needed it.

Thank you, Lingxin Hao, for teaching me a few things about statistics and how to work hard. Neither of my defenses were as intimidating or as satisfying as meeting individually with you. "Defend yourself!" takes on a new meaning when someone is banging on a desk. I also appreciate the copious notes you printed for us in your *Panel Data* and *Categorical Analysis* courses. I consulted them more than any textbook or

resource in the past three years. They are wrinkled, dog eared, and precious. The day I thought I lost them I almost had a nervous breakdown.

Candice Dalrymple, thank you for making this opportunity possible. Your initial suggestion and encouragement allowed me to pursue a dream that I quietly harbored after abandoning an engineering doctorate at Cornell University. Leaving was never a regret; it was made for the right reasons even if I did not fully understand it at the time. But giving up on things keeps you up at night over the years. I could not have started or finished without your commitment to my professional development. I learned so much working for you that directly contributed to my dissertation. You are as important as any other faculty member who served on my advising committee and have influenced my life more than anyone outside my family.

I want to thank the great Giovanni Arrighi for opening the door. I remember clearly sitting in your office and trying to remain stoic when you replied to my proposed work-school plan by saying, “Why not? They will tell us we can’t, but we will figure it out.” Your *Social Theory* class ignited my sociological imagination and gave me a new perspective on how the world functions.

Thanks to Terri Thomas, Jessie Albee, and Linda Burkhardt for arguing with the administrative umps whenever my unique student-employee status caused red flags to be thrown.

Thanks to Eric Mazur, Julie Schell, Pratibha Varma-Nelson, Mel Ganus, Stephen Carroll, Elaine Seymour, Bob Matheiu, and Arlene Russell. Without you, there would have been no data, and therefore, no project.

Karl Alexander used to say in his Sociology of Education course, “parents are the biggest predictors of success.” Mom and Dad, my first teachers, thank you for igniting my love of learning and making sure I received a good education despite the sacrifice.

I also want to thank the green chair. You supported me at all times of the day and night. In you I fretted, typed, and watched my kids grow up. You are now frayed and have lost some of your spring. It’s time to say goodbye. I hope your next home appreciates you as much as I have.

Mckinley, Shenandoah, and Hudson, I appreciate your patience. Dad is done with his duties and ready to play ball.

To Kayleen, I owe so much. When people asked, I casually talked about the demands of graduate school and my frustrations. I did not want to complain too much so no one really knew the true crushing weight suffocating me at times. Only one person was allowed inside. Kayleen, I may have doubted my ability to complete this process, but I never doubted your love for me. I never take you for granted, the most important person in my life, but ironically you made the greatest sacrifice. Thank you for simply listening in my moments of despair. Thank you for playing with the kids when I felt guilty about not being able to throw the ball in the backyard. Thank you for hauling me out of bed before the sun rose each day. This degree is as much yours as it is mine.

Over the years, I regularly doubted if this was worth it. I told myself to persist for professional reasons. Only now do I understand how much I have grown personally. I learned how to read critically, ask questions, listen, connect dots, and persevere through difficult tasks. But the most important lesson was one central to sociology: the power of relationships. Thank you to all who helped along the way.

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I. Introduction

More high school graduates are attending college than ever before (Rampell 2010), but as access expands, its value is increasingly being questioned. Research suggests that many college students graduate without improving their critical thinking and analytic reasoning skills (Arum & Roksa 2011). Peter Thiel, a billionaire entrepreneur, believes higher education is the next “bubble” to burst and established a fellowship to pay young adults \$100,000 to skip college and start a company (The Thiel Fellowships 2014). This is occurring as total student debt in America surpasses one trillion dollars (Weinberg 2013). Students, parents, watchdog groups, and government agencies want to know if colleges adequately prepare students for 21st century careers.

Colleges are under pressures to reform and are beginning to respond. The higher education community developed the Voluntary System of Accountability in response to the White House’s College Scorecard, which helps prospective students and their parent’s understand, “a college’s affordability and value” (Field 2014; Voluntary System of Accountability 2011; Department of Education 2014). For change to result in improved outcomes, however, it must be embraced by faculty and that change must occur in the classroom.

These calls for reform align with my interest in how faculty adopt and abandon educational innovations. This stems from my work in a college instructional support center where I regularly consult with faculty members on how to improve student learning. My consultations often include assisting instructors with identifying and adopting new teaching practices or educational resources. Each instructor approaches

this challenge in a unique way, but my doctoral studies have led me to examine the patterns of how educational innovations diffuse across faculty and colleges. I am interested in testing the validity of my intuitions through a formal research study.

1.1 My Interest and Experience with the Diffusion of Educational Innovations

These intuitions echo, in a muted way, what I hear and read in the higher education community. Faculty members at research universities do not care about or are not incentivized to teach (Fogg 2006). Faculty members are not trained to be teachers (Burke 2001; Grasgreen 2010). A true commitment to undergraduate learning is found at non-research intensive colleges (Olwell 2011). Whatever element of truth lies in these generalizations, there are contradictory examples that exist. Sometimes these occur within the same institution. The following example highlights this dynamic.

In a meeting I attended with tenured engineering faculty at a major research university, one participant commented that faculty members know better than to highlight teaching accomplishments in promotion and tenure reviews. While this comment reflects generally accepted stereotypes, the context did not. These professors met at the request of a peer who recently attended a *Frontiers in Engineering Education* workshop hosted by the National Academy of Engineering. The group wanted to learn about teaching innovations pioneered at elite institutions and discuss how to improve the undergraduate learning experience at their own school. This example simultaneously corroborates and contradicts the common myth about how teaching is perceived at research universities. It also supports the stereotype that faculty members only look to their peers for inspiration. No lecturers were invited to this conversation though the university employs many. The faculty members were not interested in innovations arising from anything but the most

elite engineering schools in the country. One professor even commented that he was not interested in what was happening at a local state school because, “they aren’t us.” My goal is not to accuse professors of arrogance, but to highlight the sometimes contradictory dynamics that occur in conversations about teaching innovation in higher education.

The example is anecdotal, yet likely sounds familiar. The reality is that there is much to be learned about how educational innovations diffuse in the higher education community. Minimal rigorous research exists on the topic of how teaching best practices spread in higher education while the science of learning field continues to grow (Plank, Reese, & Villenias N.d.). Many disciplines have developed new outlets for publishing on educational innovations. The *American Journal of Physics* added a dedicated physics education research supplement in 1999. *The Chemical Educator* began publishing in 1996. These publications tend to focus on student learning outcomes, however, and not the adoption or diffusion process.

My unique background as an instructional support staff member who is currently pursuing a doctorate in the field of sociology of education has prepared me to make a contribution to research on how educational innovations spread among colleges. This dissertation will contribute a sociological perspective to the literature on how educational innovations diffuse among faculty members at colleges in the United States. This will be done by exploring the association between adoption/abandonment patterns and social position along with different sources of information. I will also explore who authors those sources of information, that is, how change agency is associated with social position. Last, I will explore how potential adopters respond to these sources of information based on the status of the change agent.

1.2 What is an Educational Innovation?

I intentionally use the term “innovation,” but recognize this word often implies a creative process or novel resource adopted by pioneering individuals or groups.

Guarding against this common connotation, I rely on a dispassionate definition of innovation provided by Everett Rogers (2003) in his classic text, *Diffusion of Innovation*. “An innovation is an idea, practice, or object that is perceived as new by an individual or other unit of adoption” (p. 12). Using a broad definition from an individual’s perspective is useful because individuals learn about innovations at different times. Consider different instructor perspectives of a newly-installed, interactive SmartBoard in a department seminar room. A faculty member who used a SmartBoard as an instructor at a previous university may not categorize it as an innovation, but a colleague encountering it for the first time may (See Figure 1.1).

Confining Rogers’ definition to the educational domain will improve the analytic focus of this project. Instructional practices vary greatly across courses and disciplines, but instructional design models provide a general approach for categorizing any type of teaching approach (Dick & Carey 1996, p. 385). Faculty instructional practices include instructional methods, content, and assessment techniques. I combine Rogers’ definition with the ideas of Dick and Carey to define an *educational innovation as an instructional method, content, or assessment technique perceived as new by an instructor or other unit of adoption (e.g., academic department, institution)*. I do not specifically include educational technology as part of this definition because educational technology

describes a characteristic of an innovation.¹ Content, instructional methods, and assessment techniques are often, but not always, supported through technology. For example, the use of in-class voting systems (i.e., clickers) to quiz students in large lecture classes is an assessment innovation that runs through an integration of hardware, software, and wireless radio technologies. A similar assessment method could be conducted with students raising their hands or color-coded cards, albeit less efficiently. Content can be delivered through a book or an online simulation.

1.3 Project Relevance

Findings from this project have the potential to inform both practice and theory. First, the research questions and analyses are pertinent given the ways in which the structure and composition of the U.S. higher education teaching corps have been changing in recent years. Over the last several decades the ranks of tenured and tenure-track professors have come to comprise a smaller and smaller proportion of the faculty at most colleges (Roueche, Roueche, & Milliron 1998). In 1966, 32% of community college faculty worked part-time (Heinberg 1966). By the 1990s that number topped 50% (Scheibmier 1980) and continues to grow. Contingent faculty – those who are not tenured nor tenure-track – make up 68% of all faculty members at all American colleges (American Association of University Professors 2010). This trend is likely to continue as research documents colleges' shift toward hiring contingent, as opposed to tenure-track faculty, after economic downturns such as the recessions of 2001 and 2007-2009 because

¹ Collier defines educational technologies as the, “application of systems, techniques, and aids to improve the process of human learning” (Collier, Paula, & Koff. 1971, p. 1). Therefore, educational technologies do not equate to digital or electronic resources. Blackboard and chalk are examples of educational technologies. So, too, are various arrangements of individual and group responsibility and accountability, such as those invoked in various peer-teaching or cooperative-learning models.

of the increasing proportion of university funding that comes from endowments (Brown, Dimmock, Kang, & Weisbenner 2010).

As contingent faculty become a larger proportion of the overall faculty in U.S. colleges, it is important to understand how to motivate these professionals to improve their teaching, especially if current incentive structures are designed for a shrinking class of tenure-track faculty.² In addition, contingent faculty may participate in different peer networks than non-contingent faculty. Adjunct professors are likely to be more socially isolated. It is important to know how information about educational resources and pedagogical strategies is transmitted through faculty networks and who may or may not be receiving the information.

Colleges are also coming under increasing pressure from education leaders to change the tenure process as a result of this growing population of non-tenure track faculty. An appreciation of how and why contingent faculty's teaching practices evolve can help inform these discussions. In addition, administrators have questions about whether students learn more from instructors hired specifically to teach, or if colleges undermine the undergraduate learning experience by hiring faculty members into lower status positions with less institutional commitment to employment.

The project's findings may also be of interest to sociology of labor researchers because of the unique labor environment associated with colleges. Faculty members, regardless of their position, have significant autonomy in how they execute their day-to-day duties. Organizational control is not equated with micromanagement. Studying the

² In addition, more faculty members are teaching undergraduates. In 1969, 50% of U.S. college faculty taught undergrads, in 1998 that rose to 2/3 of faculty (Schuster & Finkelstein 2006, p. 569).

effect of labor stratification in the education sector provides an opportunity to study how individuals respond to perceived organizational pressures resulting from self-perceptions of job security as opposed to direct supervisory control. The decrease in tenure-track faculty parallels the decline of union memberships in the private sector as institutions rely more on temporary workers than in the past.

Next, the National Science Foundation, National Institutes of Health, and private foundations such as the Howard Hughes Medical Institute, Andrew W. Mellon Foundation, and the Smart Family Foundation annually grant hundreds of millions of dollars to fund thousands of educational development projects with the goal of improving undergraduate education. Collectively, colleges and faculty spend millions of dollars subscribing to discipline-specific teaching journals or professional educational organizations such as Educause and the American Society of Engineering Education. Investigating the sources of faculty teaching innovation may help granting agencies and college administrators make strategic decisions about funding allocations.

Finally, reports decry the decline of the U.S. higher education system (Douglas 2010) as its colleges slip in international ratings (Fischer 2009, p. 1; QS World University Rankings 2009; Academic Rankings of World Universities 2014). These reports claim the prestige of U.S. higher education is inextricably linked to the country's waning economic and political standing (Douglas 2010, p. 1). While international rankings can often be a comparison of apples and oranges, there is no doubt U.S. colleges face stiffer competition in recruiting students from around the world. Ensuring a high-quality undergraduate learning experience will help colleges in their struggle to remain competitive. Findings from this project have the potential to help college administrators

understand how teaching innovations diffuse. Specifically, this project can help administrators identify who within an organization is likely to be an opinion leader or early adopter of innovative teaching practices.

1.4 Dissertation Organization

My goal is to provide a sociological perspective on how educational innovations diffuse in higher education. The dissertation will include eight chapters. This first chapter has introduced the project and its potential implications in practice and theory. The second chapter will describe relevant previous research and theoretical perspectives used to contextualize and conceptualize the project. I will also present the research questions and hypotheses, along with the research design used to test my propositions. Chapter 3 will present a detailed description of the data collection methods, populations, and analytic methods used.

Four analytic chapters will follow. They are divided into two sections with two chapters each. The first section will explore use patterns. This includes a separate analysis of adoption (Chapter 4) and abandonment (Chapter 5). I am specifically interested in how these are associated with an instructor's social position and the sources of information consulted from social-exchange and anonymous-search networks. The second section will explore patterns of influence through these networks. Chapter 6 analyzes how an adopter's social position is associated with the likelihood of becoming a change agent who publishes and presents on an innovation. Chapter 7 then explores how the next generation of potential adopters respond to these change agents. That is, how does the relative difference in social position between these individuals affect which

change agents are identified as influential. Chapter 8 concludes by suggesting potential applications and future research on the topic.

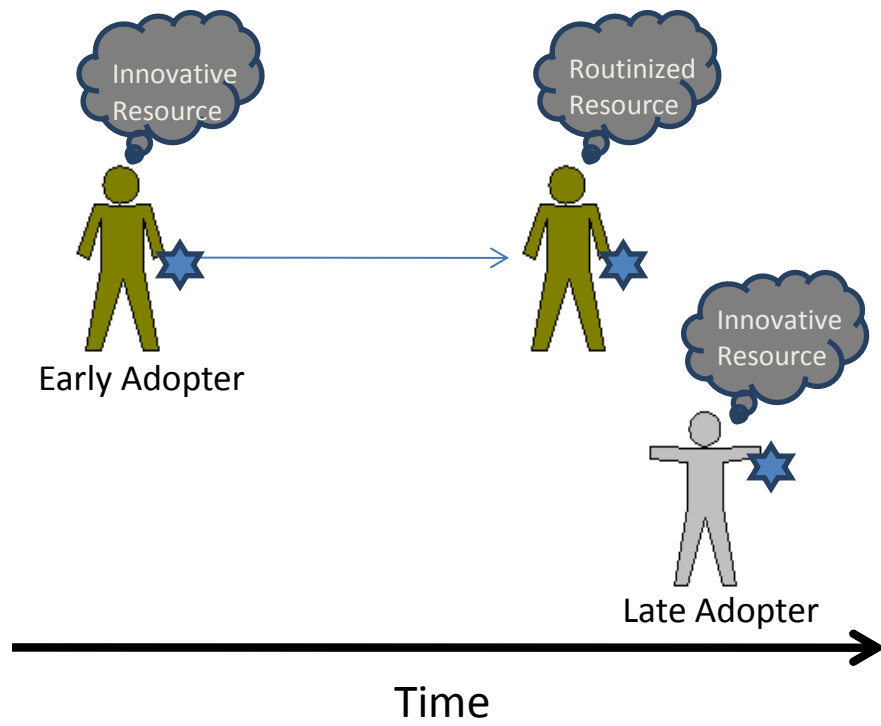


Figure 1.1: How Innovations are Perceived by Different Adopters Over Time

II. Theoretical Framework, Hypotheses, and Research Design

The goal of this dissertation is to contribute to the understanding of how educational innovations diffuse. Rogers not only provides the foundation for my definition of innovation (see Chapter 1) but the basis of the conceptual framework as well. In this chapter I present my research questions and theoretical framework – built upon Rogers’ ideas along with relevant concepts from the sociological literature. This is followed by a statement of my hypotheses and description of the research design.

2.1 What We Know: Rogers’ Legacy

2.1.1 Stages of Adoption

Rogers’ (2003) book *Diffusion of Innovations* provides a conceptual overview of research on innovation dissemination in numerous fields. It has been recognized as a classic for several decades. In this book, Rogers proposes a five-stage model for the innovation-decision process that describes how an individual goes from becoming aware of an innovation to ignoring, adopting, or abandoning it. These five stages are 1) knowledge, 2) persuasion, 3) decision, 4) implementation, and 5) confirmation (Rogers 2003, p. 168-92).³ This project will study faculty members’ use of communication channels in the first two stages of potential adopters’ experiences and their contributions

³ Rogers (2003) defines the five stages as follows. “Knowledge occurs when an individual... is exposed to an innovation’s existence and gains an understanding of how it functions. Persuasion occurs when an individual forms a favorable or unfavorable attitude towards the innovation. Decision takes place when an individual engages in activities that lead to a choice to adopt or reject the innovation. Implementation occurs when an individual puts a new idea into use. Confirmation takes place when an individual seeks reinforcement of an innovation-decision already made, but she or he may reverse this previous decision if exposed to conflicting messages about the innovation” (p 169).

Rogers does not suggest all individuals who become aware of an innovation move through all five stages. Some will decide not to adopt the innovation after becoming aware of it. Others may attempt to adopt an innovation and then abandon it. However, those that sustain an implementation after first adopting it will move through all five stages.

to communication channels during the last three stages for those who act as change agents.

The process of innovation adoption begins when an instructor first becomes aware of an innovation. Awareness can begin with discovery of a resource that may inspire the instructor to adopt it. Alternately, the desire to improve a course may lead a faculty member to search for a yet-to-be-identified innovation. The second case is more likely to result in a change because the motivation to change existed before the discovery.

Previous studies document that later adopters become aware of an innovation at roughly the same time as early adopters (Rogers 2003; Coleman, Katz, & Menzel 1966), but early adopters had a motivation to change whereas later adopters did not. Regardless of whether adopters had a pre-existing motivation to change, the awareness of the innovation led these adopters to learn more. This leads to the next stage.

So how are faculty members persuaded to adopt an innovation once they are aware it exists? Potential adopters must learn more about the instructional practice or resources and reflect on whether the innovation will work in their particular social context. Rogers (2003) defines this as the persuasion stage in which the adopter forms a favorable or unfavorable attitude toward the innovation that ultimately influences his or her decision to adopt or not (p. 174). The persuasion stage differs from the knowledge stage in that the adopter “actively seeks information about the new idea, decides what messages he or she regards as credible, and decides how he or she interprets the information that is received” (p. 175). This suggests that the persuasion stage is not simply preparing for a technical decision.

Faculty members are influenced by social cues in which other social actors signal that certain behaviors are approved or disapproved. They may also filter information by the source's social position. Potential adopters consider social norms and expectations along with technical information about an innovation before making a decision to adopt or not. The following sections will expand on these ideas in more detail.

2.1.2 Persuasion and Communication Channels

The choice to adopt an innovation is often made by an individual, but the information that persuades the adopter originates with other social actors.

Communication channels are used to transmit information about the innovation from the source to the potential adopter. Rogers defines two types of communications channels, mass media and interpersonal channels, along with how they are used differently across the stages of adoption. Rogers (2003) defines mass media channels as “means of transmitting messages that involve a mass medium, such as radio, television, newspapers, and so on, which enables a source of one or a few individuals to reach an audience of many” (p. 205). Interpersonal channels involve “face-to-face exchange” (p. 205).

Are Rogers' categories appropriate for this study? In the information age, direct interpersonal communications can occur without face-to-face exchanges through email, Skype, Facebook, Twitter, or other social media. Rogers' definition of mass media does not include Internet-specific technologies like web pages, learning object repositories, or Facebook. Another concern is the irrelevance of mass media to educational innovation diffusion. It is difficult to envision teachers from kindergarten through college learning about new instructional resources or practices from mass media such as radio, television, or newspapers. Admittedly, vendors and school districts use brochures and catalogs to

raise teachers' awareness of resources available. However, I assert that Rogers' categorization is too broad for this project and does not account for web-based communication channels. An adaption to his categorization is needed to address the particular ways information about educational resources are shared in higher education.

2.2 Extending Rogers' Paradigm

A revision or extension of Rogers' concepts will improve the analytic thinking on this topic. I propose reconceptualizing his ideas of communication channels using the broader concept of diffusion networks. I emphasize the concept of "networks" over "channels" in defining these new categories because "channel" implies a connection between two individuals.⁴ I am more interested in how instructors consult a network of multiple channels that communicate information about an innovation. I define *social-exchange networks* as existing or newly-created person-to-person relationships purposefully used to communicate information about an innovation in which the sender, receiver, and timing of exchange are known within the networks. These include face-to-face and electronic communications.

Anonymous-search networks transmit information about an innovation without involving direct, person-to-person communication. Anonymous-search networks require no social interaction. In fact, the sender of information is often unaware of who has received it. Examples of anonymous-search networks include websites or journal articles defining an innovation, explaining how it was implemented, and/or describing its impact on student learning. I include conference presentations in this category because faculty

⁴ Rogers' (2003) writes, "A communication channel is the means by which messages get from one individual to another. The nature of the information exchange relationship between a pair of individuals..." (p.18). The Free Online Dictionary defines channel as, "A course or pathway through which information is transmitted" (The Free Online Dictionary 2011).

members do not necessarily need to interact with the presenter to learn about an innovation. They can sit passively in attendance and adopt the innovation without the presenter ever knowing who they are.⁵ Figure 2.1 represents these two types of networks.

I will investigate how social-exchange networks operate alongside anonymous-search networks in diffusing educational innovations. In the information age, the challenge may no longer be gaining access to information, but filtering it. Perhaps the old saying, “it’s who you know” needs to be appended with “or how well you can search.” These networks may also play different, yet complementary, roles in the stages of adoption. Rogers (2003) implies this when he generalizes that, “mass media channels are relatively more important at the knowledge stage, and interpersonal channels are relatively more important at the persuasion stage” (p. 205).

2.3 Theory on Social-exchange and Anonymous-search Networks

2.3.1 Strength of Weak Ties

Traditionally, researchers have described diffusion networks in reference to the structure and use of social-exchange networks (Coleman 1988, p. S95; Granovetter 1973, p. 1360; Jackson 2010, p. 1). Granovetter’s (1973) classic article, “The Strength of Weak Ties,” theorized how the diffusion of influence and information is dependent on weak interpersonal relationships that connect groups of individuals (p. 1973). New ideas will spread slowly if they are only shared through close (strong) ties because of the limited number of strong ties an individual can maintain and because of the homogeneity of information shared among a “strong-tie” network. In addition, many of these

⁵ This does not preclude interpersonal interactions from occurring, such as questions and answers at a conference presentation, but it is not required for the information exchange to occur.

relationships are redundant (e.g., individuals often share common friends). It is not unreasonable to apply Granovetter's argument to assume innovations, like information and influence, will spread more effectively through weak ties because they link disparate groups together.

But what is the scope of weak ties instructors use in the diffusion of educational innovations? Rogers (2003) posits that interpersonal diffusion networks are mostly homophilous (p. 341). We can see this in the opening example of Chapter 1. Tenured and tenure-track faculty interact more frequently with each other than with lecturers and adjuncts because of their involvement in university committees and departmental meetings. Full-time lecturers at a college may establish their own support groups to share best practices in teaching. Adjunct lecturers are often more isolated in college networks and interact with fewer people like themselves because of their loose coupling to the institutions at which they work.⁶ If faculty interpersonal relationships – both strong and weak – are homophilous, how effective can they be in diffusing educational innovations broadly beyond small groups? I speculate this clustering of homophilous faculty relationships occurs across institutions as well. Faculty members likely use these relationships to not just obtain information but to signal to colleagues where their activities and interests are centered. If these networks predominantly exist to support research, faculty members will be less inclined to pose instruction-related questions to their research peers unless their research is pedagogically-based.

⁶ However, they could also establish important weak ties between colleges if they are simultaneously teaching at multiple institutions.

Structures of interpersonal relationships affect how information about innovations diffuses. These structures can be critical for the diffusion of educational innovations. In addition to the importance of the structure of these relationships, however, we must also consider how the relationships are negotiated. That is, it is necessary to account for cultural explanations as well.

2.3.2 Social Capital

Coleman's conception of social capital provides a framework that accounts for both structural and cultural explanations for how diffusion networks may facilitate the diffusion of educational innovations. Coleman (1988) defined forms of social capital by their function with one of these forms being information channels (p. S95). Coleman's conception is similar to my definition of social-exchange networks because he defines information channels by how the organization of interpersonal relationships facilitates the flow of information. "Social capital inheres in the structure of relations between actors and among actors" (p. S98). Coleman theorizes how the structure of social-exchange networks can result in social change (e.g., through networks with or without closure).

Coleman describes other forms of social capital – social norms along with trust and obligations – that address the cultural perspective. These additional forms of social capital describe how a potential adopter interprets the information communicated through diffusion networks. Adopters evaluate the applicability and impact of an educational innovation, and part of that assessment includes decoding cues from the social environment. If social trust is high, faculty members may reach out to colleagues to learn about their experiences using an innovation. A strong sense of obligation to continually

improve teaching within an organization may lead faculty members to more frequently or enthusiastically adopt educational innovations (Frank, Zhao, & Borman 2004).

Social capital can also have negative consequences when it places excessive claims on group members, restricts individual freedom, or leads to downward leveling norms (Portes & Landolt 1996, p. 18). For example, tenure-track faculty may perceive their senior colleagues do not want junior faculty members spending too much time on class preparations or making changes to a course until tenured. Social capital provides a framework for understanding how instructors' decisions to adopt or not are influenced by interpersonal relationships.

2.3.3 Micropolitics and Competition

A breakdown in social capital, however, can affect how instructors use social-exchange and anonymous-search networks to learn about educational innovations. This may be manifested as conflict within an organization. Conflict can arise from the implementation of a new educational innovation. This type of conflict can be beneficial when it leads to the development of learning communities within an organization that then support educational change (Achinstein 2002). Of course, conflict can also become a barrier to diffusion. Research suggests adopters more frequently choose to look outside the organization for knowledge about an innovation due to a lack of social trust (Menon & Pfeffer 2003, p. 497; Menon, Thomson, & Choi 2006, p. 1129). Micropolitics within an organization lead individuals to undervalue their local rivals' work because they do not want to legitimize them (Datnow 2000). Actors are willing or able to apply more objectivity in assessing knowledge from an external competitor than from an internal competitor.

Another source of internal devaluation comes from flaws more readily observable for projects within the organization than outside (i.e., there is more evidence to discredit it, even if the final product successfully hides all blemishes). Finally, better access to information originating within the organizations, even if it is positive, decreases the novelty of the innovation, thus decreasing one's motivation to learn more. Eric Mazur (2009), a renowned physics research professor at Harvard joked that his colleagues did not become interested in his educational innovations until they learned tenured faculty at Stanford and other prestigious universities had adopted his methods.⁷ This example shows how faculty members made aware of an innovation from a local source chose not to adopt, but once legitimized by an external source, are persuaded to learn more about it.

2.3.4 Trying to Make a Difference: Change Agents

The previous discussion of different types of diffusion networks assumes that someone is sharing information about the innovation. This raises the question of who authors the information in these networks. Some instructors share their resources or experiences because they are intrinsically motivated to help other instructors improve student learning. The breadth of the open source movement can be attributed to the number of individuals who voluntarily contribute their time for the good of the community (Roberts, Hann, & Slaughter 2006). But some individuals may be motivated to do so for other reasons.

Organizational incentives shape faculty behaviors. Incentives are economic and non-economic rewards offered to individuals or organizations to influence behavior (Pink

⁷ Eric Mazur developed the Peer Instruction method that is used in many large lecture courses around the country.

2009, p. 242). Incentives can include salary increases, tenure, sabbaticals, reduced teaching loads, and teaching awards (Fenker 1977, p. 453). Organizational incentives may vary across faculty ranks affecting who publishes or presents on their use of educational innovations. Most colleges communicate teaching and undergraduate education as a high priority, but incentives at institutions with intense research programs may deter faculty members from spending significant time on their teaching responsibilities. The scholarship of teaching presents an opportunity to meet both goals. Faculty at research universities are expected to present and publish in peer-reviewed outlets. This primarily occurs through scholarly conferences and journals dedicated to sharing scientific or humanities research, but the growth of discipline-specific education journals – including those embedded in scientific research like the Physics Education Research supplement in the *American Journal of Physics* – provide new outlets for publishing on the science of learning. While these new outlets exist, faculty members at research universities may not choose to participate because of perceptions about educational research. It can be viewed as “light” or “lower quality” than traditional research which may discourage research faculty from choosing to publish or present (Henderson 2011). As faculty members evaluate how to spend their time, they may feel this type of research is not worth pursuing for the minimal prestige it will bring.

Incentives can come from outside the organization as well. Faculty members hoping to increase their professional prestige and status on a national or international level will respond to incentive structures within their discipline. A faculty member once told me, “You spend 10-12 years focusing on what the institution wants, but once you get tenure, the reward structure does not disappear. Most tenured faculty members are trying

to make an international name for themselves so they begin to focus on rewards and incentives outside the university.” The perspective may be indicative of a person in a specific faculty role at a particular type of college in which research is highly valued. This opinion will not be shared by all professors, but is likely patterned by faculty rank and type of college.

Faculty members need more than incentives to get their ideas published or accepted for conference presentations. Communication skills and resources are required. Sorting mechanisms in higher education lead tenured and tenure-track faculty to have more experience publishing and presenting. In addition, tenure-track and tenured faculty at research universities often have access to travel funds that enable them to present at conferences. Lecturers are less likely to have such access and most adjuncts have minimal access to such support. Lecturers and adjunct instructors who teach higher loads will also have less time to prepare journal article submissions or propose conference presentations. In addition, these individuals may not have the same skills needed to produce materials that are accepted by peer-reviewed panels. Institutional sorting mechanisms are intended to attract individuals to the tenure-track if they are more likely to have their ideas diffused or accepted within the research community.⁸

2.3.5 Who listens to whom?

Change agents supply information to diffusion networks with the goal of persuading new instructors to adopt. Rogers (2003) defines this persuasiveness as opinion leadership, “the degree to which an individual is able to influence other

⁸ Of course, other life experiences may contribute to the type of faculty positions individuals accept (e.g., parenting demands, spousal occupational choices).

individuals' attitudes or overt behaviors informally in a desired way with relatively frequency" (p. 27). Applying this concept with a sociological perspective raises the question, does a faculty member's social position affect his or her ability to persuade others to adopt an innovation? In other words, do potential adopters filter the message about an educational innovation based on the social position of the information source regardless of whether it is communicated through social-exchange or anonymous-search networks? I have heard tenure-track faculty on multiple occasions say that an innovation might work there (name of teaching/community college), but it will not work here (name of research-intensive university).

How would a faculty member's social position affect the diffusion of educational innovations? In general, early adopters tend to be more cosmopolitan, have higher socioeconomic status, and be seen as more innovative (Rogers 2003). A study comparing characteristics of early adopters versus later adopters of distance education instruction found early adopters tended to have more teaching experience (Hixon et al. 2012). When considering institutional characteristics, Brint et al. (2001) have shown that colleges with large populations and those in close geographic proximity to each other are more likely to adopt new academic programs implemented by nearby institutions. I will explore how characteristics defined by both faculty role and institutional type affect diffusion.

2.4 Research Questions

Ideas do not spread without the interaction of social actors. This project will explore the social dynamics of how diffusion occurs through social-exchange and anonymous-search networks. I am interested in how this interaction leads to patterns of adoption and abandonment and how it is associated with the network of information

potential adopters consult. I am also interested in which adopters choose to influence others by contributing information to these networks, and how their influence is associated with their social position. The following research questions will guide this project.

- What networks of information do faculty members use to learn about an educational innovation they may adopt? How do these networks influence the likelihood of a faculty member adopting and eventually abandoning the innovation?
- How does a faculty member's social position affect his or her decision to become an advocate for an educational innovation by publishing or presenting information about the innovation?

2.5 Hypotheses

2.5.1 Hypothesized Effects of Social-exchange versus Anonymous-search Networks

The process of adoption begins with awareness (Rogers 2003, p. 168). I described how information networks can be categorized as social-exchange and anonymous-search networks. Social-exchange networks are existing or newly-created, person-to-person relationships purposefully used to communicate information about an innovation in which the sender, receiver, and timing of exchange are known within the network. These include face-to-face and electronic communications (e.g., a professor emailing his colleague information about an educational innovation). Anonymous-search networks transmit information about an innovation without involving direct, person-to-person communication. An instructor conducting a web search or attending a conference

presentation would be an example of information transmitted through an anonymous-search network because the author of the information is not aware of who is receiving it.

I am interested in how both types of networks affect faculty members' adoption of educational innovations. Social capital theory suggests that individuals may feel pressure to innovate or adopt innovations in communities with higher amounts of social capital directed at changing or improving instructional activities. These communities can be characterized as those with social-exchange networks that effectively transmit information about educational innovation along with social norms that encourage faculty members to improve or innovate their teaching. Communities characterized by high levels of competition, micropolitics, or negative social capital may lead individuals to choose anonymous-search networks over social-exchange networks to learn more about educational innovations. Social capital can also inhere in anonymous-search networks, but I do not believe it will be as motivationally powerful as social capital within social-exchange networks. This leads me to propose my first hypothesis.

Hypothesis 1: A faculty member's probability for adopting an educational innovation will be higher if she or he identifies social-exchange networks as more influential than anonymous-search networks during the persuasion stage.

I believe the increased effect of social capital in social-exchange networks that lead to higher adoption rates will also lead faculty members to persist in using the innovation and abandon at lower rates.

Hypothesis 2: A faculty member's probability for abandoning an educational innovation will be lower if she or he identifies social-exchange

networks as more influential than anonymous-search networks during the persuasion stage.

This hypothesis parallels Rogers' generalization of how communication channels operate using my conceptualization of diffusion network categories, but I believe a better prediction can be made if the hypothesis accounts for the social position of potential adopters. Social capital that leads individuals to consult social-exchange networks is not equally distributed across groups of faculty members within and across institutions. Over the following sections I will develop more nuanced hypotheses of how instructors are affected by social-exchange and anonymous-search networks based on their social position.

2.5.2 Defining Social Position Through Relevant Social Structures in Higher Education

American higher education comprises a complex array of social actors and institutions. While social networks connect these actors and institutions, their functions and forms vary greatly. It is useful to define relevant social structures in higher education that might influence faculty members' behavior before continuing to hypothesize about how instructors use different networks to learn about educational innovations. Social structure can be defined as "the persisting patterns of behavior and interaction between people or social positions" (House 1990, p. 525). An example of a social structure in higher education is the hierarchy of faculty at a college such as tenured professors, pre-tenure (i.e., tenure-track) faculty members, full-time lecturers, and adjunct instructors. Structural effects are the variations in outcomes across the social system that arise from this structure and are independent of individual effects (Blau 1960, p. 178). I propose

that two dominant social structures in higher education shape how educational innovations diffuse: intra-institutional and inter-institutional structures.

2.5.2.1 Intra-institutional Structure

I believe the primary *intra-institutional* structure associated with diffusion patterns can be characterized by the hierarchy of faculty positions that exist in higher education. I rely on the concept of internal labor markets in defining the categories of this intra-institutional structure. An internal labor market is, “an administrative unit... within which the pricing and allocation of labor is governed by a set of administrative rules and procedures” (Doeringer and Piore 1971, p. 214). This is different than an external labor market in which hiring and salaries are driven by economic variables such as supply and demand. While colleges compete for staff and faculty members within the external labor market, within these institutions bureaucratic rules define how faculty members can move between positions not available to the external labor market. For example, most colleges have tenure and promotion criteria that describe how assistant professors attain full professorship. Assistant professors do not directly compete against other candidates in the external market for the promotion. In addition, these opportunities are generally not available to adjuncts and lecturers. Within colleges are “mobility clusters” in which faculty members are on different career ladders that present different opportunities for advancement (Doeringer & Piore 1971, p.50).

I use these patterns of mobility clusters to develop a classification scheme of faculty that defines the intra-institutional structure for this project: a *tenure-track* career ladder along with a *collection of contingent faculty* – part-time adjuncts and full-time

lecturers (see Figure 2.2).⁹ These faculty positions require different skills, have different institutional expectations and incentives operating on them, and offer different levels of job security. In Section 2.5.3, I describe how I believe the intra-institutional structure interacts with social-exchange networks to affect adoption rates.

2.5.2.2 Inter-institutional Structure

The second relevant social structure I expect shapes teaching practices is an *inter-institutional* structure based on differences in colleges' missions – reflected in the scope of degrees offered and the institution's research, teaching, and service expectations for faculty members. Doctorate-granting universities hire faculty members to teach and conduct research. Associate's colleges primarily hire faculty members to teach. This inter-institutional structure is commonly recognized by accreditation agencies and students applying to college. I will define my structure as a simplification of the Carnegie Basic Classification of colleges and universities – a widely recognized typology of colleges in the American higher education system (Carnegie Foundation for the Advancement of Teaching 2010).

- *Research Universities* – universities and colleges offering graduate degrees with tenured and tenure-track faculty primarily engaged in research activities (e.g., Johns Hopkins University, University of Virginia, Cornell University).
- *Master's Universities* – universities and master's colleges offering graduate degrees with tenured and tenure-track faculty engaged in heavy teaching loads (4+ courses per

⁹ The term contingent faculty is a commonly used term to describe faculty who are outside the tenure-track system. They have fewer academic freedoms and less job security (Roueche, Roueche, & Milliron 1998).

year) and some research activities (e.g., Morgan State University, Towson University).

- *Baccalaureate Colleges* – colleges primarily granting bachelor’s degrees with some research activity conducted by tenured and tenure-track faculty (e.g., Goucher College, McDaniel College).
- *Associate’s Colleges* – colleges offering two-year degrees with few, if any, faculty members conducting research (e.g., Community College of Baltimore County, Maricopa Community College).

2.5.3 How Social Position Affects the Influence of Diffusion Networks

The reason for defining the inter- and intra-institutional structures is to develop more nuanced hypotheses about the likelihood of faculty members adopting and abandoning educational innovations. Specifically, I am interested in how a faculty member’s social position interacts with the effects of social-exchange and anonymous-search networks. I believe variations in institutional culture and mission will have an impact. Institutions with a focus on undergraduate education, as opposed to research, will more likely foster the development of social capital that facilitates conversations about teaching on campus that will lead faculty members to adopt at higher rates and abandon less frequently.

Hypothesis 1a: The positive relationship between the probability of adoption and social-exchange networks will be weaker for individuals in institutions emphasizing research.

Hypothesis 2a: The negative relationship between the probability of abandoning and social-exchange networks will be weaker for individuals in institutions emphasizing research.

Social-exchange networks are not equitably distributed. Adjuncts tend to be more isolated than faculty members with full-time jobs at an institution, and therefore, are less likely to have access to social-exchange networks relevant to teaching. Full-time lecturers may have greater access to these networks, which provides them more opportunities to learn about educational resources and to signal to the academic community that they are continually improving their teaching. Tenured and track-track faculty are the most embedded in social-exchange networks, but those networks are likely comprised of similar faculty because their positions lead them to participate on university committees, research groups, and governing bodies (e.g., academic council, academic senate) that are primarily populated by other tenured and tenure-track faculty members. Institutional characteristics likely influence the topics discussed in these forums. This includes both formal agenda topics and informal communications before and after meetings in which faculty members signal to their colleagues how their work supports the institution's mission. For example, faculty members at research universities may discuss their research accomplishments more often than their teaching activities before and after meetings. This leads me to propose my next hypotheses.

Hypothesis 1b: The negative relationship between the probability of adoption and research institutions will be more strongly negative for individuals with tenure or on the tenure-track.

Hypothesis 2b: The positive relationship between the probability of abandoning and research institutions will be stronger for individuals with tenure or on the tenure-track.

Hypothesis 1c: The positive relationship between the probability of adoption and social-exchange networks will be weaker for individuals with tenure or on tenure-track.

Hypothesis 2c: The negative relationship between the probability of abandoning and social-exchange networks will be weaker for individuals with tenure or on tenure-track.

2.5.4 Hypothesized Effects of Social Position on Change Agency

The previous hypotheses describe the influence of social-exchange and anonymous-search networks on potential adopters. This assumes someone is contributing information to the networks for others to receive. These contributors are what Rogers calls change agents. He defines change agents as resources who actively promote the innovation with the goal of increasing its adoption (Rogers 2003, p. 366).¹⁰ They play a key role in the diffusion process by sharing information and persuading others to adopt the innovation (Rogers 2003). I am curious as to which adopters transition into change agents. Again, I believe this can be understood through the inter-institutional and intra-institutional categories described above.

Section 2.3.4 describes how faculty members may be motivated to become change agents through sorting mechanisms and organizational incentives. I believe

¹⁰ Rogers defines a change agent as an individual or an organization. For this project, I am investigating faculty change agency and am only referring to change agents as individuals.

sorting mechanisms more frequently place faculty members who have experience publishing and presenting on their disciplinary scholarship into tenured and tenure-track positions. I expect this experience will be associated with faculty adopters being more likely to publish and present on educational innovations as well. The effects of sorting mechanisms will be tempered or amplified through organizational incentives. I expect that organizational incentives at research universities will place less value on educational research. This will result in faculty members at research universities becoming change agents less frequently than faculty members at teaching colleges. This logic is reflected in the following two hypotheses.

Hypothesis 3a: Tenured and tenure-track faculty members will more frequently publish and present in anonymous-search networks on educational innovations they have adopted compared to lecturers and adjunct faculty members controlling for innovation category.

Hypothesis 3b: Teaching incentives at baccalaureate colleges will lead their faculty members to publish and present more frequently in anonymous-search networks on educational innovations than colleagues in the same social position at research universities and associate colleges controlling for innovation category.

2.5.5 Hypothesized Effects of the Relative Difference in Social Position of Influential Faculty Members on Potential Adopters

I am interested in how a change agent's influence is associated with his or her relative social position compared to the potential adopters with whom she or he engages. Rogers defines this persuasiveness as opinion leadership, "the degree to which an

individual is able to influence other individuals' attitudes or overt behaviors informally in a desired way with relatively frequency" (Rogers 2003, p. 27). This persuasiveness is related to how well the change agent communicates that the innovation is applicable and useful to the potential adopter (Rogers 2003, p. 423). Potential adopters want to see data and evidence that the innovation will work for them in their particular context. I expect the strength of this opinion leadership will also be associated with the social structures described above. That is, potential adopters will also be influenced by the power and prestige associated with the change agent.

Mobility clusters used to categorize faculty members can be grouped into easily recognized "above" and "below" the line statuses. I expect tenured and tenure-track faculty will be less likely to adopt ideas from instructors "below" the line. In addition, the nature of degrees awarded and competitiveness of students attracted to different types of schools leads to a hierarchy of schools. Research-intensive universities dominate school rankings and media coverage. I expect faculty members recognize this hierarchy of prestige and filter information based on the social position of the author which includes the home institution. If this is true, then variations in opinion leadership across the social structures described above would more likely result in innovations disseminated from tenured and tenure-track faculty at research institutions (see Figure 2.3).

Does opinion leadership have the same impact across all of Rogers' stages of adoption? The previous explanation assumes that all faculty members have access to information from all sources of information. This would be more likely to occur if faculty members were primarily using anonymous-search networks to become aware of

and make decisions about an educational innovation and these networks were completely open. My first hypothesis, however, states that instructors are more likely persuaded through social-exchange networks, not anonymous-search networks. This would primarily occur across faculty members within a similar institution type and most acutely within an institution. If this is the case, I expect Figure 2.3 primarily describes the authority opinion leaders exercise during the knowledge stage. Figure 2.4 shows how opinion leadership operates in the persuasion stage when the use of social-exchange networks becomes more dominant. The thicker lines of the columns show that the influence is greater within institutional type than across all institutions.

While an opinion leader's influence functions differently across Rogers' stages of adoption, the result is similar. The following hypothesis flows from this conceptualization of how instructors use anonymous-search and social-exchange networks to learn about and make decisions on using educational innovations.

Hypothesis 4 - Faculty members will more frequently cite instructors from the same institutional category than from the same faculty rank as an influential source of information about an educational innovation.

2.6 Research Design

I use quantitative case studies to test the hypotheses. I created the cases by surveying faculty members in the United States who had become aware of three different educational innovations.¹¹ The surveys asked potential adopters how they became

¹¹ The original research design included surveying the population of a fourth innovation, Peer Instruction. This survey was completed, but I decided to not use the data in the analysis because of extremely low response rates (six percent). One reason for the low response rate was the Peer Instruction team decided not to allow me to survey the population directly as I did with the other innovations. This

familiar with the tool, who influenced them to adopt or not, and whether or not they became a change agent for the innovation. I also used archival data (e.g., user logs, workshop registrations) when available to augment the survey data.

I purposefully chose not to survey faculty members about their use of any educational innovation. The quantitative case studies facilitate comparative analyses within the population of faculty members who became aware of each innovation. I can create an event history of potential adopters' use patterns that also serves to support a longitudinal analysis of each innovation's diffusion history. I can explore how faculty adopters became change agents and potentially affected later adopters. Using three case studies allows me to compare diffusion patterns that account for each innovation's unique characteristics.

2.6.1 Criteria for Choosing Innovations for the Case Studies

My definition of an educational innovation is *an instructional method, content, or assessment technique perceived as new by an instructor or other unit of adoption (e.g., academic department, institution)*.¹² I used the following criteria to choose the cases.

- Broadly diffused – The innovation should be used by a significant population of faculty members (over 150) who teach at institutions in each of the categories of colleges listed in Section 2.5.2.2. I did not choose ubiquitous educational resources in which diffusion has stabilized at its upper limit (e.g., use of classroom projectors, Microsoft PowerPoint) because the dynamics across the diffusion process are likely so dated that faculty responders would

decision was made after I began data collection activities for the other innovations. A full description of the data collection activities for Peer Instruction are provided in Appendix E.

¹² See Chapter 1 for a description of how this definition was developed.

have a hard time remembering their adoption experience (e.g., “Tell me about your first time using PowerPoint”).

- Diffused primarily across individuals rather than institutions – While a study of institutional adoption would be interesting, the diffusion process is different because of the significant barriers limiting the spread of innovations that must be adopted at the institutional level. These include enterprise-wide coordination of resources, higher costs, and mandates that may be driving adoption (e.g., accreditation reporting).
- Used across disciplines – Choosing innovations that can be implemented in any or most undergraduate courses minimizes one barrier to adoption, disciplinary irrelevance, which may affect diffusion patterns.
- Adopted with minimal adaptation – I did not want to choose innovations that could be easily adapted as this would make it difficult to compare faculty experiences and control for derivative innovations that were significantly different than the original innovation.
- Well-documented adoption – I chose educational innovations that have a clear record of awareness, such as those that require central registration before implementing. Ideally, the entire population of individuals aware of the innovation would be known but this level of documentation is rare. The innovations chosen have accurate records of instructors who requested information, created test accounts, or formally adopted the educational innovation. I used snowball sampling techniques to recruit undocumented

faculty members to capture as much of the entire population of potential adopters as possible for each of the three innovations.

2.6.2 Educational Innovation Case Studies

My definition of educational innovation includes three categories: *instructional method, content, and assessment*. The innovations selected for my case studies will be chosen from the instructional methods and assessment categories to explore how the diffusion process may differ across innovation types. I did not choose a content innovation. Instructors regularly incorporate new content into their teaching, but often this content is discipline specific. It would be difficult to identify content adoption that has broadly diffused across many different course subjects so it will not be explored in this study.

2.6.2.1 Calibrated Peer Review

Calibrated Peer Review (CPR) is a web-based software application in which students submit writing samples to a website, and their classmates are randomly assigned to provide feedback. Author and reviewer identification remains anonymous. CPR was developed at the University of California, Los Angeles, with funding from the National Science Foundation and Howard Hughes Medical Institute (Schimpf 2002).

I met Arlene Thomas, the manager of the Calibrated Peer Review software, at the Fall 2010 Reinvention Center conference in Washington, D.C. Originally, she planned to give me contact information for every registered account, but a technical problem with the user database prevented that after I began the research project. Instead, she provided access to the administrator for each institution. CPR requires accounts be managed through an institutional administrator. For example, I became the Johns Hopkins

administrator when I became the first person from the university to create an account. Any Johns Hopkins faculty member would then contact me to create an account.

2.6.2.2 Peer-led Teaming Learning

Peer-led Team Learning (PLTL) is a peer-student tutoring program that complements a course in which, “six to eight students meet with a peer leader for 1.5 to two hours per week to discuss topics and solve problems that reinforce lecture and textbook learning” (Gafney & Varma-Nelson 2008, p. 1). Students solve homework-like problems using standardized workshop activities under the guidance of a peer leader – an undergraduate who has taken the course, received a high grade, and been formally trained on facilitating the PLTL approach. “The workshop problems and activities are constructed to reinforce these goals and provide relevant applications” (Gafney & Varma-Nelson 2008, p. 1).

This instructional method was founded in the early 1990’s and diffused to over 150 colleges (approximately 1-3 faculty members at each school) over the next 20 years through the support of a National Science Foundation (NSF) grant. Dr. Pratibha Varma-Nelson, a principal investigator on this grant, provided support to me including a list of faculty members who attended PLTL workshops. She also provided publications that listed many of the institution that have adopted PLTL.

2.6.2.3 Student Assessment of Learning Gains

The Student Assessment of Learning Gains (SALG) instrument measures students’ perceptions of how different components of a class helped them learn (Seymour et al. 2000). It is typically used as a complement to traditional course evaluations. Survey questions can be shared across courses and by instructors at different universities.

Students' responses remain anonymous, but aggregate course results can be compared among similar courses. Stephen Carroll, the current SALG director, and Mel Ganus, a research associate working on the project, provided access to the complete user log which included which semesters each account holder used the innovation. This was the only innovation for which I had this detailed use information.

2.6.2.4 Comparison of CPR, PLTL, and SALG

The three educational innovations chosen met the criteria for selection. They are broadly diffused with fidelity across individuals, not institutions. They are applicable to different disciplines. There are detailed records documenting most or all of the population that became aware of the innovation. The innovations were also chosen to reflect different characteristics to facilitate comparative analyses. See Table 2.1 for a summary of these different characteristics as described in the following subsections.

2.6.2.4.1 Pedagogical versus Technological Innovations

SALG and CPR are both technological innovations. Potential adopters must register for an account through the respective website. An instructor also implements both tools through the website by providing student access to it through a URL. PLTL is a purely pedagogical innovation (i.e., not requiring digital technology). Student groups work on problem solving skills in a classroom facilitated by advanced undergraduates.

2.6.2.4.2 Barriers to Adoption

Another difference among the innovations is the barriers to adoption. SALG is the easiest to adopt. Faculty members create surveys in which they can reuse survey questions and templates shared by other users. The faculty member then sends students a URL for them to access the survey. Because it is a supplemental assessment tool it does

not require the instructor to change anything about his or her course. CPR adoption is slightly more complicated than SALG. CPR assignments can be created with existing templates, and faculty users can borrow assignments questions from existing surveys. It is similar to SALG in that way. However, faculty members must prepare students for the assignment and arrange their course schedule to accommodate it. This makes it more disruptive to adopt than SALG.

The most complicated innovation to adopt is PLTL. Faculty members must recruit and train advanced undergraduates who lead the sessions. Schools usually identify funding to pay peer leaders or coordinate with the Registrar's office to grant course credit for student leaders' assistance. Classrooms and student groups must be scheduled. Faculty members or graduate students must also write the problem sets that student groups solve each week. These are significant institutional barriers to address making PLTL the most time and resource intensive to implement of the three innovations.

2.6.2.4.3 Structure of the Support Community

Another difference between the innovations is the structure of the support community associated with each innovation. PLTL has the largest community and is the least hierarchical. The decentralized community structure was purposefully created by the original founders. The founders drafted a dissemination strategy in the early years that was based on a decentralized model in which local users advocated for PLTL at their home institution and regional colleges (Gafney & Varma-Nelson 2008, p. 30). They applied for and received a series of NSF grants to implement this strategy. There are clearly recognized change agents associated with PLTL in its community (e.g., Jack

Kampmeier, Pratibha Varma-Nelson), but there are a number of other committed advocates who teach workshops to train future faculty adopters, run PLTL conferences, and advise new adopters on how to implement PLTL for the first time (Gafney & Varma-Nelson 2008, p. 33). In this way, PLTL had an established social-exchange network dedicated to the innovation managed by a decentralized community.

CPR support structure is much more centralized. Dissemination is primarily led by Arlene Russell, its founder. While there are users who became change agents advocating for others to adopt it, CPR technical and user support is centralized at UCLA with Dr. Russell's team. SALG's community of support falls between these two characterizations. SALG was developed by Elaine Seymour of the University of Colorado, Boulder. Overtime, other STEM educators played important leadership roles including Bob Mathieu at the University of Wisconsin, Madison. Oversight of SALG is now guided by Stephen Carroll of Santa Clara University. SALG has developed a community of support from those who have stepped into leadership roles. However, it is not a large decentralized support community like PLTL.

2.6.2.4.4 Initial Development and Grant Funding

The motivation for creating each resource was slightly different. The CPR project originated from work at the University of California, Los Angeles, to meet the needs of a specific course before it was shared. CPR received funding from the National Science Foundation and Howard Hughes Medical Institutes for development. SALG originated from the work of several modular chemistry consortia. Therefore, its launch originated with a pre-existing diffusion network that could be used to disseminate it. SALG originally received funding from the Exxon-Mobil Education Foundation, but has also

received support from NSF to increase adoption. PLTL was developed among a group of instructors at several universities like SALG, and as described above, acquired funding from NSF to implement a dissemination strategy that funded the creation of a decentralized community of support. Not surprisingly, the patterns of initial development are similar to the structure of the support community. CPR started in a course at UCLA and support continues to be centralized at this location. PLTL was started by a group of instructors at different institutions. These innovators decided to disseminate it through a decentralized support community.

What is common about the initial development for all three resources is the reliance on grant funding to develop, and in some cases to disseminate. There were multiple sources of funding, but all three communities received funding from the National Science Foundation at some point.

2.6.2.5 Summary of Key Characteristics for Educational Innovations

The three innovations listed above meet the criteria for inclusion described in Section 2.6.1. One of the criteria used to choose each innovation was that a large number of individuals had adopted it. I recognize that diffusion research has been criticized for focusing on innovations that have broadly diffused (Rogers 2003, p. 106). While there is a long history of diffusion research in general, it is less widespread in education. Focusing on successful diffusions is important as there is still much to understand about the processes, especially in higher education. Moreover, my research design – studying faculty members’ experiences through the life course of three selected innovations – will be able to account for the dynamics of abandonment because the life course of the innovations under study includes individuals who tried, but did not sustain their use of

the innovation. In addition, some instructors are slower to adopt than others who immediately adopted after learning about the innovation. These delayed and abandoned adoptions are excellent sources for understanding how social contexts can limit the diffusion process.

An unintended, commonly-shared trait between the innovations is that each project originated from the chemistry education community. The first SALG survey was developed by Elaine Seymour, Director Ethnography & Evaluation Research, at the University of Colorado, drawing directly on her findings as evaluator for ChemLinks and ModularChem. The original SALG website was developed by Sue Lottridge from the University of Wisconsin. She also was part of the evaluation team for a third major chemistry education reform initiative, “New Traditions.” Arlene Russell led the development of the CPR application. She is a chemistry lecturer at UCLA. PLTL was founded by Jack Kampmeier a chemistry faculty member at the University of Rochester. I became aware of these innovations from faculty members in different disciplines, but later realized they all originated from the same discipline-based education research domain.

2.7 Modeling Procedures

After creating the case studies I conduct my analysis using descriptive statistics and appropriate modeling procedures. I use survival analysis and discrete-time hazard models to test Hypotheses 1, 1a, 1b, 1c, 2, 2a, 2b, and 2c; Poisson regression for Hypotheses 3a and 3b; and multinomial logit modeling for Hypothesis 4. Details on each are provided in the following sections.

2.7.1 Testing Hypotheses 1, 1a, 1b, 1c, 2, 2a, 2b, and 2c

The first two sets of hypotheses explores the association between a faculty member's likelihood of adopting and abandoning an innovation with how influential she or he reports social-exchange and anonymous-search networks were in the decision-making process. I tested these hypotheses with survival analysis and hazard models. The survival function can be generally expressed as the following.

$$(1) S(t_{ij}) = Pr[T_i > j]$$

where $S(t)$ is the conditional probability of not adopting (abandoning) an innovation at time t given that no adoption (abandonment) occurred by t .

The discrete-time hazard models can be generally expressed as the following.

$$(2) \ln[h(t)] = \alpha + \beta_1 S + \beta_2 R + \beta_3 T + \beta_{12} S^*R + \beta_{23} R^*T + \beta_{13} S^*T$$

where $h(t)$ is the conditional probability of adopting (abandoning) an innovation at time t given that no adoption (abandonment) occurred before t .

and:

S = social-exchange network awareness dummy variable (anonymous-search networks are reference)

R = research universities dummy variable (all other types of colleges are reference)

T = tenured or tenure-track dummy variable (lecturers and adjuncts are reference)

An individual enters the risk set for adoption when she or he formally expresses interest in learning more about an innovation. One enters the risk set for abandonment when first adopting the innovation. Right censoring in the adoption models is applied to individuals who are aware of an educational innovation but have not adopted as of the survey date.

Right censoring for the abandonment models is applied to individuals who have continued to use the educational innovation up to the survey time.

2.7.2 Testing Hypotheses 3a and 3b

My third set of hypotheses explores the probability that a faculty member will publish or present about his or her experience using an educational innovation. Poisson regression is used because the dependent variable is count data in which I expect many of the respondents will report having made no presentations or publications about the innovation under study. These models can be generally expressed as the following.

$$(3) \log[p] = \alpha + \beta_1 I + \beta_2 T + \beta_3 C_{RI} + \beta_4 C_{SR} + \beta_5 C_A + \beta_{23} T * C_{RI} + \beta_{24} T * C_{SR} + \beta_{25} T * C_A$$

where p is the expected value for presenting (publishing) on an educational innovation in an anonymous-search network.

and:

I = innovation category

T = tenured or tenure-track dummy variable (lecturers and adjuncts are reference)

C_{RI} = inter-institutional category of adopter (research-intensive university)

C_{SR} = inter-institutional category of adopter (some-research university)

C_A = inter-institutional category of adopter (associates college)

2.7.3 Testing Hypothesis 4

The last hypothesis explores which faculty categories adopters identify as having the most influence on their decision to implement an innovation. These models can be generally expressed using a multinomial logit model with the dependent variable

described by 8 categories ($J=8$) created by intersecting relative faculty rank and relative institutional status.¹³

$$\log(p_j/p_J) = \beta_0 + \beta_j F + \beta_j C + \beta_j I$$

where $\log(p_j/p_J)$ is the log odds of a potential adopter naming a disseminator in position j compared to a baseline category as the most influential.

and:

F = Faculty rank of potential adopter

C = Institutional category of potential adopter

I = innovation category

2.8 Conclusion

The chapter described the theoretical framework used to conceptualize this project. I presented my hypotheses and the research design built around quantitative case studies. The next chapter describes the data collection activities used to create the quantitative case studies for the three innovations chosen for this study.

¹³ Except at noted for full professors and adjuncts which are subject to ceiling and floor effects, respectively, as noted above.

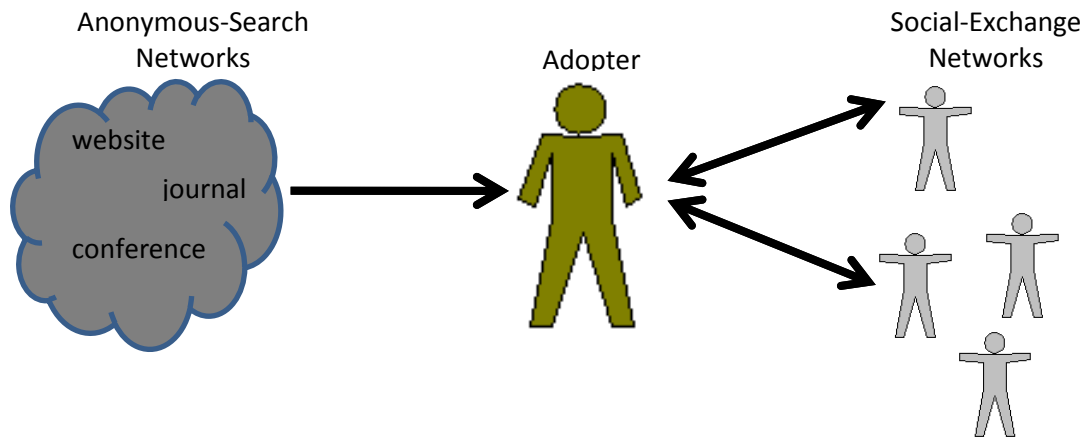


Figure 2.1: Anonymous-search and Social-exchange Networks

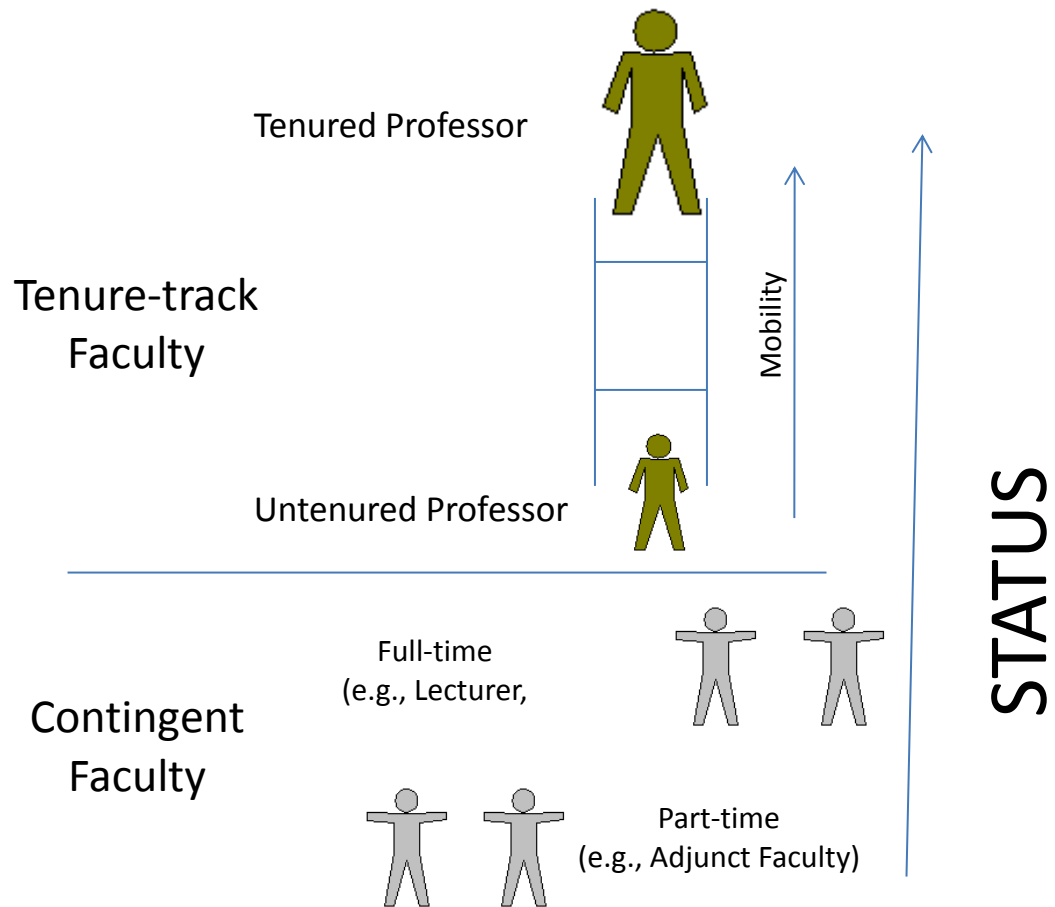


Figure 2.2: Hierarchy of Faculty Positions in Intra-institutional Structure

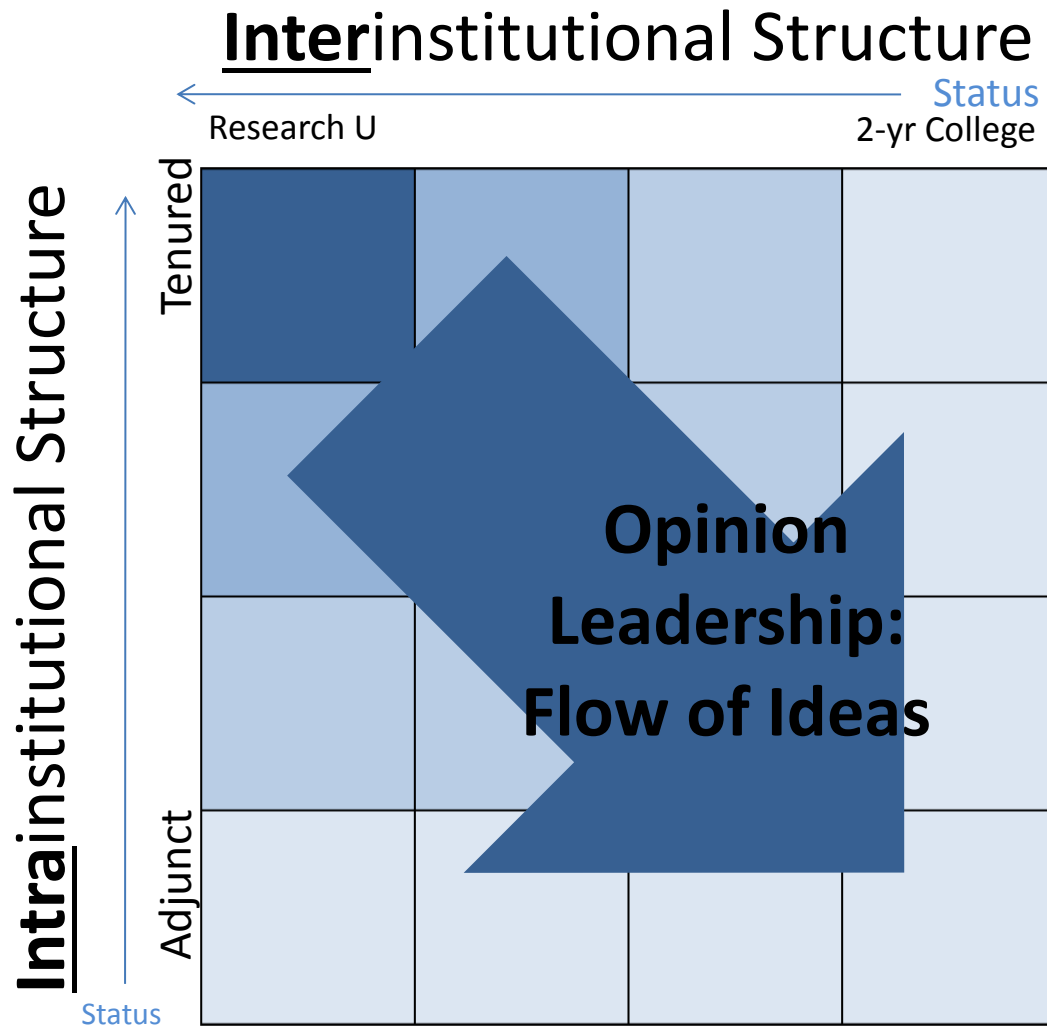


Figure 2.3: Variations in Opinion Leadership in the Awareness Stage Across Intra- and Inter-institutional Structures

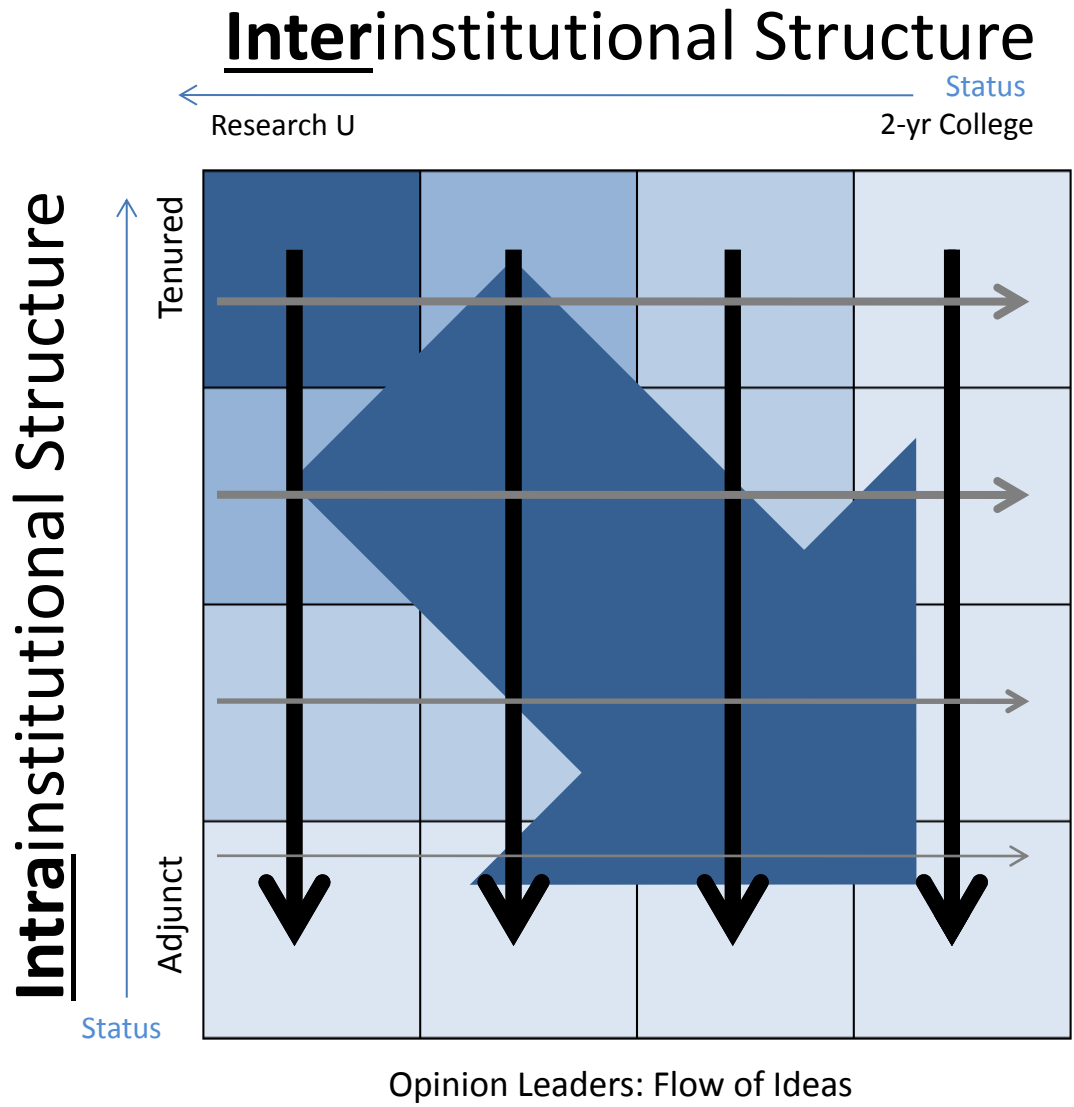


Figure 2.4: Role of Opinion Leadership in Persuasion/Decision-Making Stages in which Social-exchange Networks Dominate

Table 2.1 Characteristics of Educational Innovations Studied

Characteristic	CPR	PLTL	SALG
<i>Technology-based</i>	Yes	No	Yes
<i>Barriers to Adoption</i>	Medium	High	Low
<i>Classroom Integration</i>	Class Assignment	Supplemental	Supplemental
<i>Community of Support</i>	Intensely Centralized	Decentralized	Weakly Centralized
<i>Initial Development</i>	Arlene Russell	Consortia	Consortia

III. Data Collection Activities Used to Create the Quantitative Case Studies

I created the quantitative case studies through surveys and available user logs. Surveys allowed me to capture how potential adopters were influenced by social-exchange and anonymous-search networks. These data were not available from other sources. I was able to take advantage of user logs for the Student Assessment of Learning Gains (SALG) population and registration files for Calibrated Peer Review (CPR) and Peer-led Team learning (PLTL). However, I primarily relied on surveys of potential adopters for each innovation to collect the data I needed. This chapter describes how the surveys were piloted, which populations were surveyed, and the resulting response rates for each group. It also describes how the variables used in the analysis were created from the survey data.

3.1 Piloting the Surveys

Before launching the surveys I piloted them with faculty members from different institutions in two phases. First, I sent my dissertation advisors, Professors Stephen Plank and Lingxin Hao, a link to the draft survey. I included a scenario to guide them in answering the survey questions because they had not used the innovations chosen for the study.

Example Email Scenario: You just started working as an assistant professor at Johns Hopkins University in the Humanities Center. You decided to use the SALG survey to assess student perspectives in the first class you taught this past semester. You first learned about SALG as a TA in your advisor's class 3 years ago.

I edited the survey based on their feedback. Comments ranged from adding skip logic, changing question formats, clarifying ambiguous instructions, and correcting inaccurate instructions (e.g., “* = required question” but no questions were required).

I then asked 20 faculty members at Johns Hopkins and other institutions to take the survey. Each participant received a scenario based on his or her faculty role and home institution similar to the previous example. Several of these individuals had previously used the tool so I asked them to respond to the survey as if they were completing it as a respondent. The faculty members provided suggestions for improvement, noted confusing questions or instructions, and reported how long it took to complete the survey. Respondents reported taking between 12 and 21 minutes to complete the survey. Changes to this second version were minimal. I reformatted questions to make them easier to answer (e.g., using rating matrices) and clarified instructions (e.g., gave examples of publishing or presenting). The most significant change was adding “Don’t remember” and “Did not teach” options for the question asking respondents when they used the innovation.

The survey questions were the same for the CPR and PLTL populations (see Appendix A). I included branch logic to minimize the time to complete the survey. If someone reported having published or presented on the innovation, she or he was then taken to a second page and asked to list up to three publications or presentations they authored. Respondents also rated how different sources enabled or hindered their publishing using a Likert-scale matrix on this survey page (e.g., personal commitment to improve teaching, formal incentives at institutions, desire to gain status).

The SALG survey was based on the CPR and PLTL surveys, but did not include questions which I could collect or impute from the user logs. I was also able to customize the SALG survey for different groups. For example, I knew who registered for an account but did not implement the SALG instrument (i.e., non-users). These non-users were sent a shorter survey in which irrelevant questions were removed such as, “Did you present, publish, report, or formally communicate your experience implementing SALG to a public audience?” I also did not have to ask users to report when they used the tool because this information was documented in the user logs. This was important because the SALG population was the largest group I directly surveyed ($n \sim 3,000$). I expected that customizing the surveys would improve response rates. The SALG group was planning a major change to their website along with a service expansion so they added six questions to my survey that I did not use in my analysis. They required that I include these questions in return for providing the user logs.

3.2 Conducting the Surveys

I used an online survey tool, Survey Monkey, to conduct my surveys. I imported the population names and email addresses into the Survey Monkey address book. The major benefit of the online survey tool was that I could track who had responded and only send email reminders to non-respondents. I could also use the mail merge function to customize the survey invitation. For example, the SALG user invitations referenced how many times the individual had launched a SALG survey: “From a report we just ran, it looks like you’ve implemented __ surveys.” The goal of customizing the surveys was to make them more personally relevant so the individual would be more likely to respond.

For all the innovations I crafted personal invitations when I had unique information about the individual. Examples include the following.

- “We met at the New Media Consortium Conference in 2010. Thank you for your feedback on my dissertation proposal.”
- “Congratulations on winning a teaching award at _____.”
- “I read your article on PLTL in the *Journal of Chemical Education*.”

I sent two reminder emails to all non-respondents. The Survey Monkey collector tool allowed me to send an email invitation that appeared to originate from any personal email address. Therefore, my third reminder email was sent under the signature of a broadly recognized leader associated with each innovation. The following individuals gave me their permission to send the invitation with their signature.

- Arlene Russell for CPR
- Pratibha Varma-Nelson for PLTL
- Stephen Carroll for SALG

3.3 Population Descriptions and Response Rates for Each Innovation

This subsection describes how I collected the contact information for each innovation’s population along with the response rate for each group. For all three innovations I only surveyed faculty and staff members in the United States. There were some international institutions represented in the lists provided, but I was not sure the social structures I used to motivate the hypotheses would be relevant so I limited the study to U.S. institutions. The following subsections provide more detail about the survey process and response rates for each innovation.

3.3.1 Calibrated Peer Review (CPR)

My liaison, Dr. Arlene Russell of UCLA, was not able to share the entire database of registered users because of technical limitations of the database design. I was able to survey all registered administrators. CPR administrators are the individuals at each institution who first used the resource on their campus and are responsible for creating accounts for subsequent users. This information was publicly available on the CPR website. The original list of administrators included 719 institutions. I deleted all non-college/university institutions (e.g., high schools, middle schools), colleges not in North America, or duplicate entries. This reduced the list to 399 schools.

I sent email invitations and 2 reminders to all 399 people. Of those, 2 people had died and 53 messages were returned as undeliverable because of an incorrect or inactive email address. I was able to identify new contact information for 31 of these individuals through Internet searches. I received 182 responses at that stage.

In mid-summer 2012, Arlene Russell contacted me to offer to send my survey to all registered users because they were sending a bulk message to announce new features. This email went to approximately 3,000 - 3,200 users. They did not know the specific number because of the poor database design, which prevented them from identifying duplicate addresses, old email addresses, or non-addresses. I received 151 responses from this bulk email. Thirty-two responses were on my original administrator list. All but six responses of these 32 were duplicates from my original invitation. In total, I had 188 out of 399 responses from the original admin list (47.1 percent).

I included a question on the survey asking for email addresses of individuals the respondent knew used CPR at least once. This was part of a snowball sampling strategy

to capture users not on the administrator list (Goodman 1961). The administrators provided contact information for 55 non-administrative users; 19 responded when invited to take the survey. These 19 individuals could be combined with the 119 non-administrator responses I received from the bulk email sent by Arlene Russell, but I have chosen not to include them in my analysis. A study of all known users would be problematic because the response rate is extremely low (< 5 percent) based on estimates of the number of users (3,200). Because I was only able to survey the administrators in a systematic way, the CPR population is better described as early adopters at each campus than as the total population of users. I make this clear when interpreting the data in the analytic chapters.

3.3.2 Peer-led Team Learning (PLTL)

The list of PLTL potential adopters is not exhaustively documented like a technological innovation because instructors do not have to register on a website to use or download PLTL. Workshops, however, were facilitated through a National Science Foundation (NSF) grant and the principal investigators have detailed records of institutions that requested information or attended PLTL workshops. Dr. Pratibha Varma-Nelson, a principal investigator on the NSF-funded PLTL project, supported me by providing documentation that included an extensive contact list of 202 individuals. I then conducted a general web search to identify schools and individuals not on this list. I identified 14 additional individuals. Dr. Varma-Nelson reviewed the combined list of names and provided another 10 names for a total of 226 individuals.

I then conducted a literature review of PLTL publications to identify additional users or support staff listed as authors along with institutions mentioned in the article. I

hired a student to help with this process. We searched the list of publications on the PLTL website and conducted a literature search using the terms “peer + led + team + learning” in the following sources.

- Google Scholar – My criterion was to continue searching until no new resources were listed on two consecutive search result pages. This led me to pull articles from the 20 pages of results.
- ERIC – One of the leading databases for education literature.
- Wilson – A database that contains a listing of journals across multiple domains including education research.
- Wikipedia – This page provided a history of the program and listed several references in its bibliography.

All of the articles were reviewed to identify which discussed the PLTL program under study and identify the name of any individual or institutional users. The results of that review are the following.

- 207 articles were identified as relevant from the title.
- 81 articles were removed from the analysis after a review of the abstract (i.e., they did not describe the PLTL program under study)
- 35 new institutions or individuals were identified from the remaining 126 articles. I conducted a web search to identify local contact information for the institutions and individuals identified from the article search.

The 35 names were added to the 226 from my original list ($n = 261$). I categorized the names as user of PLTL, publisher on PLTL, or leader of PLTL. Leaders were identified by Dr. Varma-Nelson. I used these categories to customize my invitation

email so users would be more likely to respond to my survey. For example, I referenced a publication found in my literature review when inviting authors to take my survey. Thirty-six of the 261 email invitations were returned because of outdated or incorrect contact information. I was able to find current contact information for 22 of these individuals through a web search.

Snowball sampling was used to identify additional users that were not captured in the original lists. Respondents provided the names of 54 new individuals who I surveyed in a second phase, along with 54 users who were already in my population list. The overall response rate was 50.5 percent with the subgroup response rates as follows.

- Original list: 114 out of 226 (50.4 percent)
- Additional users identified from publications: 19 out of 35 (54.2 percent)
- Referrals from survey respondents: 26 out of 54 (48.1 percent)

3.3.3 Student Assessment of Learning Gains (SALG)

The SALG team provided the most complete list of potential users. Instructors create an account on the SALG website. I was able to acquire a complete list of the account holders and their registered email address as of January 2012. There are 3,584 accounts listed in the database. I dropped 571 individuals from my analysis because they did not meet my population definition. Specifically, I dropped:

- Users who signed up with multiple email addresses
- Users not affiliated with a university (e.g., high school, learning technology company, professional development training firm)

- Users who employed SALG surveys for non-course work.¹⁴

Having the user logs allowed me to group the population into categories based on their implementation history. This allowed me to customize the survey and the email invitation to each group (see Appendix B for example emails). The 3,013 users were classified into the following categories. I provide response rates for each group.

- Beta users (*response rate: 45 out of 72 – 62.5 percent*) – I piloted the survey with the SALG team’s appended questions to a group of regular users who have interacted with the SALG team members. This survey included an additional question for participants to provide feedback on the survey. This was done after my initial survey pilots described in Section 3.1. *Based on the beta-users feedback, minimal changes were made to my original survey questions beyond simple word changes to clarify the question stems. Substantive changes were made to the SALG team’s original questions but these do not affect my analysis so beta users were not asked to complete a second survey.*
- Frequent Users (*response rate: 264 out of 444 – 59.5 percent*) – users with five surveys and more than 25 student responses in total across those five surveys. The SALG team and I chose a cutoff of 25 responses because this

¹⁴ Several NSF-funded projects were required to use SALG to assess their programs. My survey questions (e.g., faculty rank, years teaching, how often do you talk about teaching with faculty or administrators, what influenced you to use SALG) were not appropriate for these users because they were mandated to use SALG and most were not faculty. For example, these included staff members who coordinate Undergraduate Research Student Self Assessment (URSSA) programs, Research Experience for Undergraduate (REU) initiatives, Science Education for New Civic Engagements and Responsibilities (SENCER) activities, and Great Lakes Innovative Stewardship through Education Network (GLISTEN) programs.

appeared to be a clear threshold for separating accounts with a large number of responses across all the surveys.

- Regular Users (*response rate: 162 out of 476 – 34.0 percent*) – Two metrics were used for this group: 1) Users with four surveys or fewer or 2) anyone with five or more surveys and fewer than 25 responses.
- Non-users (*response rate: 447 out of 2,021 – 22.1 percent*) – These registered individuals set up an account and collected 0 or 1 response. It was assumed they set up an account to create a test survey to explore the SALG tool, but never collected any student data.

The overall response rate was 30.5 percent. This number is skewed by the low response rate for the largest survey group, non-users, that made up 66.6 percent of the population. Invitations to 53 out of 992 users were returned because of inactive or incorrect email addresses. I was able to identify 15 current addresses through a web search. My invitations were returned for 220 out of 2,021 non-users.

3.4 Respondents' Follow up Questions

Over 320 individuals contacted me directly with questions or comments after receiving my survey invitation. I personally responded to every one of these email communications. Their reasons for contacting me varied (see Table 3.1 for categorization of requests). Over 90 individuals asked me whether they should complete the survey because they were not actively using the innovation, had never used the innovation, or had retired. I explained why I wanted them to respond by providing additional information about the project. I was surprised by how many individuals told me they would take the survey later or asked for a reminder in several weeks ($n = 44$). I

sent reminders to all these individuals if they had not taken the survey after three weeks. I also received general comments from individuals about my research or the innovation itself ($n = 146$). Comments included best wishes on my dissertation, details about their experience using the resource, and explanations of why they liked the resources. I received a few technical support requests for PLTL and CPR. There were many more requests for SALG. Help requests were forwarded to the appropriate person supporting each innovation ($n = 26$).

3.5 Preparing the Data for Analysis

This section describes how the survey data were used to create key variables for analysis. See Appendix A for list of survey questions referenced in this section. The descriptive statistics (e.g., central tendencies, dispersion) are not provided in this section because the statistics differ among the analyses presented in each chapter. While the independent variables used throughout this project are similar, the populations analyzed are not. In Chapters 4 and 7, the analyses are conducted on the data for all respondents. In Chapters 5 and 6, the analyses are conducted on respondents who reported adopting an innovation.

3.5.1 Dependent Variables

For the first two sets of hypotheses there are two dependent variables measuring 1) faculty adoption and 2) abandonment. The risk set for adoption is anyone who is aware of the innovation. The risk set for abandonment is anyone who used the innovation at least once. CPR and PLTL respondents reported every academic year they used the innovation through a calendar matrix. The first year a person reported using the innovation was defined as the year of adoption. “Don’t remember” was an option for

which I imputed the data as described in Chapters 4 and 5. The unit of time, academic year, was assumed to start in September and end in August. I used the SALG user logs to identify the year of adoption for the SALG respondents.

Abandonment is measured through a targeted question asking the respondent's future intention to use the tool. It is important to differentiate between a decision to abandon an innovation and a prolonged period of not using the innovation. Respondents who chose "Do not plan to use it again" were assumed to have abandoned it. Respondents who chose "May use it again" and "Definitely plan to use it again" were not interpreted as abandoning the innovation.¹⁵ The year of abandonment for those who reported they did not plan to use the innovation again was defined as the year after their last reported use.

The third set of hypotheses predict the likelihood of a faculty member becoming a change agent based on his or her social position. Survey respondents were asked, "Did you present, publish, report, or formally communicate your experience implementing _____ to a public audience?" Those who reported they did were asked to list up to three examples including when and in what forum each occurred. This information was used to check the validity of the response. I limited the request to three because I did not want to burden respondents with an excessive request that led them to stop answering survey questions. In making this decision, I expected very few instructors had presented or published more than three times because they were adopters, not innovators responsible for the initial diffusion and support of the educational innovation.

¹⁵ A more detailed explanation of why I interpreted responses this way is provided in Chapter 4.

The submissions for these questions were used to create two measures of change agency. First, respondents were coded as being a change agent if they answered “Yes” to the question about publishing or presenting. Second, I created a change agent intensity measure represented as a count variable for the number of publications or presentations about an educational innovation the respondent listed. Chapter 5 includes separate analyses for both measures of change agency.

For Hypothesis 4 the dependent variable is a categorical variable derived from a respondent’s report of the relative social position of the individual who influenced him or her most. The survey allowed respondents to separately report the relative position on the intra- and inter-institutional structures. This allowed the respondent to report at least one of the components if they did not remember the other. The respondents first chose the relative faculty rank of the individual from the following intra-institutional categories presented on the survey.

- Higher-ranked faculty position
- Same or similar-ranked faculty position
- Lower-ranked faculty position
- Don’t Remember
- No one influenced me

The respondents then chose the relative institutional rank of the individual using the following inter-institutional categories.

- Higher-status institution
- Same or similar-status college
- Lower-status college

- Don't Remember
- No one influenced me

3.5.2 Independent Variables

Several key independent variables are used to predict the outcome of the dependent variables in the analyses. This section describes how the variables were created from the survey data. Several questions had options for respondents to enter answers using a free-response format to describe experiences or responses that did not fit the pre-defined options. The following variables had an “other” option for which I manually coded the responses.

- First Source of Information: All of the responses were able to be recoded according to my original options.
- Other Influential Sources: All of the responses were able to be recoded according to my original options.
- Highest Degree: Terminal degrees such as M.D. and J.D. were coded as doctoral degrees.

3.5.2.1 Measures of Social-exchange and Anonymous-search Networks

Use of social-exchange and anonymous-search networks is measured in two ways: 1) the first source of information and 2) the number of sources listed as influential for each category. Respondents chose from a list the first source of information from which they learned about the innovation. I had already categorized the list of sources (e.g., conference presentation, website, journal article, colleague at your institution) as a

social-exchange or anonymous-search network.¹⁶ Additional responses submitted through the “other” option were categorized based on the definition for each network presented in the first chapter.

The second variable is a measure of the influential intensity of each network using a count variable. This count variable is calculated from the respondent rating each source separately. The Likert scale for each source is: Not Influential, Somewhat Influential, Influential, and Very Influential. The influence intensity count for either social-exchange or anonymous-search networks is increased by one for each associated source rated “Somewhat Influential” or higher.

3.5.2.2 Measures of Respondent’s Social Position

Social position is defined by the respondent’s position in the intra-institution structure (i.e., faculty rank) and inter-institutional structure (i.e., institution type). Institution type is measured as a dummy variable representing one of the four categories from my simplified Carnegie Classification: research universities, master’s universities, baccalaureate colleges, and associate’s colleges. Institution type is not a time-varying variable. While I know some faculty members worked at different institutions over time, I am defining their institutional category by the college at which they became aware of the innovation. I made the decision to not ask respondents for a full work history so I could limit the number of questions on my survey. I assumed the number of faculty members moving between institutions during the time of my analysis was low because many respondents recently became aware of the innovation. This is evident in the low number of survey invitations returned because of incorrect email addresses despite using

¹⁶ This categorization was not presented to the survey respondents.

contact information I was provided for individuals who had registered for an account or workshop during the initial awareness stage. I also assumed that a significant percentage of any moves would be between institutions within the same category (e.g., Cornell University to Johns Hopkins University).

PLTL and CPR respondents chose their institution from a comprehensive list of universities and colleges in the United States I downloaded from the Carnegie Foundation for the Advancement of Teaching (Carnegie Foundation for the Advancement of Teaching 2010). This list also included each institution's Carnegie classification. An "other" option was available as well. I ended up deleting this question on the SALG survey because I realized I could use the respondent's email address to identify the institution. It was a complicated matching process to implement but I wanted to drop this question because it was difficult to answer. Users had to scroll through several thousand institutions and sometimes the institution title did not match the respondent's expectation (e.g., UMBC versus University of Maryland, Baltimore County). Using an email address also allowed me to identify the institutional affiliation of non-respondents for all the innovations, which was used to identify non-response biases (See Appendix C). Therefore, I ended up using the email address to identify institutional affiliation for every surveyed individual across all three innovations. For individuals who used a non-college email address (e.g., @aol.com), I conducted an Internet search to identify their institutional affiliation.

The matching process began by truncating every faculty member's email address in Excel to the server domain (e.g., jhu.edu). I then wrote a script that used look-up tables to match this email address to the reported web address (e.g., www.jhu.edu) and

return the Carnegie classification. The truncated web address and email address did not always match (e.g., jhu.edu versus johnshopkins.edu). I had to manually code the classification for about 10 percent of the responses (e.g., more than 300 SALG respondents).

The full Carnegie Classification for institutions with undergraduate programs includes 50 separate categories. Once I had paired each unique respondent ID with the full Carnegie Classification code, I could then convert it to my simplified classification. I used scripts to translate the 50 categories into my four categories for the inter-institutional categories: research university, master's university, baccalaureate college, and associate's college. I then merged the data with the survey responses.

Faculty rank was expected to change more often than institution type during the time of my analysis so it is modeled as a time-varying variable. Respondents were asked to enter the number of years they held a range of pre-defined faculty positions so I could create a faculty position life history for each respondent. There was also an "Other" option for which I manually coded the respondents' entries. Respondents who did not want to enter this information had the option to email me their resume or curriculum vitae. I manually entered information into the survey for the respondents who chose this option ($n = 14$). The following categories were presented on the survey:

- Tenured Professor
- Tenured Associate Professor
- Untenured Associate Professor
- Untenured Assistant Professor
- Full-time Sr. Lecturer, Lecturer, Instructor (non-tenure track)

- Part-time Adjunct Faculty, Lecturer, Instructor
- Other (Free response) – I manually coded the “Other” responses.

Very few respondents reported being an untenured associate professor so this rank was collapsed with untenured assistant professor. I felt the untenured nature of both positions made them most similar. In calculating the life history, it was assumed the most senior position was the current position. The previous position was assumed to be the next most senior position reported. The number of years teaching was calculated by summing the years provided for each position.

I created dummy variables used to test my hypotheses from the reported faculty ranks. My three sets of hypotheses make predictions for tenured and tenure-track faculty. Therefore, I created a tenure-track dummy variable representing full professors, associate professors, and assistant professors. The reference group is full-time lecturers and part-time adjuncts (i.e., contingent faculty). I also expected that there may be differences between tenured and non-tenured faculty. While not specifically hypothesized, I created a second dummy variable for exploratory purposes that represented tenured faculty (i.e., full and associate professors). The reference group is assistant professors, lecturers, and adjuncts.

3.5.2.3 Year of Awareness

Respondents were asked to enter the semester and year they became aware of the innovation through a free-response question. I manually converted these to an academic year. I coded “summer semester” or summer months as part of the previous academic year. For example, August 2011 was classified as part of the 2010-11 academic year. If the respondent only entered a year, I coded it as if it fell in the spring semester. My

reason was that January through August were coded as being in the same academic year. The missing semester information was more likely to fall in this eight-month period than in the fall semester that is associated with the next academic year.

The user logs showed that no SALG accounts were created before 2007, but respondents reported learning about the innovation as far back as 1999. I consulted the SALG team about this discrepancy. Stephen Carroll said a previous assessment instrument was created in 1999 but the current version was established in 2007. I was assured by Stephen Carroll that the previous SALG instrument was nothing like the current version and I should assume the 2007 date was the official launch. See a more detailed history of the SALG tool's evolution in Appendix D. After lengthy discussion with the SALG team, I decided to replace all entries reporting awareness from 2006 and before with the value "2007."

3.5.2.4 Course Discipline

Respondents entered the courses in which they used the innovation through a free-response question. This information was manually coded to one of the four disciplinary domains: science (e.g., math, physics, chemistry), engineering (e.g., architecture, computer science, information technology, electrical engineering), social science (e.g., education, sociology, economics, business), and humanities (e.g., art history, English). I conducted an Internet search for users who did not complete this question or whose responses I did not understand. I assigned the course discipline based on the respondent's field of expertise (e.g., biologist = biology).

3.5.2.5 Measures of Motivations to Publish and Present

The survey asked participants to rate how influential a number of sources were in motivating them to publish or present. These sources were:

- Formal incentives at one's institution to publish peer-reviewed research
- Formal incentives in one's professional organizations/discipline to publish peer-reviewed research
- Personal success previously publishing research
- Formal incentives at one's institution to present research at conferences
- Formal incentive in one's professional organizations/disciplines to present research at conferences
- Personal success in previously presenting at conferences
- Resources available for travel at one's institution
- Desire to gain status within one's institution
- Desire to gain status within one's professional organization/discipline
- Personal commitment to improving teaching
- Teaching awards or recognition at one's institution
- Annual performance review
- Other

Respondents rated the sources' influence on a five-point Likert-scale: 1-hindered, 3- no effect, 5-enabled. A number of respondents only entered a rating for sources that they perceived enabled or hindered them (i.e., choices 1, 2, 4, or 5). I assumed the

sources that were not rated had no effect on the respondent and used logical imputation to replace the missing data with a “no effect” rating.

3.6 Conclusion

This chapter described the data collection activities and creating of variables for analysis. The analyses that follow are divided among four chapters organized by two sections. The first section will explore how use patterns of the three educational innovations vary by faculty members. The use of these educational innovations will be explored through patterns of adoption (Chapter 4) and abandonment (Chapter 5). I am specifically interested in how both are associated with a faculty member’s social position and the sources of information used to learn more about the innovation. The second section will explore the patterns of influence during the adoption phase. This section will analyze data describing who chooses to become a change agent once they adopt (Chapter 6). I will also analyze who potential adopters identify as persuasive based on the relative status of the change agents or other influential individuals sharing information (Chapter 7). Are instructors more likely to be influenced by more senior faculty or those whose primary responsibility is teaching (e.g., lecturers)? Which of these faculty members are more likely to become change agents who publish and present on the innovation?

Table 3.1: Number of Individuals Contacting Researcher by Category in Response to Survey Invitation

Innovation	Should I complete the survey?	I will complete survey later.	Emailed CV instead of entering faculty position history on survey	General Comments	Technical Support Requests
<i>CPR</i>	19	14	6	49	2
<i>PLTL</i>	11	7	2	26	1
<i>SALG</i>	61	23	6	59	23
<i>Totals</i>	91	44	14	146	26

Section 1: Patterns of Use

IV. Social Position, Diffusion Networks, and Adoption Patterns

This first of four analytic chapters explores how patterns of adoption are associated with a faculty member's social position and the sources of information used to learn about the innovation. The chapter is then followed by a similar exploration of abandonment patterns for those who adopt. Together they constitute Section 1. The second section exploring patterns of influence during the adoption phase is described in Chapters 6 and 7.

4.1 Understanding Why Instructors Might Adopt

The project's analysis starts with who adopts or does not. I am interested in how adoption patterns vary by social position, and specifically by faculty role and institution type. I am also interested in whether instructors are more likely to adopt if they engage with colleagues about an innovation instead of independently collecting information on their own. My interest in this topic stems from my work in a teaching and learning center in which I help instructors adopt new teaching resources and strategies to improve student learning. How they learn about these innovations varies greatly. I regularly have faculty members come to my office with a new technology they found online or learned about at a conference. "Can you help me install and test this software?" These communication channels – group presentations and websites – are useful because one person can share his or her experience with large numbers of individuals. The potential adopters, however, are usually curious to learn more rather than passionately committed to adopting at this stage. This situation contrasts with instructors who have already made a decision to use a particular innovation. These individuals tend to call because a

colleague has convinced them of the need to adopt. For example, the use of Peer-led Team Learning (PLTL) has spread rapidly at Johns Hopkins through conversations among instructors teaching introductory science and engineering courses. It entered the institution through a discussion between the Vice Dean of Education in the Whiting School of Engineering and a professor at Washington University in St Louis, Missouri. The Washington University professor made a compelling case for its impact on student learning. I remember the Vice Dean returning and telling our Center, “We need to make this happen at Homewood.” Personal interactions can be strongly persuasive. These examples are anecdotal, but led me to ask questions about how adoption and abandonment are associated with the social interactions, or lack thereof, in which instructors engage during the persuasion stage.

4.1.1 Considering Social Position

There are several research questions guiding this chapter and the following one. First, is *how does a faculty member’s social position affect his or her decision to adopt an educational innovation?* This question will be answered using two components to define social position. I will explore how adoption is patterned by both the instructor’s faculty role within the institution and the type of college at which she or he teaches. Are lecturers, whose main responsibilities are to teach, more likely to adopt than fully tenured professors? Does this dynamic depend on whether the comparison is made within a four-year liberal arts college or a research university?

4.1.2 Considering Sources of Information

I am also interested in how potential adopters are influenced by the sources of information they consult. Specifically, my research questions are the following. *What*

networks of information do faculty members use to learn about an educational innovation they may adopt? How do these networks influence the likelihood of a faculty member adopting and eventually abandoning the innovation? I will not independently compare the influence of each information source to the others. There are too many to contrast. I believe these sources can be categorized into two conceptually meaningful groups. In the previous chapters, I conceptualized two types of communication channels used to share information about educational innovations: social-exchange networks and anonymous-search networks. Social-exchange networks are characterized by the exchange of information between two individuals (or groups) in which both sides recognize the engagement of the other. For example, an instructor telling a colleague about her use of PLTL would be an example of a communication channel in a social-exchange network. Anonymous-search networks are categorized by communication channels in which the disseminator of information is not aware of who is receiving the information. Presentations on Calibrated Peer Review (CPR) at a conference or a publication about an adoption experience in a journal are examples of sources categorized as part of an anonymous-search network.

4.1.3 Social Capital and Social Position

I contrasted these two types of networks in terms of the amount of social pressure that is likely associated with each source and how it may lead to different adoption decisions. Social capital theory describes how high levels of trust and obligations in a community can shape individual actions, like adopting a new educational innovation (Coleman 1988). Social norms, another form of social capital, may motivate an instructor to adopt if the college has a strong commitment to improving undergraduate

education. The opposite could occur at institutions emphasizing research. Norms may exist that act as a barrier to adoption (Portes & Landolt 1996). In addition, communities characterized by high levels of competition, micropolitics, or negative social capital may lead individuals to choose anonymous-search networks over social-exchange networks to learn more about educational innovations (Menon & Pfeffer 2003; Menon, Thomson & Choi 2006; Datnow 2000). While social norms, trust, and obligations can be communicated through anonymous-search networks, I believe the impact will be stronger in social-exchange networks because of the direct personal interactions – including potential for positive and negative normative sanctions – characterizing these networks (Portes & Landolt 1996). Consequently, I believe that the likelihood of adoption will vary by whether potential adopters rely on social-exchange or anonymous-search networks.

The research question exploring how patterns vary by a faculty member's social position is also related to instructors' use of different networks of information. Both the access and influence of these networks will vary by social position (Rogers 2003, p. 341; Granovetter 1973; Jackson 2010, p. 1). Following my definition of social-exchange networks, access to information is dependent on personal relationships. Tenured and tenure-track faculty may have more connections within and across institutions compared to adjunct faculty who have weak linkages to the institution. I expect adjuncts are more likely to be social isolates because of their weak linkages to the institutions at which they teach. Innovations may also be more likely to diffuse across similar institutions because of existing connections.

Social position may also affect the influence of social-exchange networks because individuals respond to normative structures differently depending on where they are positioned within the organization (Georgopoulos 1965; Merton 1968). The difference in job security and status between tenured faculty and lecturers may make them more or less likely to be influenced by social norms. For example, tenured faculty at research institutions may be less likely to dedicate time to their teaching responsibilities because of the pressures to publish and present research. Lecturers and adjuncts hired to teach may be more likely to respond to teaching norms at these institutions because of their instructional responsibilities and contingent job security. Faculty members across colleges may also try to signal their acceptance of norms within cross-institutional professional organizations. When Johns Hopkins University hosted its first Gateway Science Initiative Symposium, the keynote speakers were deliberately recruited from similar or more prestigious institutions. Part of the motivation was the hope that the status of these individuals would increase attendance. The organizers also hoped these speakers would share with other institutions the innovations in science education occurring at Johns Hopkins.

4.2 Hypotheses

My first hypothesis responds to the first set of research questions about what networks of information instructors use and how they are influenced by them. Information about educational innovations is transmitted by both social-exchange and anonymous-search networks. I believe the social capital inhering in social-exchange networks would be a more powerful influence on a potential adopter in the persuasion

stage than the social capital inhering in anonymous-search networks. This leads me to propose my first hypothesis.

Hypothesis 1: A faculty member's probability for adopting an educational innovation will be higher if she or he identifies social-exchange networks as more influential than anonymous-search networks during the persuasion stage.

I believe social position can be used to refine the prediction of this hypothesis. For this project I conceptualize social position using both the instructor's faculty role and institution type. How will these different components of social position interact with social-exchange networks? First, I believe variations in institutional culture and mission must be considered. Institutions whose mission emphasize research, as opposed to undergraduate education, will hinder the development of social capital that facilitates conversations about teaching on campus. The following hypothesis incorporates institution type as a mediator on the first hypothesis.

Hypothesis 1a: The positive relationship between the probability of adoption and social-exchange networks will be weaker for individuals in institutions emphasizing research.

Social-exchange networks are not equally accessible by faculty role. Adjuncts tend to be more isolated than faculty members with full-time jobs at the institution. Adjuncts, therefore, are less likely to have access to social-exchange networks relevant to teaching. Lecturers are more embedded than adjuncts, and because their primary responsibility is to teach they are more likely than adjuncts to use social-exchange networks to discuss educational innovations. Their job responsibilities also make them

more likely than other types or ranks of faculty to use social-exchange networks to signal to the academic community that they are continually improving their teaching. Tenured and tenure-track faculty are likely the most embedded in social-exchange networks within and across institutions, but those networks are likely comprised of similar faculty because their positions lead them to participate on university committees, research groups, and governing bodies (e.g., academic council, academic senate) that are only populated by other tenured and tenure-track faculty members. The topics discussed in these forums, and the desire to communicate to other faculty members what they are working on, is more likely driven by institutional characteristics as described in the previous hypothesis. This leads me to propose my next hypotheses.

Hypothesis 1b: The negative relationship between the probability of adoption and research institutions will be more strongly negative for individuals with tenure or on the tenure-track.

Hypothesis 1c: The positive relationship between the probability of adoption and social-exchange networks will be weaker for individuals with tenure or on the tenure-track.

4.3 Testing the Hypotheses

I will use survival functions and hazard models to test the hypotheses. The survival function describes the probability that a randomly selected individual will “survive,” or not experience the event (Singer & Willet 2003, p. 334). For this chapter, the survival function will describe the probability of not adopting the innovation. The discrete-time survival function for an individual, i , in time period, j , can be written as the following.

$$S(t_{ij}) = Pr[T_i > j]$$

where $S(t)$ is the conditional probability of not adopting an innovation at time t given that no adoption occurred by t .

The survival function is a descriptive tool by which functions for different groups (e.g., tenured versus non-tenured faculty) will be compared. A more direct test of the hypotheses is done using statistical analyses based on discrete-time hazard models (Allison 1982; Singer & Willet 1993; Singer & Willet 2003). For this chapter, these models can be generally expressed as the following.

$$(1) \ln[h(t)] = \alpha + \beta_1 S + \beta_2 R + \beta_3 T + \beta_{12} S^*R + \beta_{23} R^*T + \beta_{13} S^*T$$

where $h(t)$ is the conditional probability of adopting an innovation at time t given that no adoption occurred before t .

and:

S = social-exchange network awareness dummy variable (anonymous-search networks are reference)

R = research universities dummy variable (all other types of colleges are reference)

T = tenured or tenure-track dummy variable (lecturers and adjuncts are reference)

4.3.1 *Who is More Likely to Adopt?*

An individual enters the risk set for adoption when she or he formally expresses interest in learning more about an innovation. This expression of intent is defined differently for each innovation. Calibrated Peer Review (CPR) and Student Assessment of Learning Gains (SALG) are technological innovations. Individuals who register for an account are considered to have entered the risk set. Not all registered individuals became

users. Of the 170 registered account holders who responded to the CPR survey, 113 used CPR at least once (66 percent of registered administrators). Just over 50 percent of the SALG respondents (429 out of 809) adopted the innovation.

Peer-led Team Learning (PLTL) is a classroom-based tutoring program. The list of known users is not exhaustively documented like a technological innovation because instructors do not have to register on a website to try out or download PLTL. The risk set of potential adopters was gathered through multiple sources: individuals who registered for information on the PLTL website, training workshops, or conferences; publications about PLTL; and snowball sampling from known users.¹⁷ Over 95 percent of the respondents ended up adopting (139 out of 146). Staff who responded to a survey but do not have teaching responsibilities were dropped from the analysis because they are not able to adopt the innovation for a course.

4.3.2 How Time is Measured in the Model

Time will be measured as a discrete variable in the survival functions and hazard models because adoption is typically tied to a semester. Clocking time begins when someone becomes aware of the innovation. SALG usage data were collected from the SALG website user log, which was launched in 2007.¹⁸ The CPR technical team could give me a list of registered administrators but not use logs because of a technical problem exporting the complete user log. PLTL does not have user logs as noted above. CPR and PLTL potential adopters were asked on the survey when they first learned about the

¹⁷ See Chapter 3 for a detailed description of how the PLTL risk set was created.

¹⁸ SALG was originally created as a pen and paper assessment tool in 1997. The five-question assessment was migrated to a website in 1999, but no advertising was done to market the tool. Stephen Carroll, the current SALG director, said NSF funds were secured in 2005 to completely redesign the tool. The current version, which is a completely different tool than the original assessment instrument, was launched in 2007. See Appendix D for a full description of the SALG development history.

innovation and which academic years they used the innovation. CPR and PLTL were established in the late 1990s. I only asked respondents for use data since 2001 out of concern for survey fatigue (e.g., response matrices would have been very large) and lack of confidence in users being able to report the first semester use with fidelity after 11 years. Respondents reported on the survey whether they had used the innovation during “2001-02 or a previous year.”

Individuals will be right censored in the discrete-time hazard models when they are aware of an innovation but have not adopted it by the date they responded to the survey. Some users adopt the tool immediately after registering for an account. This can cause a problem for discrete-time hazard models because the user would be left censored at time zero. I shifted all adoption times by one year to prevent left censoring. In the survival functions, year one represents those who immediately adopted. Those who adopted during year one (but not immediately) are represented at year two.

4.3.3 Populations Surveyed

My goal was to survey the entire population of potential users of the innovation (i.e., those who were aware of the innovation and received information through a social-exchange or anonymous-search network). I believe I approximated the population sought for each innovation through user logs, snowball sampling, and other sources. However, my response rates were not 100 percent. I interpreted the coefficients as if they represented the responses of a random sample taken from the population. I tested for response biases using logit and probit models on a key variable representing one of the constructs in my hypothesis. No bias was found. See Appendix C for a description of this analysis.

4.3.4 Dependent Variable – An Overview

The dependent variable, adoption, is a non-repeatable event defined by the first use of the innovation. Adopters can use the innovation multiple times in additional courses in future semesters, but they can only adopt once (i.e., first use). The discrete-time survival function describes the probability of a random individual adopting at various time intervals. All three survival functions show that the hazard of adoption for each risk set is highest in the first two years (see Figures 4.1 - 4.3), but there are sharp differences in the initial adoption rates. The initial hazard rate for adopting is 25 percent and 15 percent for CPR and SALG, respectively. For PLTL it is almost 60 percent. Almost all of the PLTL risk set, the population of instructors who had become aware of the innovation, eventually adopted (97 percent). For CPR and SALG, 25 percent and 30 percent of the risk set survived (i.e., have not adopted) by the final year of the analysis. These survival functions will be compared by subgroups – tenured/non-tenured, institution type, social-exchange/anonymous-search networks – for each innovation in the *Results* Section (4.4).

4.3.5 Addressing Missing Dependent Variable Data

SALG user data were provided by the SALG director, Stephen Carroll. These data were merged with respondent survey data to create historical use patterns so there were no missing data for the dependent variable. For PLTL and CPR, survey respondents reported their use of each innovation by academic year. One of the response options was “Don’t remember.” Respondents did not choose this option often. For CPR, 34 “Don’t remember” submissions were reported out of 1,567 person-periods (two percent). There were eight “Don’t remember” reports out of 1,604 person-periods for PLTL (0.5 percent).

The most common response pattern was for respondents to enter a “Don’t remember” response for one year that was followed by a report of using the innovation over subsequent, consecutive years. I assumed these responses indicated the individual didn’t remember the first year she or he used the tool. I used a fair, six-sided die to impute these responses.¹⁹ I replaced “Don’t remember” with “Not used” for rolls of one through three and “Used” for rolls of four through six. This method was employed for five CPR respondents and five PLTL respondents.

Several CPR respondents reported a string of three to six consecutive years of “Don’t remember” responses but no other years in which they used the innovation. I interpreted these responses as users not remembering what year they started using the tool, but once they did, they continued to use it annually. I only need to know the first year the respondent used the innovation (i.e., the adoption year) for the survival function and discrete-time hazard models. I used hot deck imputation to replace the missing data for the adoption year. I chose the first year used (i.e., adoption) for these individuals based on the average time to adopt by the other respondents for each innovation. This method was employed for three CPR respondents and no PLTL respondents (i.e., all PLTL respondents missing data fit the first category described in the previous paragraph-reporting “Don’t Remember” for one year).

4.3.6 Independent Variables – An Overview

This section describes the independent variables used (see Table 4.1) in the analyses including descriptions of how they were generated and how missing data were

¹⁹ Special thanks go to Mckinley and Hudson Reese for rolling the die. Their contributions were much appreciated.

addressed. Mean values and standard deviations of the independent variables for each innovation are provided in Table 4.2. The independent variables are grouped into three categories. This categorization reflects the model testing based on 1) the faculty member's background characteristics, 2) social position variables associated with the hypotheses, and 3) additional variables associated with the adopter's experience.

Background data not provided by the respondents were supplemented by conducting web searches (e.g., faculty title and discipline identified through the faculty member's web page).

4.3.6.1 Social Position

Social position was measured by two components: faculty role and institution type. Institution type was categorized by the simplified Carnegie Classification: research universities, master's universities, baccalaureate colleges, and associate's colleges. In the analyses below, I included a dummy variable representing only research universities because the hypotheses predicted differences in outcomes based on the intensity of research activities at the institution. Additional models were run in which dummy variables were included for three of the four categories (i.e., associate's college category excluded). The research universities dummy variable was the only coefficient to reach significant difference from associate's colleges in the models.²⁰ Therefore, I used a simpler model that includes a dummy variable for research universities only. Institution type was a time-invariant variable.²¹

²⁰ A model was also run in which I included a dummy variable representing both research and masters universities (i.e., the categories were combined). The variable was not significant so I used the dummy variable that only represents research universities.

²¹ Faculty members change institutions over their careers, but this occurs much less frequently than changes in faculty role. In addition, changing colleges also does not mean the Carnegie Classification

Faculty role was measured in two ways. First, a dummy variable was created to differentiate faculty members who were contingent (i.e., lecturers and adjuncts) versus non-contingent (i.e., assistant, associate, and full professors). Contingent faculty were the excluded reference group in the estimated models, which facilitates a direct test of both groups described in Hypotheses 1b and 1c: tenured or tenure-track faculty. I also created a dummy variable differentiating whether someone had received tenure or not. I chose to investigate this group separately from tenure-track faculty because I wanted to explore whether the strong institutional commitment to employment for these instructors affected decisions to adopt or not. The institutional commitment for tenured faculty is much stronger than what an institution provides for other faculty roles. Untenured faculty (e.g., lecturers and assistant professors) were the reference group for the tenured dummy variable.

Both of these representations of faculty role were time-varying variables. That is, they were adjusted for each person-period to account for a respondent's changing faculty position across the longitudinal analysis.²² Respondents entered the number of years they held each faculty rank (e.g., full professor: 6 years, tenured associate: 3 years, untenured associate: 0 years, untenured assistant: 5 years, lecturer: 2 years, and adjunct: 0 years).²³ It was assumed the most senior position was the current position. The previous position was assumed to be the next most senior position reported.

characterizing one's institution of employment changed. For these reasons I did not expect much variation in institution type over a respondent's career. Therefore, institution type was considered a time-invariant variable.

²² Time-invariant variables were centered at the grand mean (i.e., mean value of the sample) before including them in the hazard models. Time varying variables were centered around the within-person mean.

²³ Due to the infrequency of respondents reporting untenured associate professor as their rank it was collapsed with untenured assistant professor.

4.3.6.2 Social-Exchange and Anonymous-Search Networks

The impact of social-exchange and anonymous-search networks was evaluated in the models in two different ways. Respondents were asked to indicate what their first source of information about the innovation was. They chose from a pre-determined list and were also given an “other” option in which they could enter a source not on the list. The pre-defined list of choices had been categorized during the study design stage as either social-exchange or anonymous-search networks. “Other” choices submitted by respondents were coded based on the definition of each network. I coded “Don’t remember” responses for first source of information as anonymous-search networks. My rationale was that if the respondent could not remember the source than they were unlikely significantly influenced by social pressures associated with social-exchange networks that motivated the hypotheses.

The distribution of the initial source varies by each innovation. For PLTL, 65 percent of respondents report first finding out about PLTL from a social-exchange network as opposed to an anonymous-search network. For CPR, the percentages are reversed: Respondents first learned about CPR from anonymous-exchange networks 65 percent of the time. SALG respondents were more evenly split: 53 percent first became aware through social-exchange networks and 47 percent from anonymous-search networks.

The second method for testing the hypothesis was to create a measure of the influence of social-exchange and anonymous-search networks as reported by the respondents. In addition to responding on the survey which source of information was consulted first, respondents ranked how influential each of the sources were in their

decision to adopt or not. Respondents rated the influence of each source on a four-point Likert Scale: not at all, somewhat important, important, very important (see Appendix F for responses for each innovation). Each source contributed to the overall network influence count variable if the respondent rated the source as somewhat important or higher. These data were used to create a count variable for the number of social-exchange network sources and anonymous-search network sources that the respondent reported as influential. Both variables were included in the model because the variables represented independent counts.

4.3.6.3 Time

For this analysis, time represents the number of years since the respondent became aware of the innovation. The year of awareness varies by individual, so the time variable cannot represent the actual year in the Gregorian calendar. Time was converted to a clocking time variable with the value zero for the year when the potential adopter became aware of the innovation.

I tested several time functions to identify the best fit for the discrete-time hazard models. A simple logit model with a time function and one additional independent variable, first source of information, was used to identify the best time function for the full model. I compared the Bayesian Information Criterion (BIC) for a model with a constant, linear, quadratic, cubic, and general time function. A smaller BIC value indicates a better fit. For all three innovations a cubic time function gave the best fit for the time function. In the models below (see Tables 4.3 - 4.5) the second and third degree polynomial time functions were statistically significant and the coefficients consistent, which support that a cubic function was an appropriate way to model the time function.

The shape of the hazard function graphs also provided support for a cubic time function (not shown). The hazard function for all three innovations generally displayed an increasing adoption rate across the first two years, followed by a decrease in the subsequent years before increasing again.

4.4 Results

4.4.1 First Source of Information by Innovation

The distribution of the first source of information varied widely by innovation. The percentage of respondents choosing social-exchange networks for each innovation were as follows.

- CPR: 15 percent
- PLTL: 65 percent
- SALG: 53 percent

The high percentage of PLTL users that became aware through social-exchange networks can likely be explained by the fact that PLTL is not a web-based innovation, unlike the other innovations. There is also a large PLTL user community actively advocating for the innovation. This group holds conferences and trainings around the country to encourage its adoption.

CPR's low rates of awareness through social-exchange present a useful comparison highlighting or invoking innovation characteristics. CPR is a web-based application. Faculty members register for an account online, which is easily located through web searches. The CPR main promoter is Arlene Russell, the resource's founder. She is a dedicated advocate, but does not have a large, organized user community like PLTL to assist her in recruiting potential users. This likely explains why

more of the risk set learned about CPR from an anonymous-search network. Even when potential adopters learn about CPR from Russell, it is often through conferences or publications which are categorized as anonymous-search networks.

SALG is also a web-based tool similar to CPR. It does not have a large support community like PLTL, but it does have more institutional partners supporting it than CPR. Multiple people like Bob Mathieu from the University of Wisconsin, Stephen Carroll from the Santa Clara University, and Elaine Seymour from University of Colorado, Boulder, have presented and published on the innovation in multiple forums. The slightly larger support community of SALG (as compared with CPR) that spans multiple institutions might explain why more people learn about SALG from social-exchange networks. I cannot test for causality, but the data suggest a positive relationship between the likelihood of a potential adopter learning about an innovation through social-exchange networks and the size and activity of the support community. The question is, are potential users more likely to adopt if they learn about the innovation from social-exchange networks? The following analyses respond to that central question.

4.4.2 Results of Modeling Adoption

4.4.2.1 Calibrated Peer Review (CPR)

4.4.2.1.1 CPR Adoption Patterns

As noted previously, 25 percent of the risk set adopted CPR in the first year and 40 percent of the remaining risk set the following year (see Figure 4.1). After year two the hazard rate for adopting was not higher than 16 percent. There was weak support for the hypothesis in that the survival function for the first source of information does not diverge between social-exchange and anonymous-search networks until after year seven

(see Figure 4.4), at which point the survival function was separated by five percentage points.

Adoption rates diverge more sharply when comparing faculty members in different roles. Tenured faculty have much higher adoption rates during the first year (31 percent) compared to non-tenured faculty (18 percent). The rate gap narrowed in year two, but then expanded again in year three (see Figure 4.5), but ultimately converged over time. The tenured faculty adoption pattern appears to be the main driver between the differences in adoption rates of contingent and non-contingent faculty as well. A possible explanation for this will be given in the *Discussion* section (4.5). Figure 4.6 showed the survival functions for contingent and non-contingent faculty were very similar except in the mid-range years (years four through seven).

Figure 4.7 displays the survival functions for all four institution types. Respondents from research universities and baccalaureate colleges had the highest survival rates in the initial year (approximately 80 percent). The first year survival rates for the risk set from associate's college and master's universities were 66 percent and 72 percent, respectively. Over the entire analysis, however, faculty members from research universities had the lowest survival rate (20 percent) and faculty members from baccalaureate colleges had the highest (32 percent).

4.4.2.1.2 CPR Hazard Models

The hazard logit models provided mixed support for the hypotheses (see Table 4.3). I used Models 3 and 5 to test the first hypothesis for each innovation. Models 4 and 6 included the intersected terms that test Hypotheses 1a - 1c. The coefficient representing if social-exchange networks are the first source of information was not

significant (Model 3). This test of Hypothesis 1 aligns with the results in Figure 4.4 which show the survival functions for social-exchange and anonymous-search networks did not diverge much.

I conducted another test of Hypothesis 1 that provided contrary evidence (Model 5). Respondents were asked how influential a number of sources of information were in their decision. They could choose multiple sources of information, which were used to create a count variable representing the number of influential sources for both social-exchange and anonymous-search networks. For example, faculty members could cite both a colleague at their institution and another institution as influential. In this case, the social-exchange influence variable would equal two.

The coefficient for the social-exchange network intensity was not significant but the anonymous-search network variable was ($p < 0.1$). The odds of adoption increased by eight percent for each additional anonymous-search network source cited as influential. This contradicts the hypothesis because I predicted that the more potential adopters relied on social-exchange networks the more likely they would be to adopt.

There was support for Hypothesis 1a: the positive relationship between the probability of adoption and social-exchange networks will be weaker for individuals at institutions emphasizing research. This is evident by analyzing the interaction term created between research institutions and social-exchange networks as the first source of information (Model 4). The estimated odds ratio for the variables representing research universities and social-exchange networks were both greater than one suggesting these variables predict a higher likelihood of adopting – higher relative to estimated likelihoods for non-research universities or when social-exchange networks were not reported as the

first source of information. The estimated odds ratio for the product term (i.e., interaction variable) was less than one ($p < 0.10$). This estimate can be interpreted to suggest that the positive influence of social-exchange networks on the likelihood of adopting was weaker at research universities than in other institution types. Alternatively, but perhaps less convincingly, the estimate can be interpreted to suggest that the increased likelihood of adoption for faculty at research universities is diminished if one's first source of information about the innovation was via social-exchange networks.²⁴ No support for Hypothesis 1a was found in Model 6.

Support for Hypothesis 1c is shown in Model 6, but not for Model 4. Model 6 replaced the dummy variable representing whether a respondent first learned of the innovation through social-exchange networks with count variables for how many social-exchange and anonymous-search networks a respondent cited as influential. The odds ratio for social-exchange networks and tenured faculty were greater than one, though statistically significantly different from zero only for the social-exchange networks' odds ratio ($p < 0.01$). The estimated odds ratio for the interaction term was less than one ($p < 0.10$), consistent with the prediction of Hypothesis 1c. The most straight-forward interpretation is that the positive association between the number of influential social-exchange networks and likelihood of adoption was diminished for tenured faculty. No support was found for Hypothesis 1b in either Model 4 or 6.

²⁴ Additional models were run with interaction terms created between social-exchange networks and a dummy variable that represented both research and master's universities. This was done to see if the of the interaction term effect was limited to research universities specifically or universities at which faculty have greater research responsibilities than baccalaureate colleges and associates colleges. The interaction terms created from the collapsed dummy variable were not significant so they are not interpreted.

The models run for CPR were the only ones in which the coefficient for non-contingent faculty were significant. The model predicted that tenured and tenure-track faculty were almost 50 percent less likely to adopt CPR than contingent faculty ($p < 0.10$). An interaction term was created to test the hypothesis that the relationship between the probability of adoption and social-exchange networks were weaker for individuals with tenure or on the tenure-track. It was not significant (model not shown).

The only background characteristic variables with significant coefficients were those representing science courses and social science courses. Instructors teaching these courses were more likely to adopt CPR than humanities faculty. The greater likelihood of science faculty adopting CPR compared to humanities faculty likely stems from the fact the CPR was developed and initially diffused through the science education community. Because CPR respondents were administrators who were also more likely to be the first to adopt at their institution, it is reasonable to assume that they learned about CPR from someone outside the institution. Connections to discipline-based communication networks (e.g., chemistry education community) likely exerted a large effect. The large odds ratio for the variable social science faculty may result from the low number of respondents in this category. Social science faculty were only 3.8 percent of respondents and almost all of them adopt.

4.4.2.2 Peer-led Team Learning (PLTL)

4.4.2.2.1 PLTL Adoption Patterns

The initial and overall adoption rates were highest for PLTL, as compared to the other two innovations under consideration (See Figure 4.2). A larger percentage of the PLTL risk set adopted within the first year (58 percent) compared to CPR (25 percent),

and the hazard of adoption remains high for the following two years. The annual hazard rate of adoption was greater than 40 percent for those who had not adopted at the beginning of years one and two. A comparison of the survival function for social-exchange networks and anonymous-search network risk sets provided some support for the hypothesis, although the differences in survival functions was small (see Figure 4.8).

When comparing adoption rates by faculty role, the data showed that tenured and tenure-track faculty members adopt PLTL more often than contingent faculty members (see Figure 4.10). This pattern started within the first year with the gap in the survival function narrowing the following year but then expanding again over the entire analysis period. Faculty members at different types of institutions had similar initial adoption patterns (see Figure 4.11). Most adopted the innovation within the first three years. Almost all members of each risk set adopted the innovation by year 12. The only notable divergence were the faculty members of the baccalaureate college risk set have all adopted PLTL after year two.

4.4.2.2.2 PLTL Hazard Models

The hazard models provided mixed, weak support for the hypothesis (see Table 4.4). The coefficient for dummy variable representing the first source of information being from a social-exchange network, a test of Hypothesis 1, was not significant (Model 3). However, the coefficient for the variable representing overall social-exchange network influence (see Model 5) was significant in the direction predicted ($p < 0.05$). The coefficient predicted that a potential adopter's likelihood for adopting increases by 17 percent for each additional social-exchange network consulted.

The intersected variables used to test Hypothesis 1b and 1c were significant but not in the direction expected (see Model 6). Regarding Hypothesis 1b, the estimated odds ratio for being a tenured faculty member suggests they were less likely to adopt than faculty from other ranks ($p < 0.05$). While the estimated odds ratio for being based at a research university was also less than one, this was not statistically significant. The estimated odds ratio for the interaction of tenured status and a research university institutional home was greater than one and significant ($p < 0.10$). This odds ratio is used to test Hypothesis 1b, and contrary to the original prediction suggests that any negative association between probability of adoption and research institutions was diminished for tenured faculty.

Regarding Hypothesis 1c, the estimated odds ratio in Model 6 for social-exchange network was less than one but not statistically significant. The estimated odds ratio for the interaction of tenured status with social-exchange influence is greater than one and significant ($p < 0.10$). This finding runs contrary to the original prediction of Hypothesis 1c, suggesting the association between social-exchange networks and probability of adoption was stronger (and in a positive direction) for tenured faculty than for others. The coefficients used to test Hypotheses 1a - 1c were not significant in Model 4. As noted in Section 4.3.6.1, a dummy variable representing tenured and tenure-track faculty was created to test Hypotheses 1b and 1c, but neither the coefficients for this dummy variable nor the interaction terms were significant in any of the models (estimated odds ratio for the interaction terms not shown).

There were several PLTL background characteristics with significant coefficients. As with CPR, science faculty had a higher likelihood of adoption ($p < 0.01$). Gender was

only significant in the PLTL hazard models. Males were almost 50 percent less likely to adopt than females ($p < 0.05$). The grant variable was significant for Models 3 and 4 ($p < 0.10$). Once the variable for first source of information was replaced with social-exchange network influence, the grant variable was no longer significant. The PLTL community has helped colleges acquire funds to support the implementation of PLTL so the drop in significance of the grant variable may have been caused by the addition of the social-exchange network influence in Models 5 and 6.

4.4.2.3 Student Assessment of Learning Gains (SALG)

4.4.2.3.1 SALG Adoption Patterns

SALG had the lowest initial and overall adoption rates compared to the other innovations. It also provided the strongest support for Hypothesis 1. Figure 4.12 showed that over time instructors who first learn about SALG through social-exchange networks were more likely to adopt than those who first learn about SALG through anonymous-search networks. The difference between the survival functions was 10 percent in the initial year and ultimately increased to 15 percent by the last year of analysis. An analysis of the difference in survival functions by faculty role and institution type did not show substantial differences (see Figures 4.13 - 4.15).

4.4.2.3.2 SALG Hazard Models

Further support for the main hypothesis was found in the hazard models (see Table 4.5). As shown in Model 3, the odds of adopting SALG were 80 percent higher for respondents who first learned about SALG from a social-exchange network as compared to an anonymous-search network ($p < 0.001$). The overall influence of social-exchange and anonymous-search networks were included as independent variables in Model 5.

The odds of adopting SALG increased 15 percent for every additional social-exchange network source named as influential ($p < 0.001$). The coefficient for the influence of anonymous-search network sources was not significant.

The hazard models did not provide broad support for Hypotheses 1a - 1c in either Model 4 or 6. Only one coefficient for the variable representing the intersected variables used to test each of these hypotheses was significant. In Model 6, the coefficient for the intersected term for social-exchange influence and tenured faculty was significant ($p < 0.10$) in the direction expected. The odds ratio for tenured faculty is greater than one but not statistically significant. The estimated odds ratio for social-exchange network intensity was greater than one as described in the previous paragraph. The odds ratio for the intersected variable was less than one ($p < 0.1$). This can be interpreted to mean that the positive association between social-exchange networks and the probability of adoption was weaker for tenured faculty compared to non-tenured faculty. A dummy variable representing both tenured and tenure-track faculty (i.e., non-contingent faculty) was created to test Hypotheses 1b and 1c, but the coefficients for this dummy variable nor the interaction terms were significant in any of the models (coefficients for the interaction terms not shown in Table 4.5).

As with the other innovations, science faculty had a higher likelihood of adopting the innovation ($p < 0.01$). An interesting finding was the coefficient for the variable representing grant funding was significant ($p < 0.001$) for SALG adoption, but not for the other innovations (see Models 5 and 6). This finding will be explored in more detail in the *Discussion* section (4.5), but I believe this reflected that SALG is a resource to help instructors assess student learning instead of facilitating student learning directly. The

significant finding for having received a grant may reflect instances in which faculty members received grant funding to implement another innovation (other than SALG). A typical requirement of grants is to assess the impact of whatever intervention or implementation is funded, and respondents may have been employing SALG to facilitate any such impact assessments.

4.4.3. How Well Do the Models Fit the Adoption Patterns?

The models presented above are pooled analysis logit models. That is, the logit models cluster the analysis associated with each individual to account for correlations between person-periods for each respondent. I tested whether a random effects logit model, which can address the issue of unobserved heterogeneity due to correlations between individuals, would be a better fit than the pooled analysis models. The value of ρ describes the proportion of the total variance contributed by the panel-level variance component. A ρ value of zero indicates that the panel-level variance component is inconsequential, and the panel estimator is no different from the pooled estimator (StataCorp 2013, p 50). The value of ρ for each innovation was close to zero so I used a pooled analysis logit model to interpret the coefficients.

4.5 Discussion

This section describes general trends in the data along with my interpretations. There were clear differences by innovation, but also some similarities or consistent patterns existed across innovations.

4.5.1 Social-Exchange Network Patterns

This chapter's first hypothesis predicted that instructors would be more likely to adopt if they first learned about a particular innovation from a social-exchange network.

The SALG data provided the clearest evidence for the impact of social-exchange networks. Figure 4.12 showed a clear difference between the survival functions for the first source of information with social-exchange networks and anonymous-search networks. The hazard models also provided support that potential users were more likely to adopt if they 1) first learned about the innovation from social-exchange networks and 2) consulted additional social-exchange network sources.

The CPR survival function provided weak support for the hypothesis. Those who first learned about CPR from social-exchange networks had similar adoption rates with those who learned about it from anonymous-search networks until year seven when the survival rates began to diverge (see Figure 4.4). This suggests that the impact of social-exchange networks, while not initially more impactful, may have a more durable influence. The odds of adopting CPR increased, however, for every additional anonymous-search network consulted as shown in the hazard models (Table 4.3 - Model 5), which contradicted Hypothesis 1.

The PLTL data also provided support for Hypothesis 1. The hazard model (5) estimated that the odds of adopting increased by 17 percent for each social-exchange network identified as influential. It is more difficult to discern an effect of social-exchange networks from the survival functions because the high adoption rates in the initial years obscured any differences. Figure 4.2 contrasted survival functions between those who first became aware of PLTL through a social-exchange network and those who learned about it from an anonymous-search network. Only 20 percent of the risk set had not adopted the innovation at the end of the second year (see Figure 4.8). This suggests

that the benefits of the innovation were so apparent that it did not matter from which source someone became aware of it.

While not a direct test of the hypothesis, it should be noted the coefficient for the influence of anonymous-search networks did not reach significance for PLTL and SALG (Models 5). This implies that an instructor's odds of adopting do not increase as she or he consults additional anonymous-search networks.

I believe the higher likelihood of science faculty adopting the innovation in all three models also provided indirect support for the hypothesis. It was not my intention, but I happened to choose three innovations that were all originally developed by the science education community. The innovations can be used by faculty members in any discipline. However, the fact the science faculty were predicted to adopt at higher rates suggests the social-exchange networks associated with the founding communities may have had an impact in increasing the diffusion among science faculty.

4.5.2 Adoption Patterns by Faculty Role

Hypothesis 1b predicted that the negative relationship between the probability of adoption and research institutions will be more strongly negative for individuals with tenure or on the tenure-track. Hypothesis 1c stated that the positive relationship between the probability of adoption and social-exchange networks will be weaker for individuals with tenure or on the tenure-track. None of the models provided support when the hypotheses were tested with a dummy variable representing both tenured and tenure-track faculty. The data for CPR and SALG supported the hypothesized interaction between tenured faculty and social-exchange networks. PLTL models provided conflicting evidence for the

hypothesized interaction between tenured and research universities and tenured and social-exchange network intensity.

The positive test of the hypothesis using the CPR hazard models is interesting because Figure 4.5 showed tenured faculty have much higher adoption rates during the first year (31 percent) compared to non-tenured faculty (18 percent). This finding was contrary to my initial expectation. This may reflect the unique population for CPR. The CPR team was not able to provide me with a list of all known users due to a technical problem with the user database. The population represents the CPR administrators at each institution. These administrators were often the first to adopt CPR at their college, and therefore, would be less likely to learn about the innovation from a colleague at their institution. Because tenured faculty are more likely to have inter-institutional relationships, they are more likely to be the first to learn about and adopt CPR at their college. Even though the hazard model suggests social-exchange networks may not be as influential on tenured faculty, tenured faculty's greater access to external social-exchange networks may have increased their adoption rates for those that adopted in the first three years.

The PLTL data contradicted Hypothesis 1b and 1c in that the models predicted tenured faculty are more likely than non-tenured faculty to adopt at research institutions (Hypothesis 1b) and tenured faculty are more likely than non-tenured faculty to adopt if they learn about PLTL from social-exchange networks (Hypothesis 1c). This contradiction may be explained by the influence tenured and tenure-track faculty have at their institutions. Adopting PLTL requires institutional commitments to pay PLTL student leaders or award them course credit for their service. Faculty members or

teaching assistants must write problem sets and rooms must be scheduled. Institutions may be more willing to commit these resources when non-contingent faculty request resources to support PLTL because their employment status is typically more permanent than contingent faculty. Non-contingent faculty may also be more likely involved in departmental and school-wide administrative decision-making which gives them additional influence. This rationale suggests that tenured and tenure-track faculty may still be less influenced by social-exchange networks, but once convinced of the need to adopt a resource-intense innovation, are more influential in convincing their institutions to implement it (i.e., better able to garner institutional resources necessary for adoption).

4.5.3 Adoption Patterns by Institution Types

Hypothesis 1a predicted that the influence of social-exchange networks in diffusing educational innovations would be muted for faculty members at research institutions because of the predominant use of these interpersonal communication channels to discuss research. There was weak support for this hypothesis. Some evidence of this could be documented by the slightly lower initial adoption rates for faculty members at research institutions for CPR and PLTL, however, over time, faculty members at research universities eventually adopted at similar rates.

While not specifically predicted, it is implied that faculty members at baccalaureate colleges would be more likely to adopt. This was the case for instructors from baccalaureate colleges adopting PLTL (see Figure 4.11). Their survival rate reached zero by the end of year two. This was not the case for CPR. Their adoption rates were lower in the initial years and overall, thus providing indirect contradictory evidence for Hypothesis 1a.

4.5.4 Adoption Rates and Innovation Complexity

While not originally hypothesized, it would be expected that more complex innovations would take more time to adopt. The complexity means the potential adopter must overcome more barriers to implementation. There was evidence of this with CPR. There was a large spike in the CPR adoption rate during the second year. CPR is used as an assignment and a faculty member must plan for its inclusion. CPR may be an easy tool to implement, but may require planning to integrate it into the curriculum.

PLTL data did not display a delayed spike in the cumulative survival rate during year two despite being the most difficult innovation to adopt (see Figure 4.2). In addition, PLTL had the highest initial adoption rate among the three innovations. Student leaders need to be hired, trained, scheduled, and paid or assessed; rooms must be reserved; and problem sets written. All of these logistics make it difficult for instructors or schools to adopt PLTL shortly after learning about it, especially mid-semester. The high rate of adoption in the initial year likely reflected the strong appeal of PLTL and dedicated support provided by the existing PLTL community. These two characteristics were also reflected in the low rate of abandonment by those who adopt (see next chapter). Research documents the effectiveness of PLTL on improving student learning that may convince potential users of its utility (Hockings, DeAngelis, & Frey 2008). In addition, the community of users is very active in advocating for its advance (Gafney & Varman-Nelson 2008), which creates a large social-exchange network. The impact of this advocacy is reflected in the number of respondents who said they first learned about PLTL from a social-exchange network instead of an anonymous-search network. As the data analyzed in this chapter have shown, instructors who consult social-exchange

networks were more likely to adopt. Almost 70 percent of respondents said they learned about PLTL from a personal interaction with a colleague, and overall, PLTL had the highest adoption rates of the three innovations.

CPR does not have as large a community of users who advocated for the tool and organized conferences. CPR is led by Dr. Arlene Russell, who acts as the primary charismatic leader. Her ability to inspire and support potential adopters is limited compared to the large PLTL support community. Not surprisingly, CPR had the lowest number of respondents who reported learning about the innovation from a social-exchange network (15 percent). The lower initial adoption rate for CPR may also be influenced by the population studied. A limitation of the user database prevented Dr. Russell from sharing all known users, but only a list of the CPR administrators at each school. In most cases, these individuals were the first adopter at their school. They, therefore, had less support at their own school in implementing the application for the first time.

SALG is the innovation that would be easiest to adopt immediately (e.g., mid-semester). As an assessment tool, instructors do not need to plan for its implementation before the semester begins. They can register for an online account and set up survey-like questions that can be copied from other users' surveys. Despite these low barriers to entry, it had the lowest initial adoption rates. This further supports the idea that it is not simply innovation complexity that hinders quick adoption, but perhaps how well the tool matches the needs of the potential user, and most important, their ability to recognize it. PLTL's impact on student learning is well documented and its approach can be used at

any institution. As such, its adoption rate was high despite the logistics required for implementation.

4.5.5 Grant Funding

The coefficient for the variable representing grant funding was only consistently significant for SALG. This is interesting because there is almost no cost to adopt SALG. It is free to use and requires little labor to implement. The significant coefficient for grant funding may result from faculty members receiving grant funding to implement a different innovation that requires assessment (see Table 4.5). Grant funding agencies typically require the recipient to assess and report on the project's impact annually or at the end of the grant cycle. It may be the grant requirements for adopting another innovation that lead to the adoption of SALG. In my work with several faculty users at Johns Hopkins, it was the assessment of a different innovation that led us to use SALG surveys in the course.

4.6 Conclusion

The analysis of this chapter shows that for PLTL and SALG there is support for the hypothesis (1) that a faculty member's probability for adopting an educational innovation will be higher if she or he identifies social-exchange networks as more influential than anonymous-search networks during the persuasion stage. The hazard models suggest that the influence amplifies as the potential adopter consults additional sources from social-exchange networks. Only for SALG was the effect of social-exchange networks associated with the first source of information about the innovation.

There was weak, mixed support for the corollary hypotheses (1a - 1c).

Hypothesis 1a: The positive relationship between the probability of adoption and social-exchange networks will be weaker for individuals in institutions emphasizing research.

Hypothesis 1b: The negative relationship between the probability of adoption and research institutions will be more strongly negative for individuals with tenure or on the tenure-track.

Hypothesis 1c: The positive relationship between the probability of adoption and social-exchange networks will be weaker for individuals with tenure or on tenure-track.

The interaction between social-exchange networks and research universities (Hypothesis 1a) was only found to be significant in Model 4 for CPR. The multiplicative effect of tenured faculty interacting with social-exchange networks (Hypothesis 1c) was significant in the direction predicted for CPR and SALG, but in the opposite direction for PLTL. Contradictory evidence for Hypothesis 1b was found in Model 6 for PLTL.

The next chapter discusses the next phase of use patterns. I explore how abandonment patterns are associated with social position and the sources of information used to learn about the innovation before adoption.

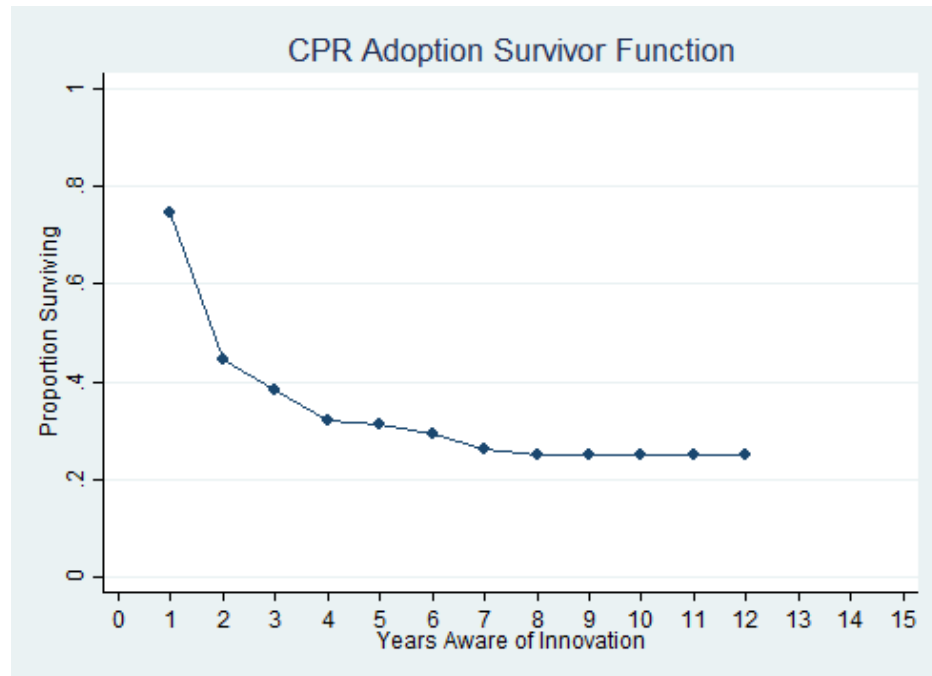


Figure 4.1: CPR Adoption Survival Function

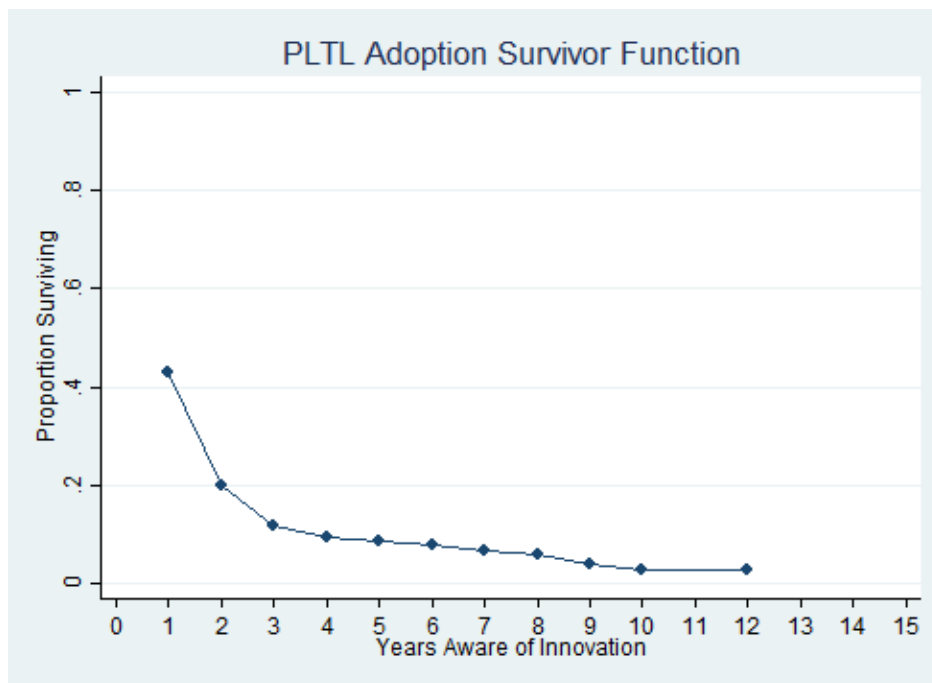


Figure 4.2: PLTL Adoption Survival Function

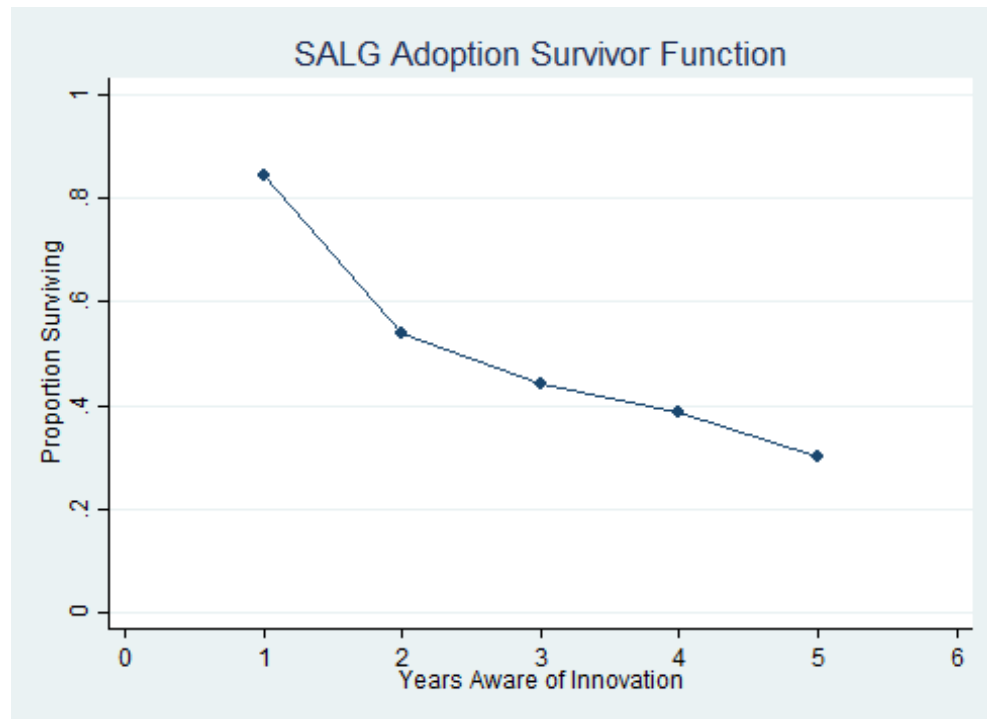


Figure 4.3: SALG Adoption Survival Function

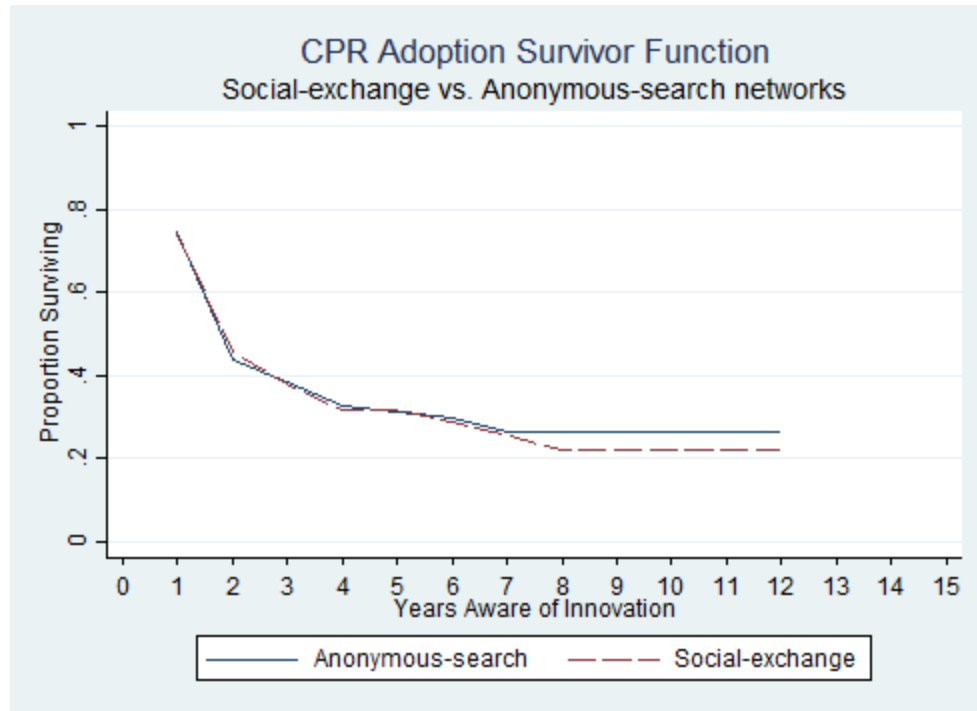
Table 4.1: Descriptions of Independent Variables

Variable	Description
<i>Background Characteristics</i>	
Gender	Male is the reference.
Discipline	Dummy variables for each of the four categories: natural sciences, engineering, social sciences, and humanities. The reference group changes in each model because not all 4 groups were represented for each innovation (e.g., PLTL is not used by social scientists or humanists).
Doctoral Degree	Modeled as a dummy variable representing doctorate or not because a high percentage of respondents listed their terminal degree as a Ph.D. (80 percent for each innovation).
<i>Social Position</i>	
Faculty role	Faculty role is an ordinal variable that is represented in several ways throughout the models: 1) dummy variable representing non-contingent faculty(tenured and tenure-track). The reference were contingent faculty (lecturer and adjunct) 2) dummy variable representing tenured (e.g., full and associate professors) or not 3) dummy variables representing each of the ordinal categories with lecturers being the reference group
College type	College type is an ordinal variable based on a collapsed version of the Carnegie Classification: research universities, master's universities, baccalaureate colleges, associate's colleges.
Interaction: Faculty role X College type	Created from previous two variables.
<i>Adoption Experience</i>	
Grant funding	Dummy variable with no grant funding as reference.
Years since first use	Respondents listed the year they first used the innovation. This response was reverse coded to represent the number of years since the individual first used the innovation.
First source of information used	Dummy variable representing the first source of information consulted. The reference is Anonymous-search network.
Interaction: First Source X Faculty role	Created from First source of information used and Faculty role.
Interaction: First Source X College type	Created from First source of information used and College type.

<i>Adoption Experience Continued</i>	
Social-exchange network influence	A count variable representing the number of Social-exchange network sources the respondent listed as influential.
Anonymous-search network influence	A count variable representing the number of Anonymous-search network sources the respondent listed as influential.
Interaction: Social-exchange network influence X faculty role	Created from Social-exchange network influence and Faculty role.
Interaction: Social-exchange network influence X College type	Created from Social-exchange network influence and College type.

Table 4.2: Mean Values of Independent Variables

Variable			CPR n = 164	PLTL n = 143	SALG n = 809
Years Aware			2.804 (2.937)	1.842 (2.389)	1.415 (1.296)
Gender: Male (Female reference)			0.506 (0.500)	0.547 (0.498)	0.611 (0.524)
Science Course			0.708 (0.455)	0.878 (0.327)	0.701 (0.458)
Engineering Course			0.033 (0.180)	0.122 (0.327)	0.058 (0.234)
Social Science Course			0.038 (0.192)	-	0.141 (0.348)
Doctoral Degree			0.820 (0.384)	0.833 (0.373)	0.836 (0.370)
Non-contingent Faculty	Tenured Faculty	Full Professors	0.418 (0.493)	0.408 (0.492)	0.304 (0.460)
		Associate Professor	0.196 (0.397)	0.218 (0.413)	0.240 (0.427)
	Untenured Faculty	Assistant Professor	0.212 (0.409)	0.141 (0.348)	0.251 (0.434)
		Lecturers	0.114 (0.318)	0.169 (0.375)	0.124 (0.330)
Contingent Faculty					
Research University			0.309 (0.462)	0.476 (0.500)	0.344 (0.475)
Master's University			0.269 (0.444)	0.226 (0.419)	0.354 (0.478)
Baccalaureate College			0.124 (0.330)	0.075 (0.263)	0.179 (0.384)
Grant Funding			0.107 (0.309)	0.699 (0.459)	0.075 (0.263)
First Source: Social-exchange network (Anonymous-search reference)			0.328 (0.470)	0.699 (0.459)	0.514 (.500)
Social-exchange network influence			4.988 (1.790)	6.541 (1.857)	2.408 (1.836)
Anonymous-search network influence			7.989 (2.358)	9.983 (4.074)	2.511 (2.563)



**Figure 4.4: CPR Adoption Survival Function by Initial Awareness:
Social-exchange and Anonymous-search Networks**

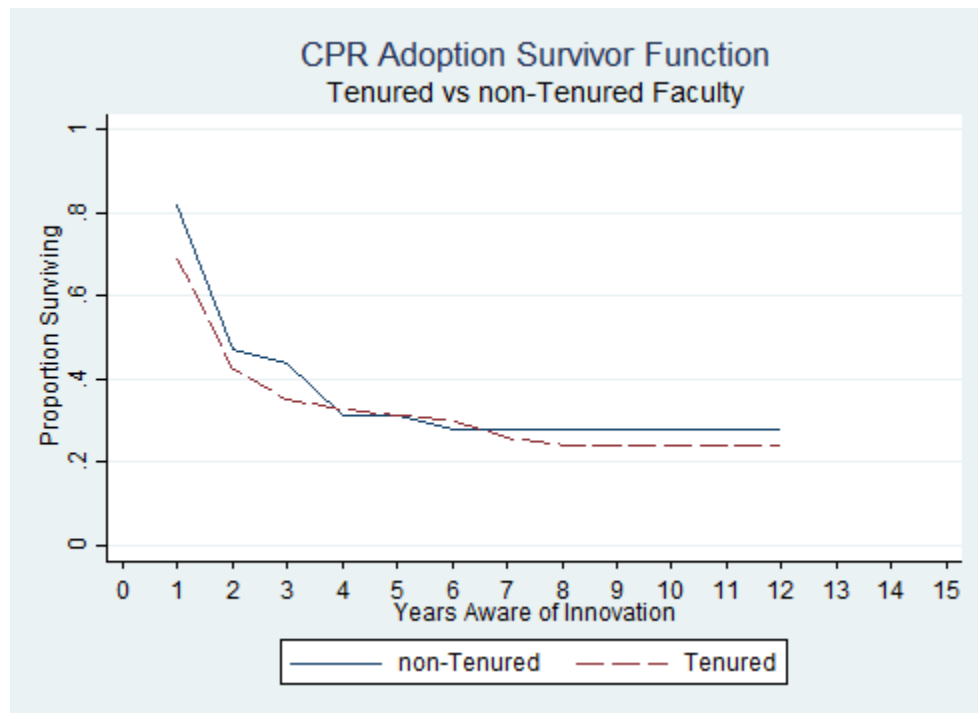


Figure 4.5: CPR Adoption Survival Functions for Tenured and Non-tenured Faculty Members

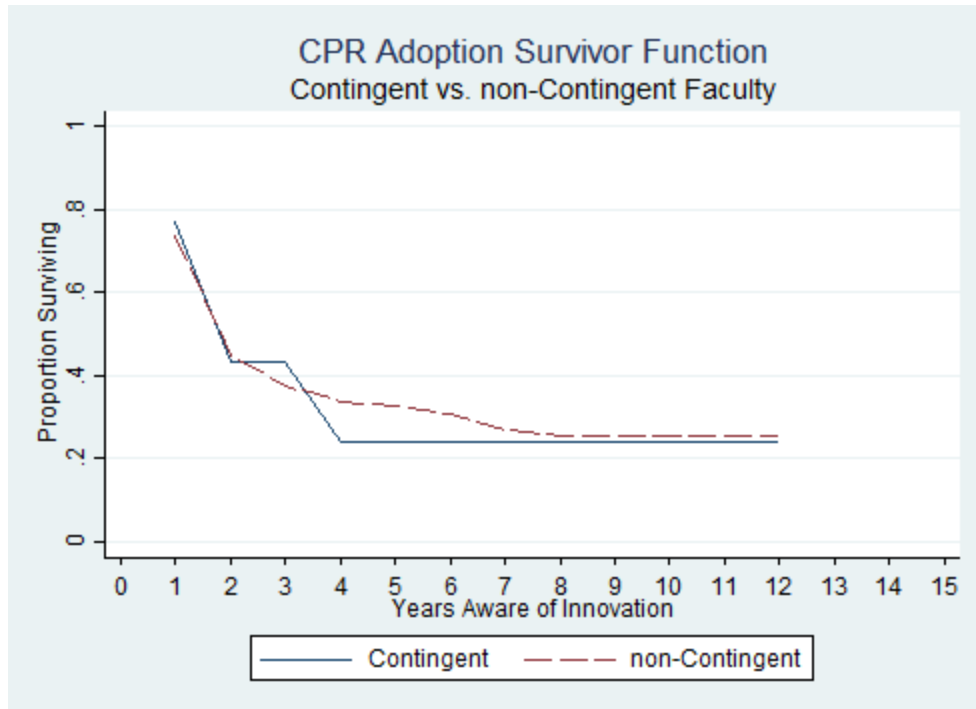


Figure 4.6: PLTL Adoption Survival Functions for Non-contingent and Contingent Faculty Members

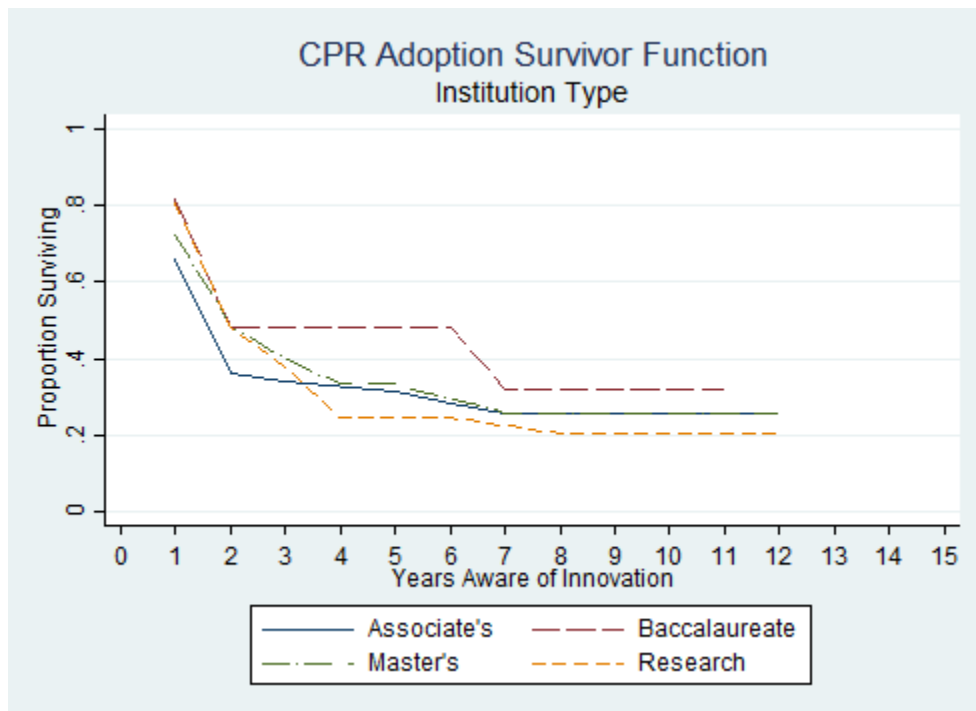


Figure 4.7: CPR Adoption Survival Functions by Institution Type

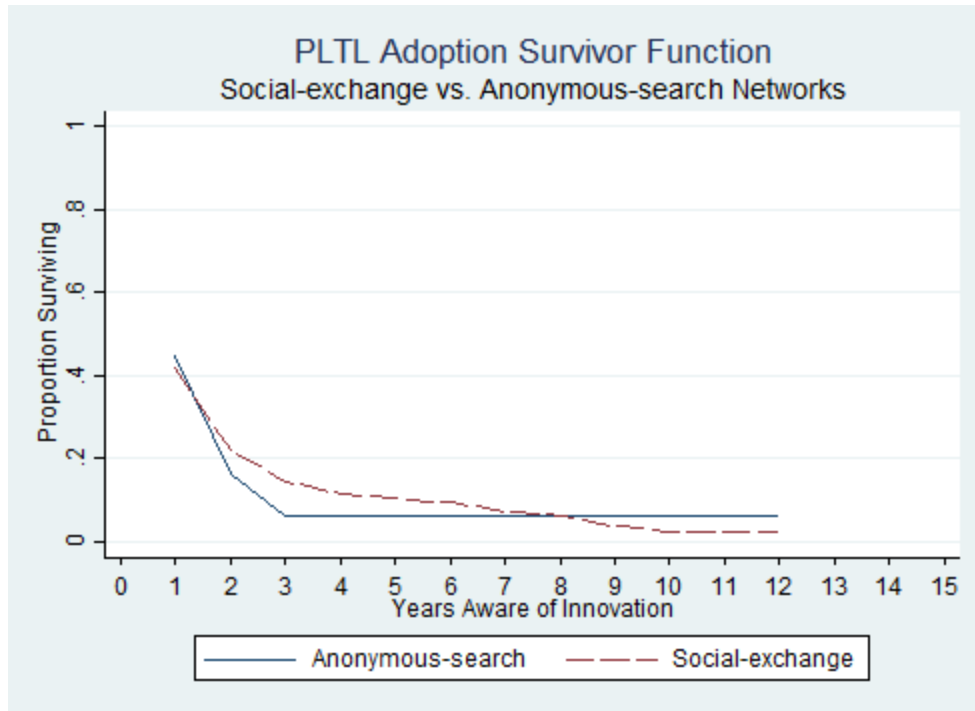


Figure 4.8: PLTL Adoption Survival Function by Initial Awareness: Social-exchange and Anonymous-search Networks

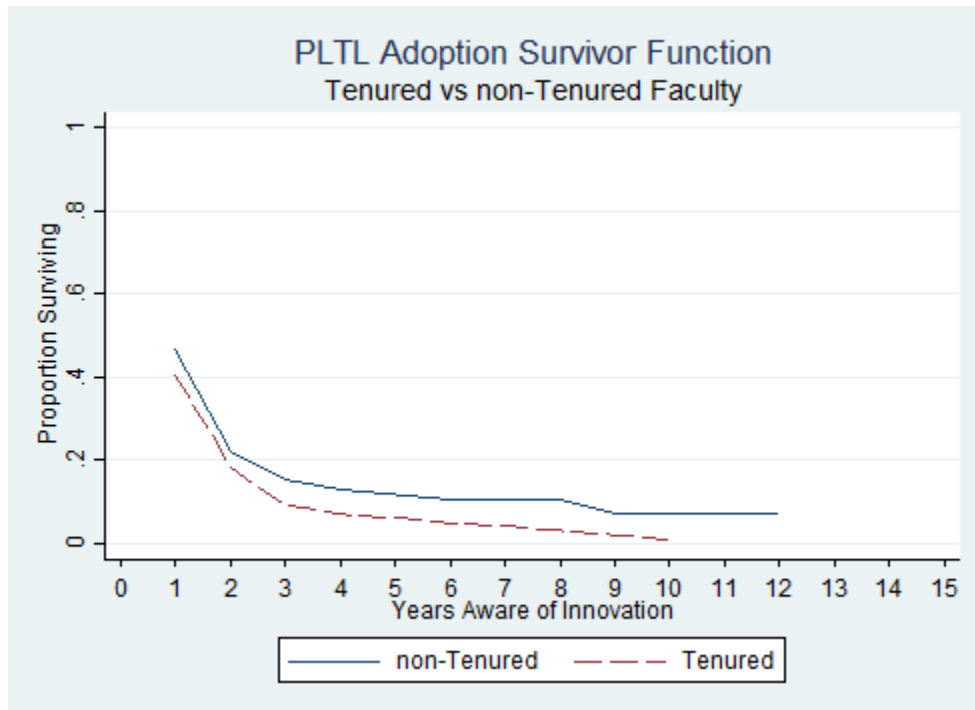


Figure 4.9: PLTL Adoption Survival Functions for Tenured and Non-tenured Faculty Members

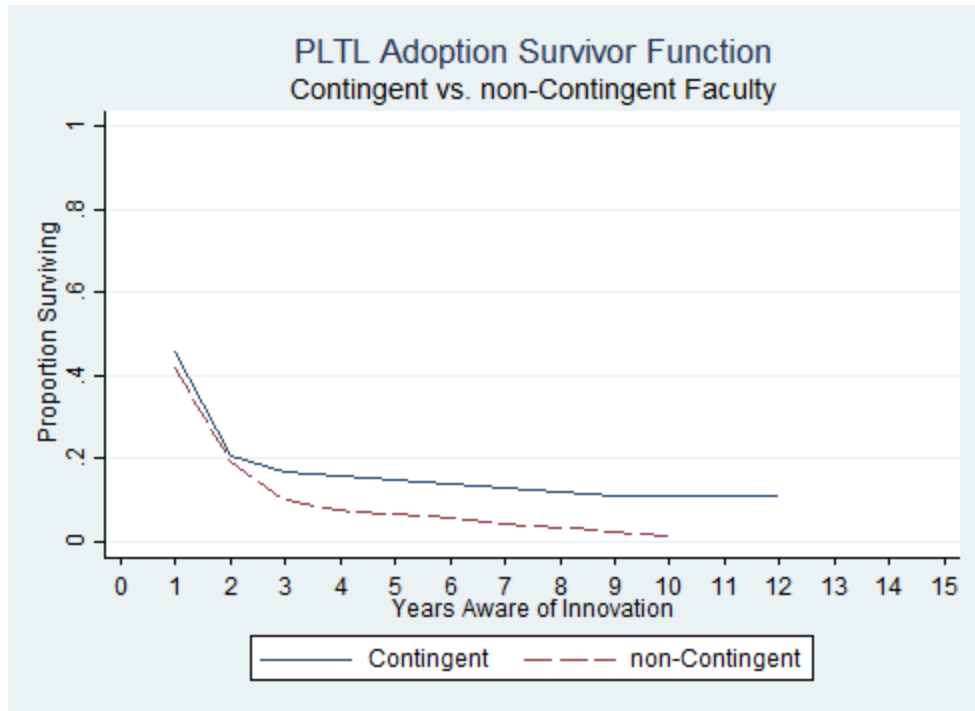


Figure 4.10: PLTL Adoption Survival Functions for Non-contingent and Contingent Faculty Members

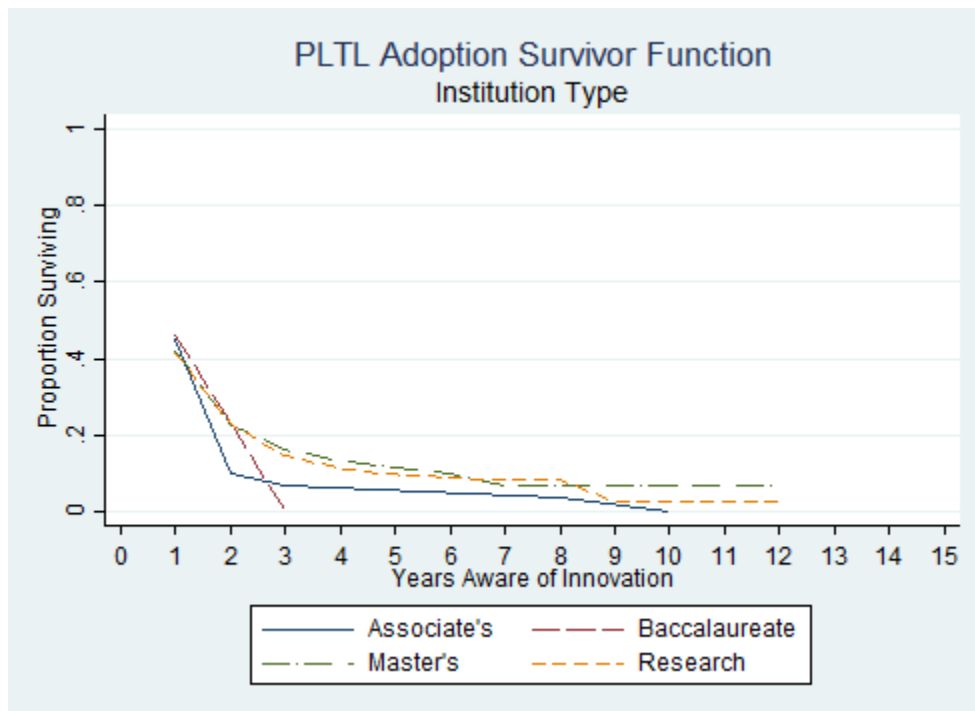


Figure 4.11: PLTL Adoption Survival Functions by Institution Type

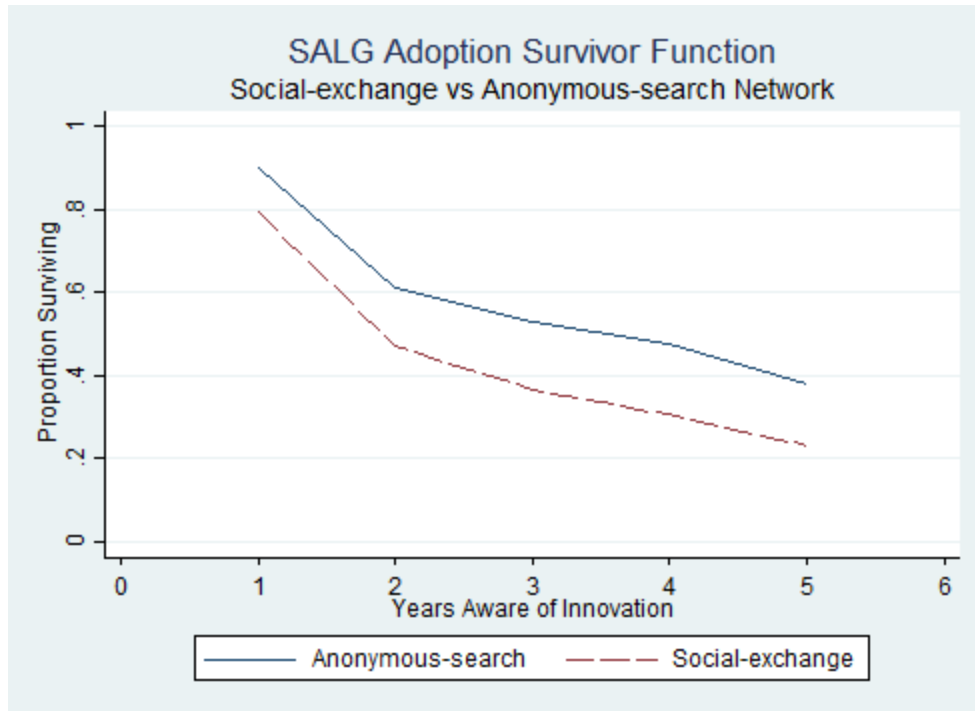


Figure 4.12: SALG Adoption Survival Function by Initial Awareness: Social-exchange and Anonymous-search Networks

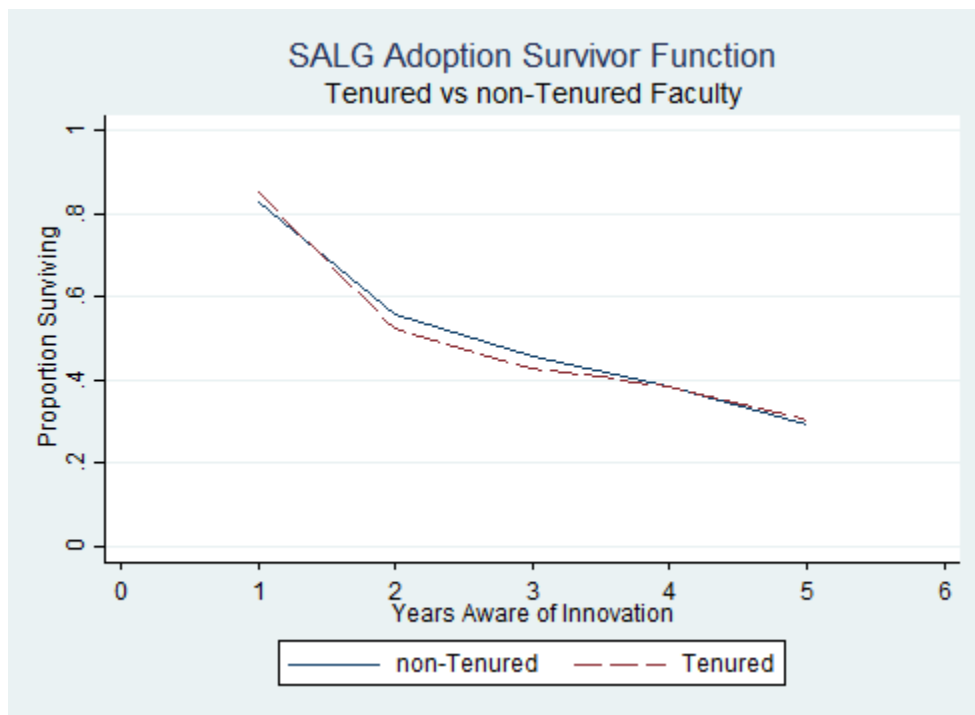


Figure 4.13: SALG Adoption Survival Functions for Tenured and Non-tenured Faculty Members

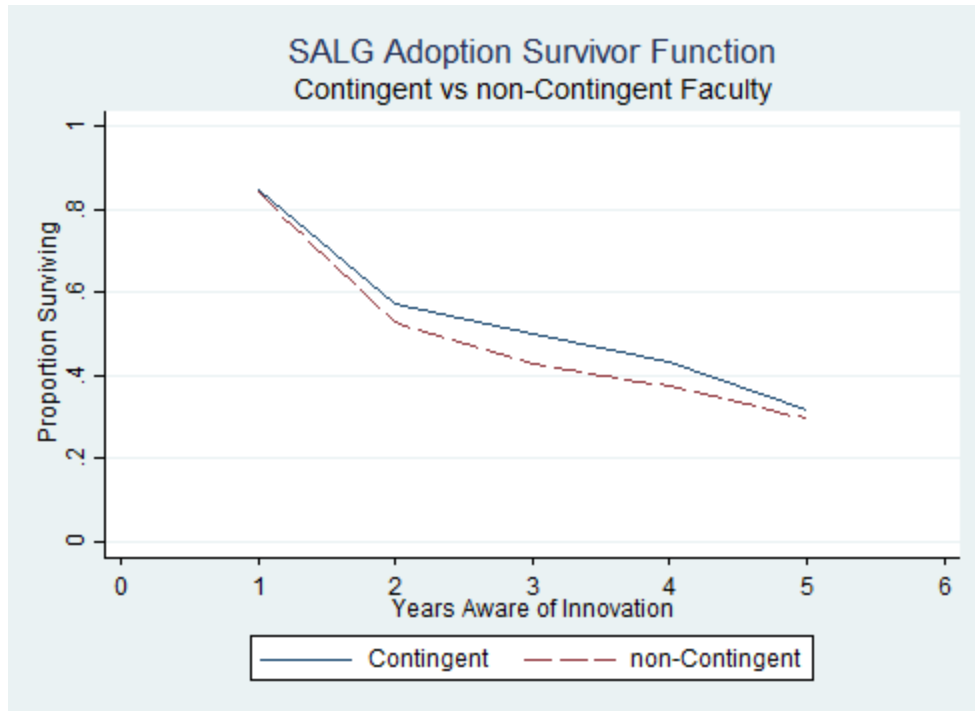


Figure 4.14: PLTL Adoption Survival Functions for Non-contingent and Contingent Faculty Members

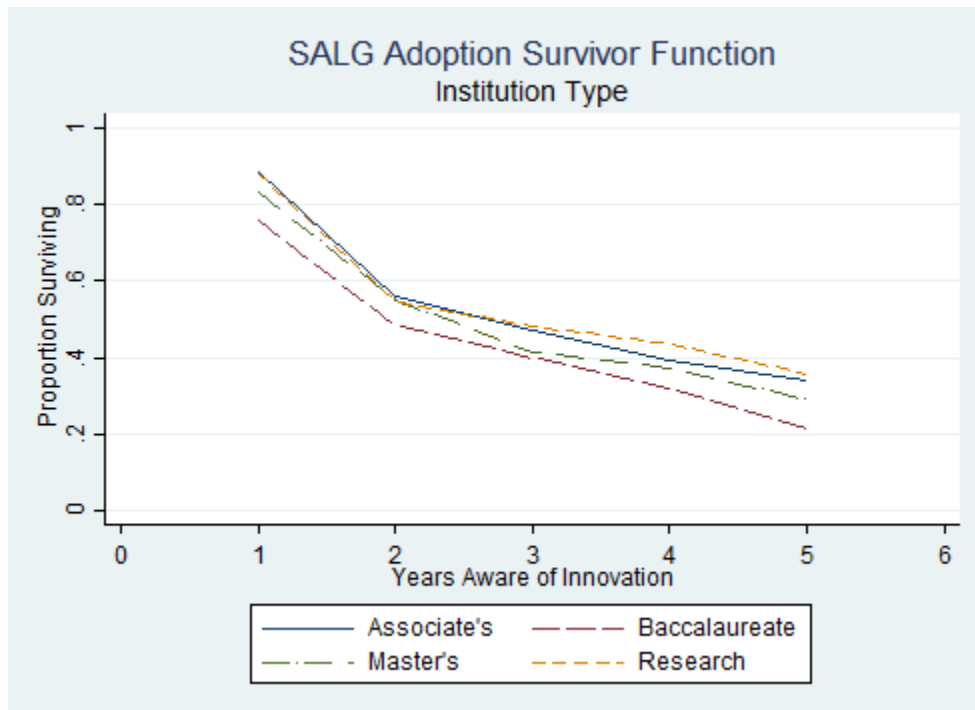


Figure 4.15: SALG Adoption Survival Functions by Institution Type

Table 4.3: Effects of Social Position and Network Influence on the Odds of Adopting CPR

	Model1	Model 2	Model 3	Model 4	Model 5	Model 6
	Background	Model 1 + Social Position	Model 2 + First Source	Model 3 + Intersection Terms	Model 2 + Adoption Influencers	Model 5 + Intersection Terms
Intercept	0.011*** (0.006)	0.014*** (0.008)	0.014*** (0.007)	0.009*** (0.005)	0.005*** (0.003)	0.001*** (0.001)
Years Aware	10.030*** (3.658)	10.247*** (3.783)	10.234*** (3.765)	10.560*** (3.937)	10.284*** (3.736)	10.982*** (4.077)
(Years Aware) ²	0.556*** (0.061)	0.555*** (0.062)	0.556*** (0.062)	0.553*** (0.062)	0.560*** (0.062)	0.553*** (0.062)
(Years Aware) ³	1.034*** (0.007)	1.034*** (0.007)	1.034*** (0.007)	1.034*** (0.007)	1.033*** (0.007)	1.034*** (0.007)
Gender	1.325 (0.308)	1.338 (0.310)	1.320 (0.309)	1.281 (0.309)	1.269 (0.296)	1.273 (0.307)
Science Course	3.719*** (1.395)	4.003*** (1.524)	4.127*** (1.582)	4.509*** (1.777)	3.756*** (1.416)	3.825*** (1.468)
Engineering Course	0.409 (0.482)	0.428 (0.505)	0.452 (0.535)	0.414 (0.515)	0.521 (0.612)	0.513 (0.614)
Soc Science Course	9.190*** (4.195)	11.837*** (5.968)	12.266*** (6.351)	11.145*** (6.046)	11.322*** (5.982)	10.553*** (5.780)
Doctoral Degree	1.010 (0.313)	1.087 (0.354)	1.066 (0.348)	1.062 (0.353)	1.085 (0.346)	1.181 (0.386)
Tenured (a)		1.329 (0.378)	1.283 (0.38)	1.739 (0.652)	1.324 (0.384)	5.856 (5.112)

Non-contingent faculty	0.514+	0.523+	0.541+	0.472*	0.533+	
	(0.182)	(0.186)	(0.181)	(0.163)	(0.183)	
Research University (b)	0.987	0.951	1.790	0.923	8.604*	
	(0.248)	(0.24)	(0.645)	(0.238)	(7.617)	
Grant Received		1.284	1.460	1.352	1.457	
		(0.424)	(0.508)	(0.417)	(0.460)	
Social-Exchange Source (c)		1.040	2.012			
		(0.250)	(0.962)			
a x c			0.605			
			(0.302)			
b x c			0.405+			
			(0.205)			
a x b			0.615			
			(0.294)			
Social-Exchange Influence (d)				1.079	1.455**	
				(0.064)	(0.187)	
Anonymous-Search Influence				1.084+	1.066	
				(0.048)	(0.048)	
a x d					0.767+	
					(0.108)	
b x d					0.691	
					(0.100)	
a x b					0.659	
					(0.318)	
Log Pseudolikelihood	-257.022	-255.459	-255.156	-252.803	-252.465	-248.333
n	729	729	729	729	729	729
*** p<0.001, **p<0.01, *p<0.05, + p<0.10						

*** p<0.001, **p<0.01, *p<0.05, + p<0.10

Table 4.4: Effects of Social Position and Network Influence on the Odds of Adopting PLTL

	Model1	Model 2	Model 3	Model 4	Model 5	Model 6
	Background	Model 1 + Social Position	Model 2 + First Source	Model 3 + Intersection Terms	Model 2 + Adoption Influencers	Model 5 + Intersection Terms
Intercept	0.078*** (0.041)	0.057*** (0.037)	0.037*** (0.028)	0.049*** (0.035)	0.048*** (0.035)	0.068* (0.093)
Years Aware	13.425*** (5.649)	14.250*** (5.992)	17.292*** (9.118)	17.854*** (9.452)	18.281*** (9.372)	19.395*** (9.956)
(Years Aware) ²	0.519*** (0.058)	0.515*** (0.056)	0.483*** (0.084)	0.480*** (0.084)	0.481*** (0.084)	0.481*** (0.082)
(Years Aware) ³	1.039*** (0.006)	1.040*** (0.007)	1.045** (0.015)	1.046** (0.015)	1.046** (0.015)	1.046** (0.015)
Gender	0.498** (0.125)	0.570* (0.150)	0.571* (0.153)	0.607+ (0.161)	0.531* (0.141)	0.550* (0.143)
Science	2.177** (0.697)	2.423* (0.850)	2.878** (1.103)	2.778* (1.184)	3.155** (1.273)	3.302** (1.279)
Doctoral Degree	0.788 (0.277)	0.503* (0.170)	0.686 (0.236)	0.665 (0.224)	0.799 (0.28)	0.738 (0.265)
Tenured (a)		1.111 (0.391)	0.972 (0.335)	0.863 (0.489)	1.091 (0.438)	0.120* (0.125)
Non-contingent faculty		1.566 (0.802)	1.127 (0.564)	0.937 (0.458)	0.967 (0.495)	0.818 (0.396)
Research University (b)		1.148 (0.333)	0.949 (0.268)	0.590 (0.298)	0.934 (0.27)	0.207 (0.226)

Grant Received	1.741+			1.704+	1.598	1.643
	(0.545)			(0.542)	(0.532)	(0.542)
Social-Exchange Source (c)	1.926			1.258		1.172
	(0.847)			(0.706)		(0.089)
a x c				0.707		
				(0.408)		
b x c				0.854		
				(0.424)		
a x b				2.305		
				(1.253)		
Social-Exchange Influence (d)					1.173*	0.942
					(0.089)	(0.153)
Anonymous-Search Influence					1.006	1.009
					(0.030)	(0.032)
a x d						1.294+
						(0.201)
b x d						1.130
						(0.161)
a x b						2.642+
						(1.417)
Log Pseudolikelihood	-224.631	-219.587	-213.079	-211.742	-210.241	-207.548
n	434	434	434	434	434	434
*** p<0.001, **p<0.01, *p<0.05, + p<0.10						

Table 4.5: Effects of Social Position and Network Influence on the Odds of Adopting SALG

	Model1	Model 2	Model 3	Model 4	Model 5	Model 6
	Background	Model 1 + Social Position	Model 2 + First Source	Model 3 + Intersection Terms	Model 2 + Adoption Influences	Model 5 + Intersection Terms
Intercept	0.001*** (0.000)	0.001*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Years Aware	2497.969*** (1669.386)	2575.074*** (1729.056)	2737.145*** (1868.154)	2746.413*** (1876.63)	2522.762*** (1691.822)	2587.382*** (1740.823)
(Years Aware) ²	0.050*** (0.014)	0.049*** (0.014)	0.049*** (0.014)	0.049*** (0.014)	0.051*** (0.014)	0.051*** (0.014)
(Years Aware) ³	1.397*** (0.048)	1.398*** (0.048)	1.394*** (0.048)	1.394*** (0.048)	1.389*** (0.047)	1.390*** (0.047)
Gender	0.908 (0.100)	0.899 (0.100)	0.939 (0.105)	0.939 (0.106)	0.901 (0.099)	0.916 (0.102)
Science Course	2.226*** (0.508)	2.241*** (0.513)	2.189*** (0.498)	2.157*** (0.488)	1.942** (0.460)	1.918** (0.451)
Engineering Course	1.835+ (0.620)	1.927+ (0.661)	1.631 (0.552)	1.626 (0.546)	1.606 (0.539)	1.590 (0.537)
Soc Science Course	1.025 (0.290)	1.034 (0.294)	1.004 (0.288)	0.998 (0.287)	1.002 (0.291)	0.974 (0.282)
Doctoral Degree	0.937 (0.148)	0.951 (0.161)	0.854 (0.141)	0.864 (0.144)	0.899 (0.154)	0.915 (0.160)
Tenured (a)		0.889 (0.124)	0.961 (0.136)	1.072 (0.228)	0.890 (0.125)	1.087 (0.249)
Non-contingent faculty		1.077 (0.199)	1.123 (0.214)	1.126 (0.225)	1.130 (0.214)	1.104 (0.220)

Research University (b)	0.792+	0.878	0.726	0.817	0.768	
	(0.101)	(0.113)	(0.177)	(0.106)	(0.200)	
Grant Received		3.024***	3.064***	2.813***	2.882***	
		(0.516)	(0.527)	(0.451)	(0.463)	
Social-Exchange Source (c)		1.803***	1.963***			
		(0.209)	(0.415)			
a x c			0.761			
			(0.182)			
b x c			1.242			
			(0.313)			
a x b			1.159			
			(0.301)			
Social-Exchange Influence (d)				1.150***	1.232***	
				(0.035)	(0.065)	
Anonymous-Search Influence				0.991	0.991	
				(0.023)	(0.023)	
a x d					0.899+	
					(0.055)	
b x d					0.969	
					(0.061)	
a x b					1.310	
					(0.339)	
Log Pseudolikelihood	-959.888	-957.7545	-929.372	928.069	-925.137	-923.159
n	2736	2736	2736	2736	2682	2682
*** p<0.001, **p<0.01, *p<0.05, + p<0.10						

V. Social Position, Diffusion Networks, and Abandonment Patterns

Once someone adopts an educational innovation, how likely is she or he to continue using it? This chapter explores patterns of abandonment. It is the second empirical chapter in this section analyzing use patterns of three innovations. There are many reasons why someone may stop using an innovation. An instructor may pilot a new resource and decide not to continue using it after that experience. Another faculty member may continue using it until replacing it with what she or he perceives to be a more effective resource. Other situations may cause faculty members to abandon innovations. One may take a position at a different college or no longer teach the course in which she or he first used the innovation. While the last two examples demonstrate external factors that may impact a user's decision, I believe personal choice is more influential. An instructor will likely continue to use a particular pedagogical strategy or educational resource even if she teaches in a different course or at a different college. One of the reasons the particular innovations were chosen for this study was because of their broad appeal and relevance so that a faculty member's decision was less likely to be influenced by a new course assignment or institutional move.

5.1 Understanding Abandonment Through the Adoption Analysis

I will rely on the same theoretical rationale I used to understand adoption patterns for this chapter. The previous chapter provides a description of how social capital – specifically social norms and information channels – operate

differently in social-exchange and anonymous-search networks. In addition, I explain how sources of information from these networks may influence faculty members differently depending on an instructor's social position. Social position is defined by both faculty role and institution type. Based on the interaction between diffusion networks and social position described in the past chapter, I am suggesting a teacher's decision to use an innovation is not just based on a rational decision of whether the innovation is a proper match for an instructional need (Rogers 2003, p. 423). A faculty member's use of an innovation also reflects the influence of the institution's teaching norms (Eimers, Braxton, & Bayer 1996).

I believe that social influences communicated through social-exchange and anonymous-search networks that motivate someone to adopt also motivate them to persist in using the innovation. Additional factors may lead a faculty member to stop using the resource such as a reduction in organizational support or obsolescence by new innovations. These factors are independent of network effects hypothesized, however, so the theoretical reasons used in the last chapter to create hypotheses on adoption patterns are applicable to hypotheses on abandonment.

5.2 Hypotheses

The last chapter found evidence that an instructor's likelihood of adoption increases the more she or he identifies social-exchange networks as influential. I hypothesized this was because norms signaled, monitored, and enforced through these networks are stronger than those communicated through anonymous-search networks. For this same reason, I believe a faculty member will be less likely to

abandon an innovation the more she or he consults social-exchange networks.

Those norms not only pressure someone to adopt, but to also persist in using it.

Hypothesis 2: A faculty member's probability for abandoning an educational innovation will be lower if she or he identifies social-exchange networks as more influential than anonymous-search networks during the persuasion stage.

Do social-exchange networks influence all faculty members equally? As explained in the previous chapter, I believe they do not. The following hypotheses state how the likelihood of abandonment varies by social position. Social position is defined by both the instructor's faculty role and institution type. Please see the *Hypotheses* section (4.2) of the previous chapter for a description of how the two components of social position are categorized and how I expect they interact with social-exchange networks.

Hypothesis 2a: The negative relationship between the probability of abandonment and social-exchange networks will be weaker for individuals in institutions emphasizing research.

Hypothesis 2b: The positive relationship between the probability of abandonment and research institutions will be stronger for individuals with tenure or on the tenure-track.

Hypothesis 2c: The negative relationship between the probability of abandonment and social-exchange networks will be weaker for individuals with tenure or on the tenure-track.

Admittedly, these hypotheses sound confusing because they describe a negative association between social-exchange networks and the likelihood of abandonment along with interactions that amplify or attenuate the negative association. The following example explaining my logic of Hypothesis 2a may assist in clarifying the hypothesized interactions. Consider two instructors both of whom first learned of Student Assessment of Learning Gains (SALG) through social-exchange networks and who are alike on all aspects of teaching discipline, faculty rank, years of teaching experience, the experience of having initially adopted SALG, and other relevant variables with the exception of institution type. One of these instructors is employed at a research university while the other is employed at a teaching college. On average, I predict that having learned about SALG through a social-exchange network will reduce the odds of abandonment especially strongly at the teaching college. This is because I expect social norms are strongly centered on decisions and actions that can potentially benefit classroom learning. Having learned about SALG through a social-exchange network will not reduce the odds of abandoning as strongly at a research university. I expect this because the establishment and enforcement of social norms regarding classroom teaching decisions are less central at research universities.

A similar example can be given for Hypothesis 2c. On average, I predict that having learned about SALG through a social-exchange network will reduce the odds of abandonment more strongly for contingent faculty compared to non-contingent faculty. This is because I expect adjuncts and lecturers (i.e.,

contingent faculty) are most responsive to teaching social norms on campus than tenured and tenure-track faculty (i.e., non-contingent faculty), whose responsibilities more often include non-teaching activities (e.g., research).

The logic of these examples can be used to provide an example for Hypothesis 2b. If faculty at research universities are more likely to abandon an innovation than faculty at non-research universities (again because of weaker social norms on teaching at research universities), then this effect will be stronger for tenured and tenure-track faculty compared to contingent faculty (i.e., lecturers and adjunct instructors) at research universities. This is because tenured and tenure-track faculty at research universities will be less receptive to the weaker social norms on teaching at research universities compared to adjuncts and lecturers, whose primary responsibility is teaching.

5.3 Testing the Hypotheses

I will use survival function graphs and hazard models to test the hypotheses. The survival function in this chapter will describe the probability of not abandoning the innovation. The discrete-time survival function for an individual, i , in time period, j , can be written as the following.

$$S(t_{ij}) = Pr[T_i > j]$$

where $S(t)$ is the conditional probability of continuing to use the innovation at time t given that no abandonment occurred before t .

I will also use discrete-time hazard models to test the hypotheses (Allison 1982; Singer & Willet 1993; Singer & Willet 2003). For this chapter, these models can be generally expressed as the following.

$$(2) \ln[h(t)] = \alpha + \beta_1 S + \beta_2 R + \beta_3 T + \beta_{12} S^* R + \beta_{23} R^* T + \beta_{13} S^* T$$

where $h(t)$ is the conditional probability of abandoning an innovation at time t given that no abandonment occurred by t .

and:

S = use of social-exchange networks dummy variable (anonymous-search networks are reference)

R = research universities dummy variable (all other types of colleges are reference)

T = tenured or tenure-track dummy variable (lecturers and adjuncts are reference)

An individual enters the risk set for abandonment when she or he adopts the innovation (i.e., uses it for the first time). For Calibrated Peer Review (CPR) 113 of the 170 registered account holders used CPR at least once (66 percent of respondents) and, therefore, were considered part of the risk set. Nearly all of the Peer-led Team Learning (PLTL) respondents adopted (139 out of 146). Those who did were included in the risk set. About 50 percent of the SALG respondents (429 out of 809) adopted the innovation. Staff that responded to a survey but did not have teaching responsibilities were dropped from the analysis because they are not able to adopt the innovation for a course.

Individuals will be right censored in the discrete-time hazard models when they have adopted the innovation but not abandoned it by the date they responded to the survey. Left censoring is not a concern because no respondent can abandon

the innovation before time zero which equates to the year the individual first adopted the innovation.

My goal was to survey the entire population of potential adopters of the innovation (i.e., those who were aware of the innovation and received information through a social-exchange or anonymous-search network). I believe I approximated the population sought for each innovation through user logs, snowball sampling, and other sources. However, my response rates were not 100 percent. I interpreted the coefficients as if they represented the responses of a random sample taken from the population. I tested for responses biases using logit and probit models on a key variable representing one of the constructs in my hypothesis. No bias was found. See Appendix C for a description of this analysis.

5.3.1 Dependent Variable – An Overview

The dependent variable, abandonment, is a non-repeatable event defined by two survey questions. To be coded as having abandoned a particular innovation, first, respondents had to answer, “Do not plan to use it again,” to the question asking about their future plans for using the tool.²⁵ For those who did not plan to use the resource, the year of abandonment was defined as the year after the last reported year of use. If a respondent reported last using the tool in the 2008-09 academic year, then the abandonment year was 2009-10.

I had considered defining abandonment to also include those who had not used the innovation for five consecutive years and had indicated they, “may use

²⁵ The three options for this question were: 1) Definitely use it again, 2) May use it again when appropriate, and 3) Do not plan to use it again.

the innovation in the future when appropriate.” I considered a five-year hiatus a significant time and a “maybe” response a weak commitment. The problem with using this metric to define abandonment is that 1) the SALG respondents’ life history can only be five years at most because the clocking time starts at 2008-09 and 2) many CPR and SALG respondents had only recently adopted the innovation (i.e., 2010 or later) so their life histories would be less than five years. The most concrete measure of abandonment was the reply of no longer planning to use the innovation.

Figures 5.1 through 5.3 show the overall abandonment rates for each innovation. The hazard rate for abandoning CPR was highest in the first year (10 percent), and the survival function steadily declined with about four percent of the risk set abandoning each year for the next three years (see Figure 5.1). Ultimately about 25 percent of the risk set abandoned the innovation before being right censored during the span of my data inquiries. The slope of the survival function for PLTL was the most linear of the three innovations; about 1-2 percent of the risk set abandoned the innovation each year of the analysis (see Figure 5.2). By the end of the analysis about 16 percent of the risk set had abandoned PLTL. SALG had the lowest levels of abandonment (see Figure 5.3). By the end of the five-year analysis, less than five percent of users had abandoned the innovation. It should be noted that the SALG life histories were more limited than the other innovations because that innovation was released more recently than CPR and PLTL. Five years is the longest possible life history for a SALG respondent compared to 12 years for a CPR and PLTL respondent.

5.3.2 Addressing Missing Dependent Variable Data

SALG user data were provided by the SALG director, Stephen Carroll. These data were merged with respondent survey data to create historical use patterns so there were no missing data for the dependent variable. For PLTL and CPR, survey respondents reported their use of each innovation by academic year. One of the response options was “Don’t remember.” Respondents did not choose this option often for when they last used the innovation. For CPR, 12 “Don’t remember” submissions were reported out of 1,567 person-periods for CPR abandonment (0.8 percent). There were two “Don’t remember” reports out of 1,604 person-periods for PLTL (0.1 percent). The most common response pattern was for respondents to enter a “Don’t remember” response for the year immediately after a report of using the innovation for consecutive years. I assumed these responses indicated the individual did not remember the last year she or he used the tool. I used a fair, six-sided die to impute these responses.²⁶ I replaced “Don’t remember” with “Not used” for rolls of one through three and “Used” for rolls of four through six. This method was employed for two CPR respondents and two PLTL respondents.

Several CPR respondents reported a string of three to six consecutive years of “Don’t remember” responses but no other years in which they used the innovation. I interpreted these responses as a user not remembering in what year she or he started and stopped using the tool. I only need to know the last year the respondent used the innovation (i.e., the adoption year) for the survival function

²⁶ Special thanks go to Shenandoah Reese for rolling the die. Her contributions were much appreciated.

and discrete-time hazard models. I used hot deck imputation to replace the missing data for the abandonment year. I chose the last year used (i.e., abandonment) for these individuals based on the average time to abandon the innovation by the other respondents. This method was employed for one CPR respondent and no PLTL respondents (i.e., all PLTL respondents missing data fit the first category described in the previous paragraph – reporting “Don’t Remember” for one year).

5.3.3 Independent Variables – An Overview

The independent variables used (see Table 5.1) were basically the same as those in the previous chapter except for the time variable. The independent variables are grouped into three categories. This categorization reflects the model testing based on 1) the faculty member’s background characteristics, 2) social position variables associated with the hypotheses, and 3) additional variables associated with the adopter’s experience. Please see the *Independent Variables – An Overview* section (4.3.6) of the previous chapter for a description of the key independent variables used to test the hypotheses: social-exchange and anonymous-search networks along with faculty role and institution type. Mean values and standard deviations of the independent variables for each innovation are provided in Table 5.2. The time variable differs from the previous chapter because the risk set is different (i.e., all adopters instead of all survey respondents).

5.3.4 Time

For this chapter's analysis, time represented the number of years since the respondent started using the innovation (i.e., adoption). Time will be measured as a discrete variable in the survival functions and hazard models because adoption and abandonment is typically tied to a semester. The year of adoption varied by individual, so the time variable cannot represent the actual year in the Gregorian calendar. Time was converted to a clocking time variable with the value zero for the year when adoption occurred.

I tested several time functions to identify the best fit for the discrete-time hazard models. A simple logit model with a time function and one additional independent variable, first source of information, was used to identify the best time function for the full model. I compared the Bayesian Information Criterion (BIC) for a model with a constant, linear, quadratic, cubic, and general time function. A smaller BIC value indicates a better fit. For all three innovations a linear time function gave the best fit for the time function. The shape of the hazard function graphs also provided support for a linear time function (not shown).

5.4 Results from Modeling Abandonment

Once users adopt, what is their likelihood for abandoning the innovation? Abandonment rates were generally low but did vary by innovation as described above. This section provides a detailed analysis of abandonment for each of three innovations across the key groups used to test the hypotheses.

5.4.1 Calibrated Peer Review (CPR)

5.4.1.1 CPR Abandonment Patterns

The data provided contradictory evidence for Hypothesis 2 on abandonment (see Figure 5.4). The survival function was initially lower (i.e., cumulative abandonment was higher) for those who reported learning about CPR from social-exchange networks compared to anonymous-search networks, which was opposite the hypothesis' prediction. The function was higher (i.e., less cumulative abandonment) in years four and five for those who learned about CPR from social-exchange networks before becoming increasingly lower over the remaining years of analysis. About 29 percent of the risk set who became aware of the innovation through social-exchange networks abandoned the innovation while 23 percent of the anonymous-search network risk set abandoned it.

Non-tenured faculty abandoned CPR at increasingly greater rates than tenured faculty over time (see Figure 5.5). The initial gap between the two groups' survival functions was three percent. By the end of the analysis, 18 percent of tenured faculty had abandoned the innovation but over 39 percent of non-tenured faculty had. There was an increasing gap in the survival functions between contingent and non-contingent faculty (see Figure 5.6), but most of this was explained by the high survival rates of tenured-faculty.

The survival functions for institution type vary considerably (see Figure 5.7). Faculty members in the baccalaureate college risk set have the lowest survival rate (i.e., highest cumulative abandonment) across the entire analysis. Almost 40 percent of the risk set working at teaching colleges having dropped

CPR by the end of the analysis. About 20 percent of the risk set working at master's and research universities abandoned it.

5.4.1.2 CPR Abandonment Hazard Models

Based on multivariate hazard models, there was weak support for Hypothesis 2 that faculty members who learn about the innovation from social-exchange networks will be less likely to abandon (see Table 5.3). There was no evidence that faculty members who first learned about the innovation from a social-exchange network were less likely to abandon it. The coefficient for this variable in Model 3 was not significant when controlling for the other variables. In Model 5, however, each additional social-exchange network source cited as influential decreased the odds of abandonment by 18 percent ($p < 0.10$).

Models 4 and 6 provided a test of Hypotheses 1a - 1c. None of the interaction terms used to test Hypotheses 1a and 1c reached statistical significance in either model. In Models 4 and 6, the interaction term created by the product of tenured faculty and research universities reached statistical significance ($p < 0.01$). The estimated odds ratio in both models value were very large (i.e., greater than 14), however, so it will not be interpreted. The large coefficient is likely caused by low cell counts for the number of tenured faculty who abandon the innovation. The survival function graph in Figure 5.5 documented that tenured faculty are the least likely to abandon CPR.

5.4.2 Peer-led Team Learning (PLTL)

5.4.2.1 PLTL Abandonment Patterns

The data for PLTL provided stronger contradictory evidence for the hypothesis compared to CPR. The percentage of the risk set abandoning PLTL was initially similar between those who first learned about the innovation from anonymous-search networks and social-exchange networks (See Figure 5.8). After three years, the percentage of faculty members in the risk set not abandoning was higher for those who first learned about the innovation from social-exchange network. But by the end of the analysis 10 percent of the anonymous exchange network risk set had abandoned PLTL, but 20 percent of the social-exchange network risk set had. This was opposite the prediction of Hypothesis 2.

An interesting finding was that none of the contingent faculty members abandoned the innovation (see Figure 5.10). By the end of the analysis time frame, about 20 percent of the tenured and tenure-track faculty risk set abandoned PLTL. Few members of the research university risk set abandoned the innovation (see Figure 5.11). About three percent of the research university risk set abandoned the innovation by the last year of analysis. Members of the other three institution type risk sets had a survival rate of about 70 percent by the end of the analysis time frame (i.e., about 30 percent abandoned the innovation). This abandonment occurred with different delays. Members of the associate college risk set reached its floor survival rate by year seven. Members of the

baccalaureate college risk set did not reach the floor survival rate until year eight. Members of the master's college risk set did not stabilize until year 12.

5.4.2.2 PLTL Abandonment Hazard Models

Estimated hazard Models 3 - 6 for PLTL were different than those for the other innovations in that variables representing tenured faculty and non-contingent faculty were not included (see Table 5.4). The models would not converge with their inclusion because both variables perfectly predicted non-abandonment. As such, the interaction terms used to test Hypothesis 2b (tenured/non-contingent faculty X research institution) and Hypothesis 2c (tenured/non-contingent faculty X social-exchange network) were not included in Models 4 and 6 as well. The hazard models did not provide support for Hypothesis 2 or Hypothesis 2a. None of the coefficients for the variables associated with these hypotheses were significant. The addition of the interaction term used to test Hypothesis 2a caused Model 4 to not converge.

Models 2, 3, and 5 consistently showed that faculty members at research institution were less likely to abandon PLTL than those at other institutions. The odds of abandoning were consistently about 90 percent less for faculty members who work at research universities ($p < 0.05$). This was not a direct test of Hypothesis 2a, which predicts negative association between social-exchange networks and abandonment would be weaker for faculty at research universities. The direct test of Hypothesis 2a was only possible in Model 6 where an interaction term was included for social-exchange network influence and research universities. It was not statistically significant.

The coefficient representing how long the adopter knew about the innovation was significant. Models 3 - 6 show that the odds of abandoning decrease by about 15 percent for each additional year the instructor knew about PLTL ($p < 0.05$). Early adopters appear to be more committed to using the innovation.

5.4.3 Student Assessment of Learning Gains (SALG)

5.4.3.1 SALG Abandonment Patterns

It is difficult to discern patterns in abandonment between different groups because the overall abandonment of SALG was so low – less than five percent of the SALG risk set abandoned the innovation. That said, there was again contradictory evidence for Hypothesis 2. The rate of abandonment was higher for respondents who first learned about SALG through a social-exchange network compared to an anonymous-exchange network (see Figure 5.12). While the difference was slight, it did align with the findings from the PLTL and CPR risk set. There was not much difference in the survival functions for faculty members in different roles. There was a difference in survival functions by institution type (See Figure 5.15). Faculty members from research universities had the lowest abandonment rate (two percent) compared to other types of colleges (about four percent) although, again, this difference was slight.

5.4.3.2 SALG Abandonment Hazard Modeling

The hazard models presented additional contradictory results for Hypothesis 2 (see Table 5.5). Model 3 shows the odds of abandoning SALG increased by 223 percent if the first source of information about it was from a

social-exchange network ($p < 0.10$). Model 5 also provided contradictory evidence. The coefficient for social-exchange network influence was not statistically significant, but the coefficient for anonymous-search network influence was. The odds of abandoning SALG decreased by 32 percent for each additional anonymous-search network source identified as influential ($p < 0.001$). This indirectly contradicts the Hypothesis 2 prediction. The hypothesis states that abandonment will decrease the more a user consulted social-exchange networks compared to anonymous-search networks. Model 6 did not provide any support for or against Hypotheses 1a - 1c as none of the interaction terms used to test these hypotheses were significant. Model 4, which is also used to test Hypotheses 1a - 1c, did not converge (like the PLTL Model 4).

5.5 Discussion

In general, abandonment rates were quite low. This does not mean that all respondents were still actively using the innovation, but that they few verified their abandonment by responding on the survey that they, “Do not plan to use it again,” when asked about their future use. Those who had not used the innovation for several consecutive years but chose the option indicating they “may” or “definitely will” use the innovation were not categorized as abandoning the innovation.

Hypothesis 2 predicted that users of an innovation who adopted through the influence of social-exchange networks would be less likely to abandon it because the social pressures that led to adoption would also prevent abandonment. The data presented in this chapter provided contradictory evidence. The survival

graphs and hazard models for PLTL and SALG predict individuals who learn about the innovation through social-exchange networks abandon at higher rates. CPR provides mixed support in that the survival function comparing first sources of influence (see Figure 5.4) contradicts the hypothesis and Model 5 (Table 5.3) testing overall social-exchange network influence provides weak support for the hypothesis.

In considering all these results, it appears social-exchange networks are associated with higher rates of abandonment. Perhaps social pressure exerted by change agents through social-exchange networks – consciously or unconsciously – makes the user more likely to abandon it. Users who adopted partially because of social pressure may not have made decisions that were as objective or well-researched as those made by users influenced by anonymous-search networks. These adopters guided by social-exchange networks may not be as personally committed to the innovation or practice. After implementation, the innovation flaws or mismatch may become apparent making them more likely to drop it. In addition, users may not continue to discuss their use of the innovation with the colleague who influenced them to adopt. These results could be interpreted to mean that social influences communicated through social-exchange networks may not have a lasting effect if the change agent disengages with the adopter.

5.5.1 Abandonment Patterns by Faculty Role

The only faculty members who abandoned PLTL were tenured and tenure-track faculty. This is interesting as tenured and tenure-track faculty members adopted PLTL at higher rates. One of the explanations given in the discussion

section of the previous chapter was that PLTL requires more institutional resources to implement than the other innovations. Tenured- and tenure-track faculty are more likely to garner these resources because of their status and job security (see Section 4.5.2 in Chapter 4). The findings about abandonment appear to support this explanation. Once PLTL is implemented, contingent faculty (i.e., lecturers and adjuncts) may be hesitant or not have the influence to suggest the college divest itself of a commitment to a major academic program.

SALG abandonment rates were so low that it is difficult to discern differences in abandonment between faculty roles. CPR survival functions showed that contingent faculty abandoned at higher rates. It is not clear why this is the case. A possible explanation is that contingent faculty are more likely to leave the institution than tenured and tenure-track faculty. Unfortunately, respondents did not explain why they abandoned the innovation so the data cannot be used to identify whether a faculty member's institutional abandonment (i.e., departure) drives innovation abandonment. It appears that characteristics of the innovation may be more influential than faculty roles.

5.5.2 Abandonment Patterns by Institution Type

Across the innovations, faculty members at research and master's universities had lower rates of abandonment than faculty members at baccalaureate colleges (See Figures 4.7, 4.11, and 4.15). For all three innovations, faculty at baccalaureate colleges abandon at the highest rates. For PLTL and SALG, the abandonment rate was the lowest (i.e., they abandon the least) for faculty members at research universities. For CPR, faculty at research

universities had the second lowest rate. A possible explanation is that faculty members at baccalaureate colleges, which have a more focused mission regarding teaching, are constantly exploring new teaching innovations and experimenting with them which requires instructors to replace existing teaching practices. Flipping this logic, the commitment displayed by faculty members at research institutions could reflect that they have less time to research new resources and integrate them into their teaching. Once they adopt something new, they stick with it.

5.6 Conclusion

Respondents did not report abandoning the innovations at high rates. Survival function graphs present contrary evidence to Hypothesis 2 because the graphs for each innovation show faculty members who first learn about an innovation through a social-exchange network are more likely to abandon it. Hypothesis 2 stated that faculty who first learned about an innovation from anonymous-search networks would abandon first. There was little evidence for Hypotheses 2a - 2c in the hazard models.

Hypothesis 2a: The negative relationship between the probability of abandoning and social-exchange networks will be weaker for individuals in institutions emphasizing research.

Hypothesis 2b: The positive relationship between the probability of abandoning and research institutions will be stronger for individuals with tenure or on the tenure-track.

Hypothesis 2c: The negative relationship between the probability of abandoning and social-exchange networks will be weaker for individuals with tenure or on tenure-track.

The coefficients for the associated variables were not significant for PLTL and SALG. The CPR coefficients were significant for the interaction term testing Hypothesis 2c, but the large value was driven by a low cell count so it was not interpreted as an accurate test of the hypothesis.

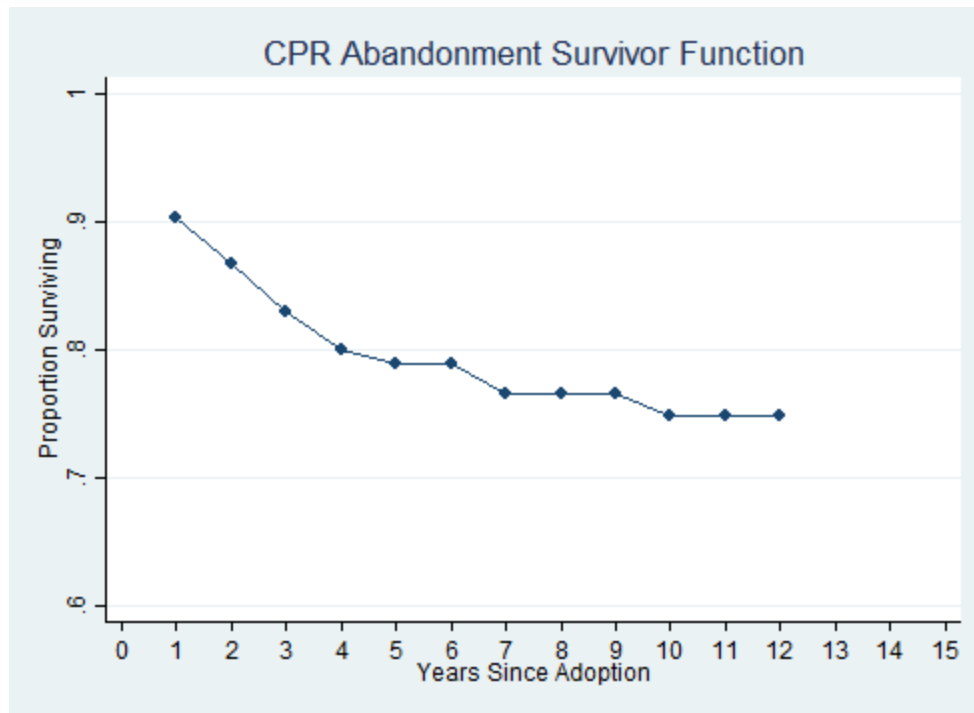


Figure 5.1: CPR Abandonment Survival Function

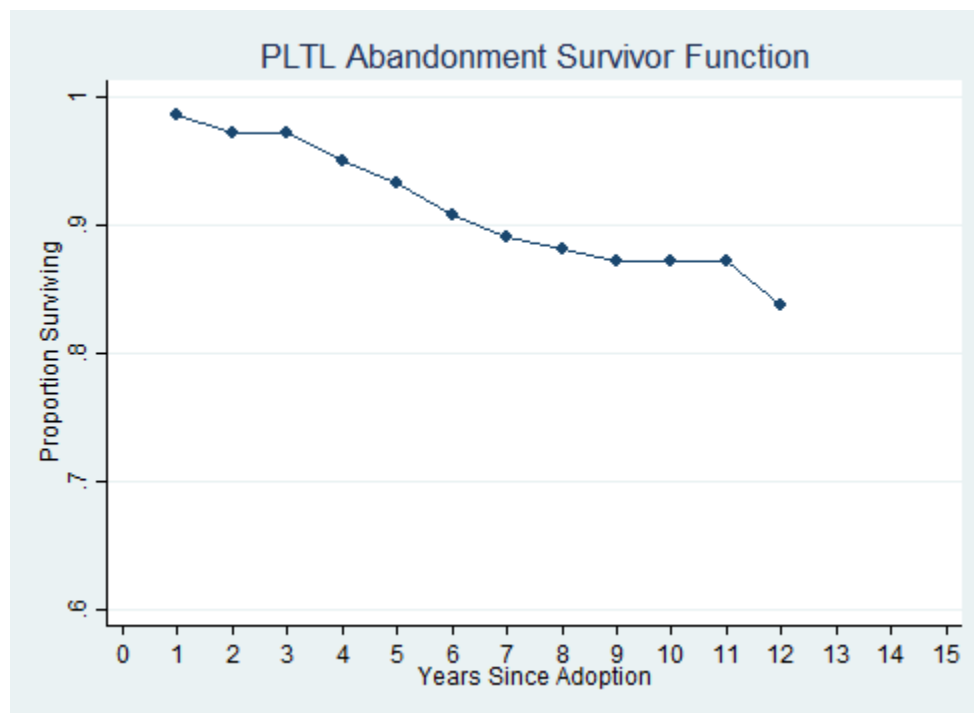


Figure 5.2: PLTL Abandonment Survival Function

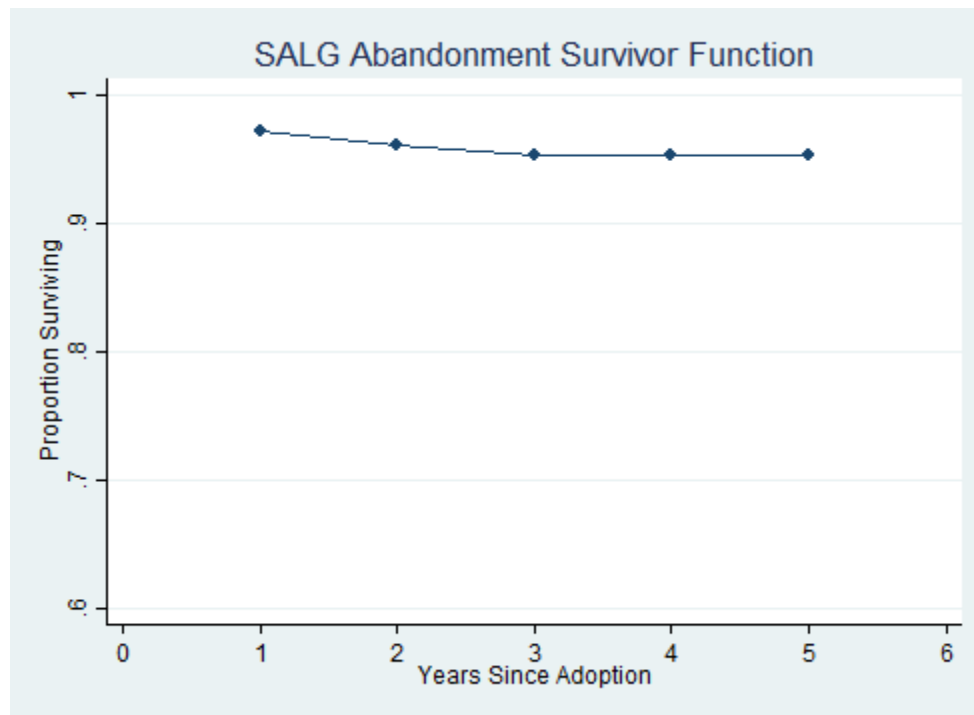


Figure 5.3: SALG Survival Abandonment Function

Table 5.1: Descriptions of Independent Variables

Variable	Description
<i>Background Characteristics</i>	
Gender	Male is the reference.
Discipline	Dummy variables for each of the four categories: natural sciences, engineering, social sciences, and humanities. The reference group changes in each model because not all 4 groups were represented for each innovation (e.g., PLTL is not used by social scientists or humanists).
Doctoral Degree	Modeled as a dummy variable representing doctorate or not because a high percentage of respondents listed their terminal degree as a Ph.D. (80 percent for each innovation).
<i>Social Position</i>	
Faculty role	Faculty role is an ordinal variable that is represented in several ways throughout the models: 1) dummy variable representing non-contingent faculty(tenured and tenure-track). The reference were contingent faculty (lecturer and adjunct) 2) dummy variable representing tenured (e.g., full and associate professors) or not 3) dummy variables representing each of the ordinal categories with lecturers being the reference group
College type	College type is an ordinal variable based on a collapsed version of the Carnegie Classification: research universities, master's universities, baccalaureate colleges, associate's colleges.
Interaction: Faculty role X College type	Created from previous two variables.
<i>Adoption Experience</i>	
Grant funding	Dummy variable with no grant funding as reference.
Years since first use (usecount)	Respondents listed the year they first used the innovation. This response was reverse coded to represent the number of years since the individual first used the innovation.
Years aware of innovation	Respondents listed the year they first learned about the innovation. This response was reverse coded to represent the number of years since the individual first learned about the innovation.

<i>Adoption Experience Continued</i>	
First source of information used	Dummy variable representing the first source of information consulted. The reference is anonymous-search network.
Interaction: First Source X Faculty role	Created from First source of information used and Faculty role.
Interaction: First Source X College type	Created from First source of information used and college type.
Social-exchange network influence	A count variable representing the number of social-exchange network sources the respondent listed as influential.
Anonymous-search network influence	A count variable representing the number of anonymous-search network sources the respondent listed as influential.
Interaction: Social-exchange network influence X faculty role	Created from Social-exchange network influence and faculty role.
Interaction: Social-exchange network influence X College type	Created from Social-exchange network influence and college type.

Table 5.2: Mean Values of Independent Variables

Variable			CPR n = 113	PLTL n = 137	SALG n = 417
Years Used			5.094 (3.089)	5.673 (3.287)	2.159 (1.104)
Gender: Male (Female reference)			0.522 (0.500)	0.423 (0.494)	0.589 (0.527)
Science Course			0.861 (0.346)	0.930 (0.255)	0.812 (0.391)
Engineering Course			0.001 (0.035)	0.070 (0.255)	0.058 (0.234)
Social Science Course			0.031 (0.173)	----	0.076 (0.266)
Doctoral Degree			0.855 (0.352)	0.878 (0.328)	0.855 (0.353)
Non-contingent Faculty	Tenured Faculty	Full Professors	0.436 (0.496)	0.468 (0.499)	0.288 (0.453)
		Associate Professor	0.243 (0.429)	0.268 (0.443)	0.300 (0.458)
	Untenured Faculty	Assistant Professor	0.131 (0.338)	0.116 (0.321)	0.236 (0.425)
Lecturers		0.159 (0.366)	0.131 (0.338)	0.121 (0.326)	
Research University			0.311 (0.463)	0.494 (0.500)	0.328 (0.470)
Master’s University			0.289 (0.453)	0.208 (0.406)	0.332 (0.471)
Teachers College			0.090 (0.287)	0.098 (0.297)	0.212 (0.409)
Grant Funding			0.160 (0.367)	0.756 (0.430)	0.142 (0.349)
First Year Aware			2002.03 (2.573)	2000.09 (3.81)	2007.011 (3.197)
First Source: Social-exchange network (Anonymous-search reference)			0.387 (0.487)	0.632 (0.482)	0.584 (0.493)
Social-exchange network influence			5.704 (2.187)	6.889 (1.714)	2.811 (1.761)
Anonymous-search network influence			8.700 (2.419)	0.494 (0.500)	2.750 (2.629)

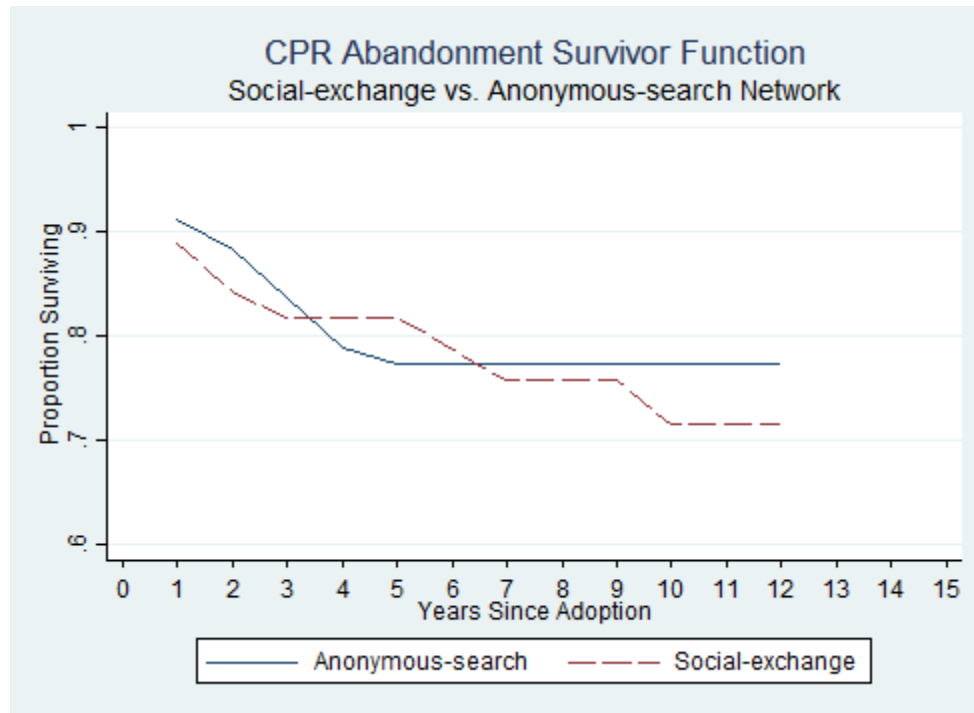


Figure 5.4: CPR Abandonment Survival Function by Initial Awareness: Social-exchange and Anonymous-search Network

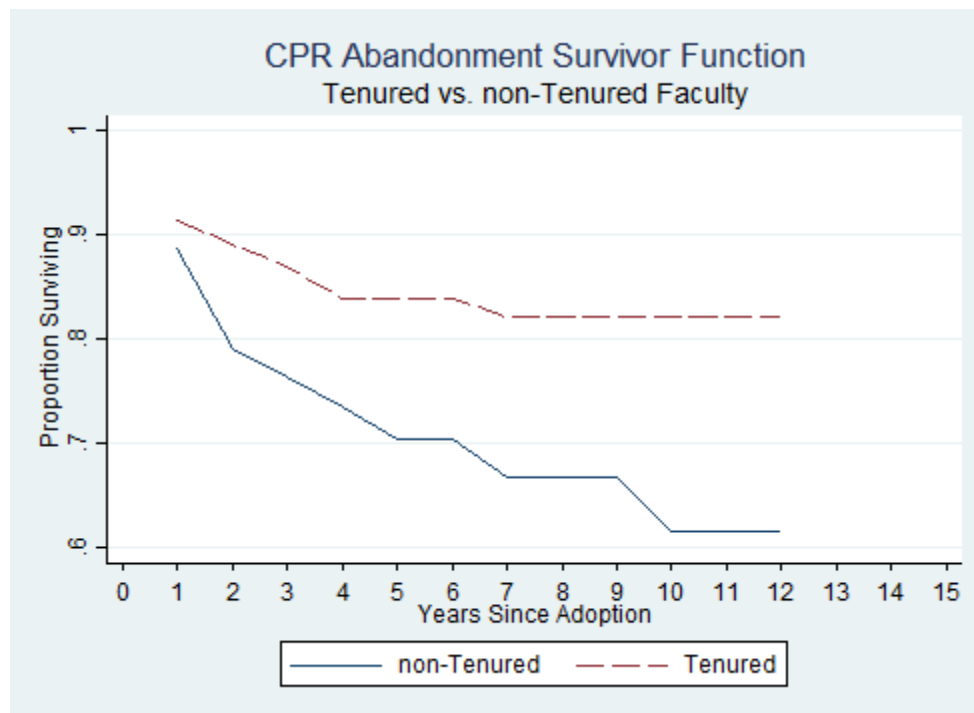


Figure 5.5: CPR Abandonment Survival Functions for Tenured and Non-tenured Faculty Members

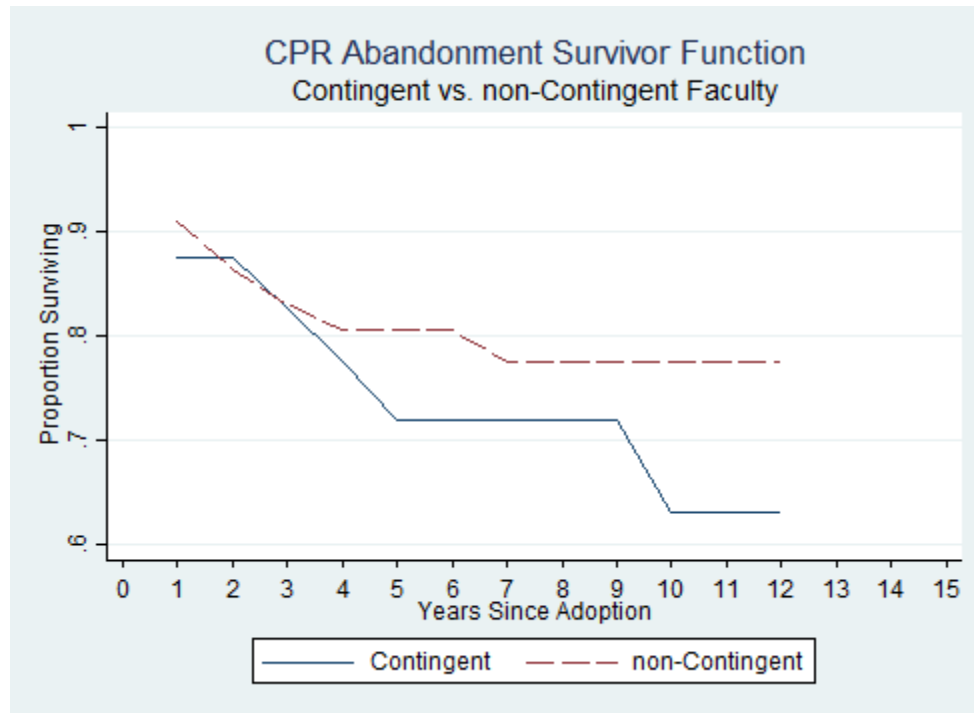


Figure 5.6: CPR Abandonment Survival Functions for Contingent and Non-contingent Faculty Members

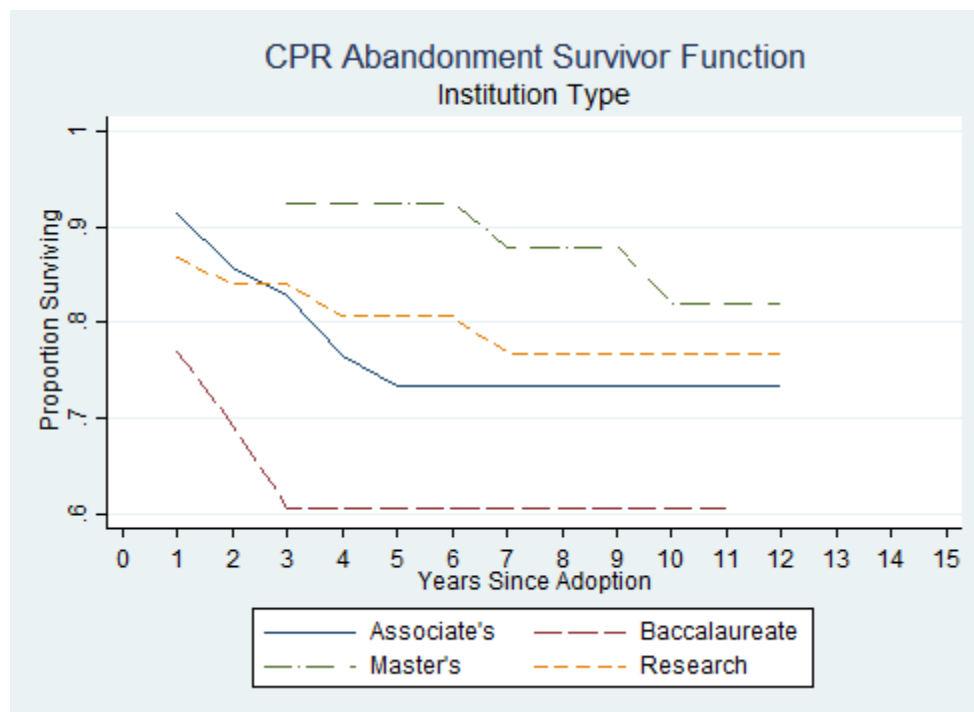
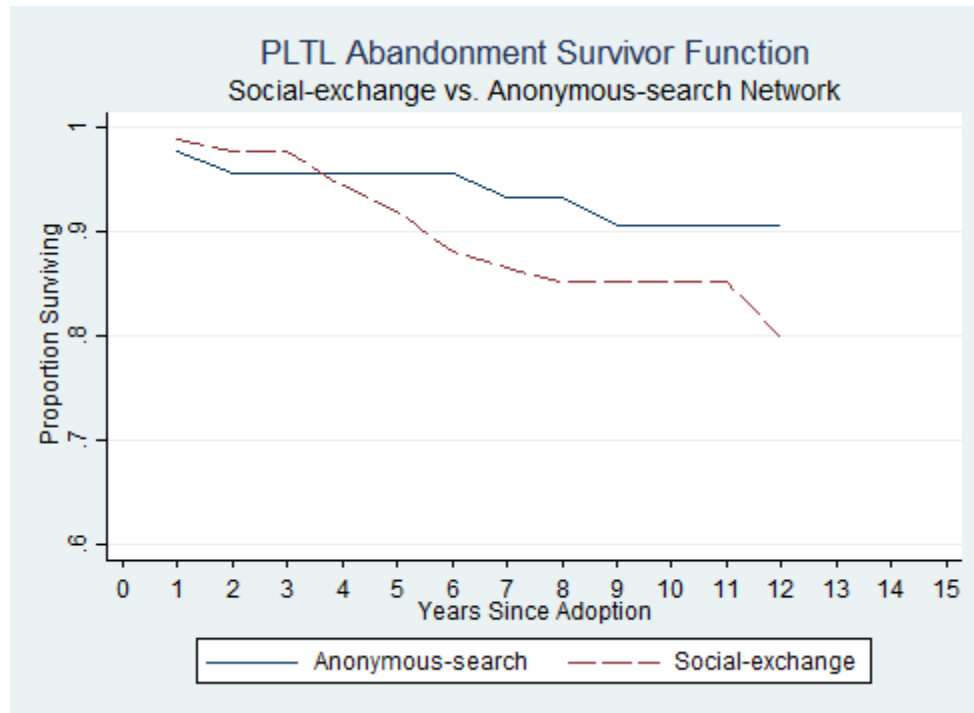
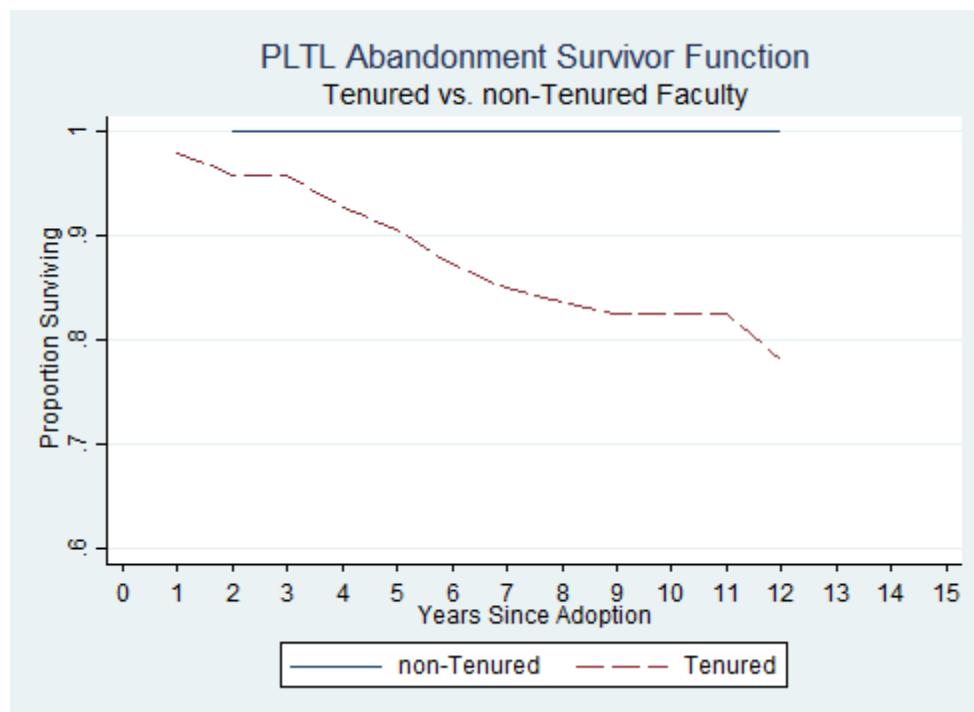


Figure 5.7: CPR Abandonment Survival Functions by Institution Type



**Figure 5.8: PLTL Abandonment Survival Function by Initial Awareness:
Social-exchange and Anonymous-search Network**



**Figure 5.9: PLTL Abandonment Survival Function for Tenured and Non-tenured Faculty
Members**

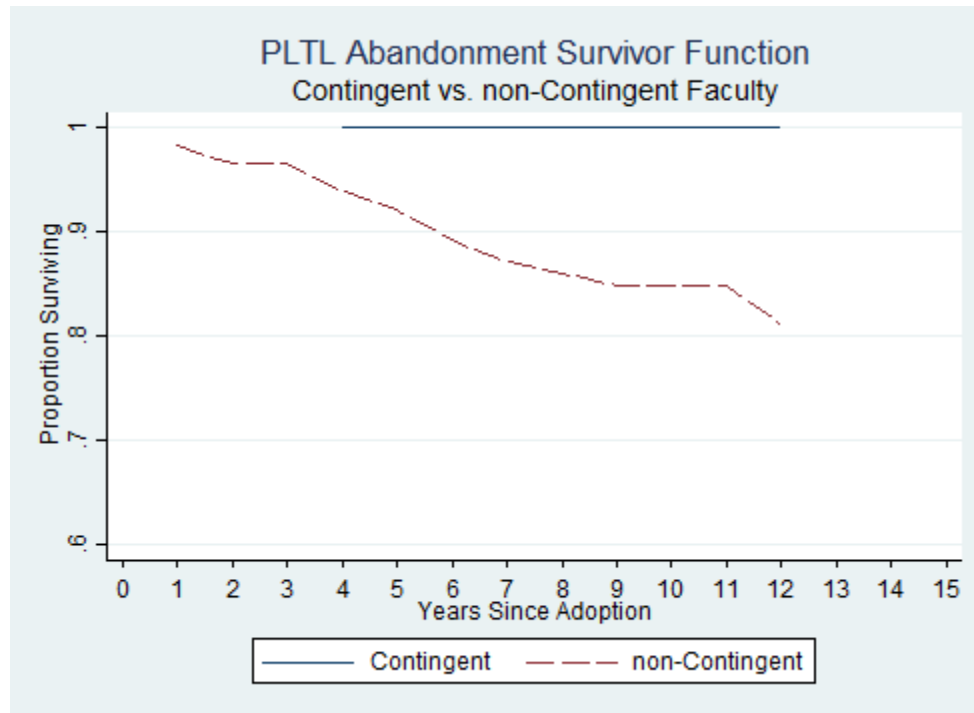


Figure 5.10: PLTL Abandonment Survival Functions for Contingent and Non-contingent Faculty Members

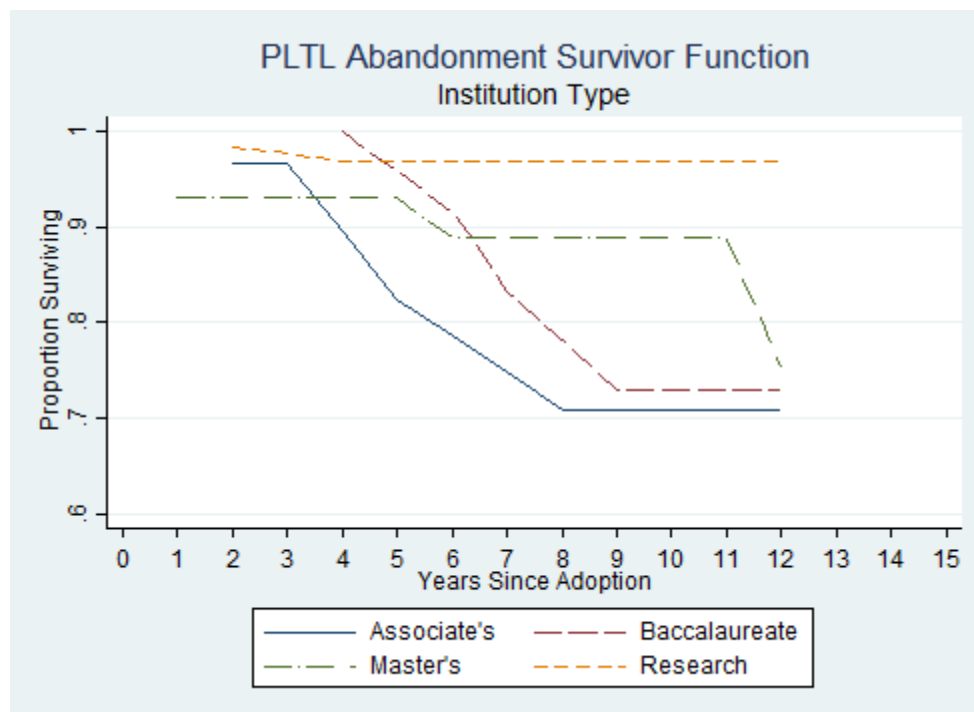
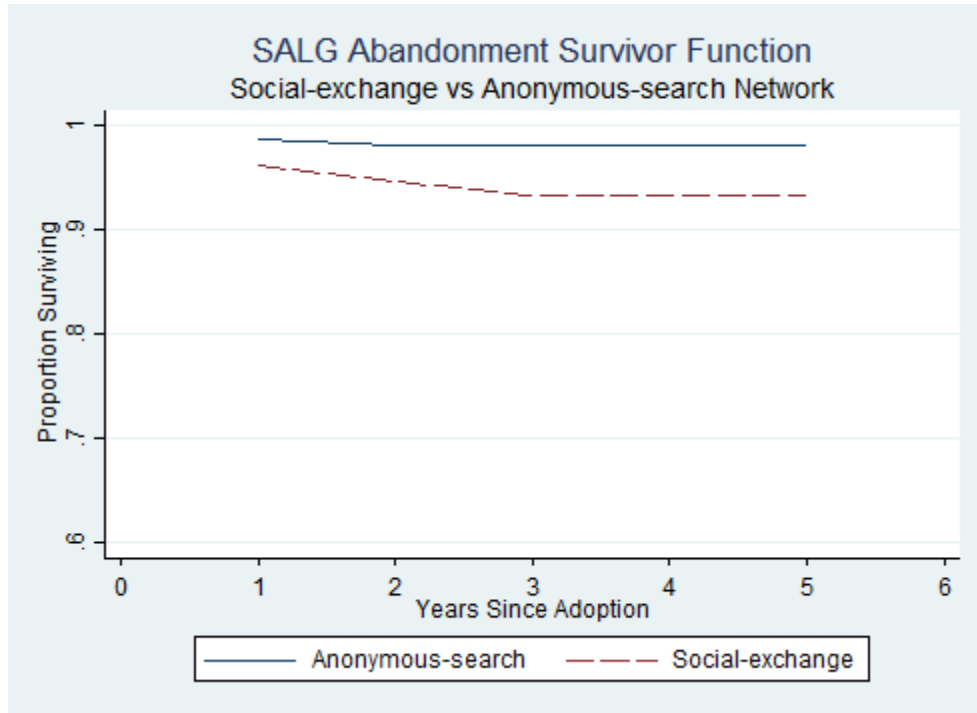
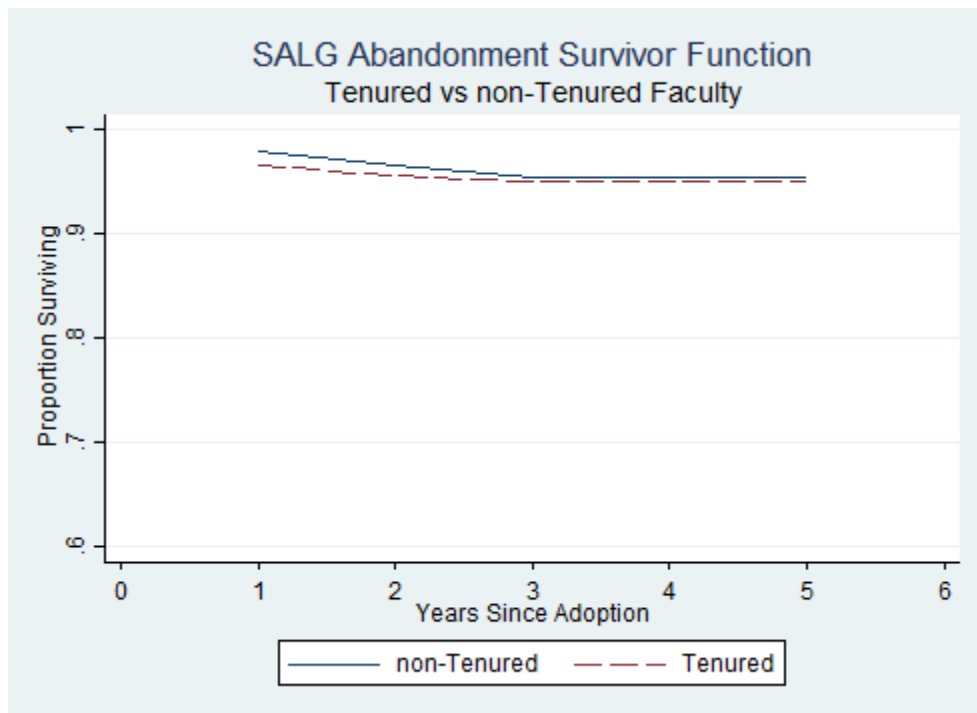


Figure 5.11: PLTL Abandonment Survival Functions by Institution Type



**Figure 5.12: SALG Abandonment Survival Function by Initial Awareness:
Social-exchange and Anonymous-search Network**



**Figure 5.13: SALG Abandonment Survival Function for Tenured and Non-tenured Faculty
Members**

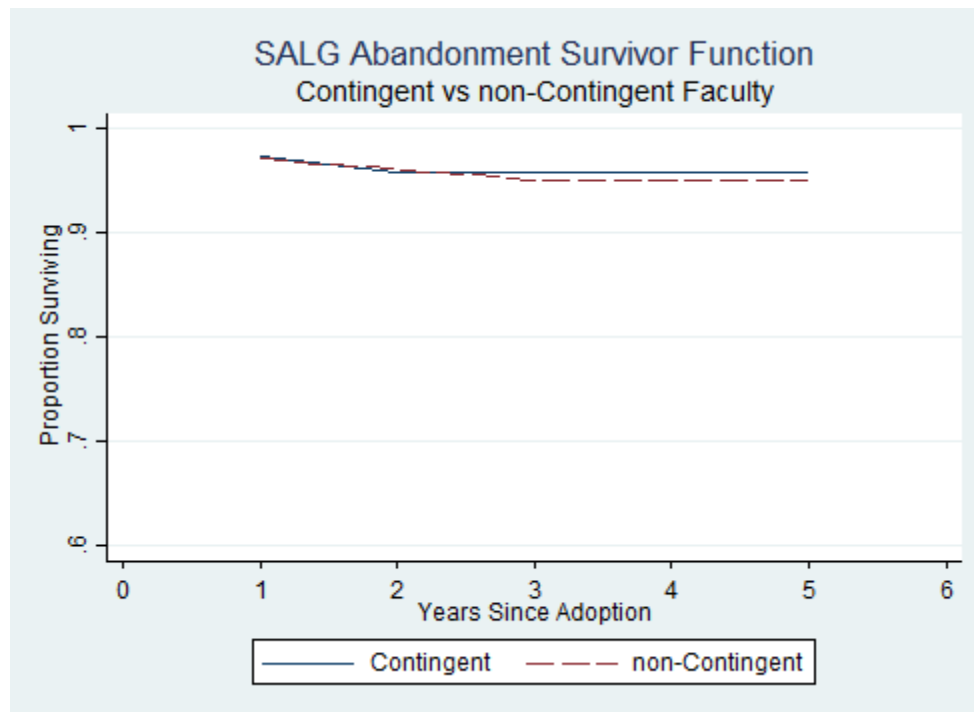


Figure 5.14: SALG Abandonment Survival Functions for Contingent and Non-contingent Faculty Members

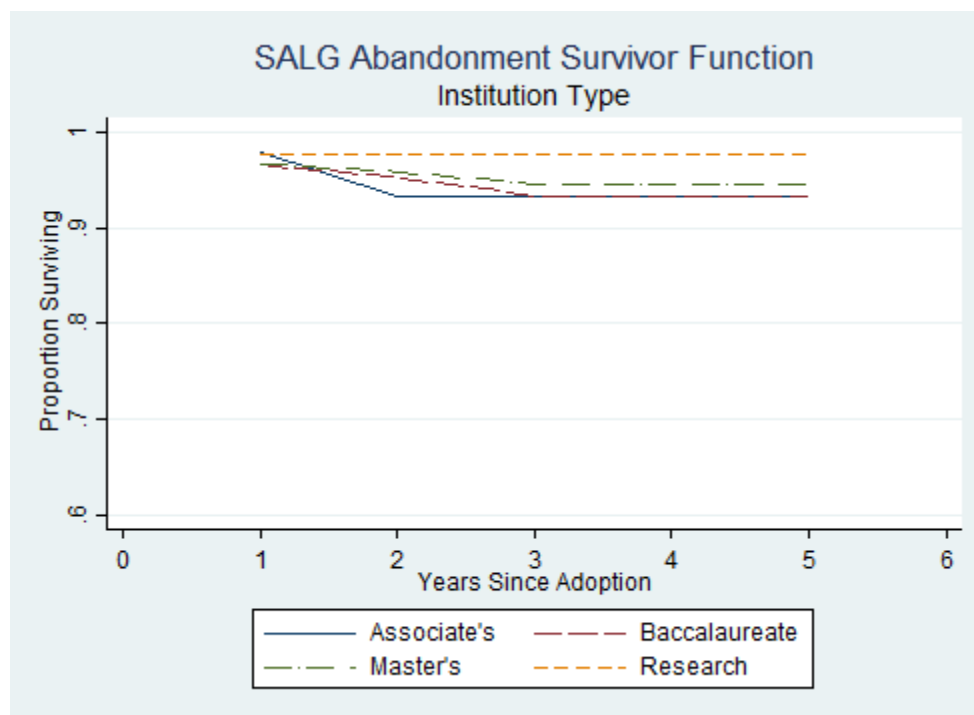


Figure 5.15: SALG Abandonment Survival Functions by Institution Type

Table 5.3: Effects of Social Position and Network Influence on the Odds of Abandoning CPR

	Model1	Model 2	Model 3	Model 4	Model 5	Model 6
	Background	Model 1 + Social Position	Model 2 + First Source	Model 3 + Intersection Terms	Model 2 + Adoption Influencers	Model 5 + Intersection Terms
Intercept	0.485 (0.292)	0.615 (0.399)	0.355* (0.257)	0.729 (0.626)	4.218 (5.37)	2.029 (2.790)
Years Used	0.716** (0.077)	0.726** (0.079)	0.778* (0.087)	0.794* (0.090)	0.777* (0.085)	0.784* (0.085)
Gender	0.460+ (0.189)	0.419* (0.175)	0.378 (0.187)	0.398+ (0.220)	0.433 (0.234)	0.507 (0.308)
Science Course	0.711 (0.480)	0.710 (0.434)	0.717 (0.432)	0.556 (0.384)	0.883 (0.576)	0.696 (0.441)
Soc Science Course	1.225 (1.099)	0.846 (0.750)	0.346 (0.328)	0.451 (0.476)	0.591 (0.556)	0.926 (1.012)
Doctoral Degree	0.360* (0.178)	0.406 (0.207)	0.476 (0.232)	0.577 (0.314)	0.435 (0.244)	0.447 (0.295)
Tenured (a)		0.323+ (0.200)	0.475 (0.267)	0.172* (0.122)	0.446 (0.265)	0.929 (1.299)
Non-contingent faculty		1.723 (1.024)	1.426 (0.847)	1.281 (0.856)	1.61 (1.117)	1.538 (1.244)
Research University (b)		0.764 (0.469)	0.778 (0.467)	0.176* (0.152)	0.834 (0.496)	0.505 (0.689)

Grant Received			0.285 (0.347)	0.179 (0.280)	0.324 (0.389)	2.321 (1.776)
First Year Aware			1.209* (0.095)	1.204+ (0.122)	1.172+ (0.103)	1.147 (0.133)
Social-Exchange Source			1.227 (0.508)	0.770 (0.508)		
a x c				1.526 (1.786)		
b x c				1.465 (1.447)		
a x b				17.326** (16.828)		
Social-Exchange Influence (d)					0.813+ (0.100)	0.908 (0.163)
Anonymous-Search Influence					0.881 (0.101)	0.881 (0.101)
a x d						0.733 (0.183)
b x d						0.894 (0.223)
a x b						14.068** (14.446)
Log Pseudolikelihood	-101.477	-99.491	-95.023	-90.160	-91.9711	-86.168
n	807	807	807	807	807	807
*** p<0.001, **p<0.01, *p<0.05, + p<0.10						

Table 5.4: Effects of Social Position and Network Influence on the Odds of Abandoning PLTL

	Model1	Model 2	Model 3	Model 4	Model 5	Model 6
	Background	Model 1 + Social Position	Model 2 + First Source	Model 3 + Intersection Terms	Model 2 + Adoption Influencers	Model 5 + Intersection Terms
Intercept	0.021*** (0.024)	0.067* (0.074)	0.066+ (0.097)	Did Not Converge	0.389 (0.846)	0.367 (0.876)
Years Used	0.998 (0.073)	1.006 (0.074)	1.026 (0.076)		1.026 (0.076)	1.025 (0.076)
Gender	1.200 (0.584)	0.910 (0.423)	0.871 (0.457)		1.066 (0.535)	1.066 (0.535)
Science Course	1.552 (1.759)	0.799 (0.880)	0.313 (0.378)		0.452 (0.584)	0.450 (0.583)
Doctoral Degree	0.361+ (0.194)	0.411+ (0.22)	0.279* (0.161)		0.249+ (0.186)	0.251+ (0.192)
Research University (b)		0.127** (0.100)	0.120* (0.11)		0.132* (0.111)	0.181 (0.343)
Grant Received		0.127 (0.1)	1.246 (0.824)		1.078 (0.767)	1.077 (0.767)
First Year Aware			0.854* (0.053)		0.871* (0.053)	0.870* (0.177)
Social-Exchange Source			2.990 (2.114)			

a x c

b x c

a x b

Social-Exchange Influence (d)

0.869
(0.177)

Anonymous-Search Influence

0.982
(0.085)

0.981
(0.084)

a x d

0.953
(0.244)

b x d

--

--

a x b

--

--

Log Pseudolikelihood	-92.121	-86.548	-79.265	-80.382	-80.376
n	1216	1216	1216	1216	1216

*** p<0.001, **p<0.01, *p<0.05, + p<0.10

Table 5.5: Effects of Social Position and Network Influence on the Odds of Abandoning SALG

	Model1	Model 2	Model 3	Model 4	Model 5	Model 6
	Background	Model 1 + Social Position	Model 2 + First Source	Model 3 + Intersection Terms	Model 2 + Adoption Influencers	Model 5 + Intersection Terms
Intercept	0.133+ (0.155)	0.142 (0.17)	0.048+ (0.072)	DID NOT COVERGE	0.090+ (0.118)	0.093 (0.141)
Years Used	0.442** (0.135)	0.441** (0.135)	0.452* (0.150)		0.468* (0.152)	0.470* (0.151)
Gender	0.515 (0.247)	0.511 (0.246)	0.566 (0.281)		0.519 (0.25)	0.491 (0.263)
Science Course	0.838 (0.899)	0.786 (0.836)	0.762 (0.799)		0.707 (0.746)	0.652 (0.689)
Engineering Course	1.106 (1.597)	1.462 (2.171)	1.174 (1.676)		1.083 (1.459)	0.993 (1.268)
Soc Science Course	3.065 (3.507)	3.270 (3.623)	2.979 (3.342)		3.646 (4.138)	3.451 (3.915)
Doctoral Degree	0.608 (0.349)	0.487 (0.424)	0.489 (0.423)		0.430 (0.374)	0.488 (0.476)
Tenured (a)		1.302 (0.825)	1.510 (0.933)		2.001 (1.259)	2.887 (4.229)
Non-contingent faculty		1.275 (1.398)	1.298 (1.414)		1.530 (1.672)	1.145 (1.366)

Research University (b)	0.406 (0.258)	0.430 (0.282)	0.414 (0.263)	6.43e-08*** (1.47e-07)
Grant Received		1.803 (1.039)	2.025 (1.106)	2.270 (1.249)
First Year Aware		1.011 (0.093)	1.004 (0.089)	1.006 (0.086)
Social-Exchange Source		3.234+ (2.180)		
a x c				
b x c				
a x b				
Social-Exchange Influence (d)			1.247 (0.185)	1.381 (0.345)
Anonymous-Search Influence			0.681*** (0.070)	0.675 (0.069)
a x d				0.813 (0.284)
b x d				1.056 (0.36)
a x b				13000000 (19500000)
Log Pseudolikelihood	-85.637	-84.105	-81.211	-77.226
n	1157	1157	1157	1157
*** p<0.001, **p<0.01, *p<0.05, + p<0.10				

Section 2: Patterns of Influence

VI. Change Agents: Who Publishes and Presents in Diffusion Networks

The previous section explored how social position is associated with a faculty member's adoption and abandonment of an educational innovation. This section will explore the role of change agents in the persuasion stage. This particular chapter, the first of the second section, will investigate how the likelihood of becoming a change agent is associated with social position. The next chapter will explore how the influence of change agents is associated with their relative social status compared to potential adopters (e.g., does perceived influence almost always flow "downstream," or are there circumstances under which tenured faculty have an appreciable likelihood of identifying lecturers as influential change agents?).

6.1 Defining Change Agents

Change agents are not simply individuals who share information about an innovation. Rogers defines them as resources who actively promote the innovation with the goal of increasing its adoption (Rogers 2003, p. 366).²⁷ They play a key role in the diffusion process by sharing information and persuading others to adopt the innovation (Rogers 2003). Without these individuals, the adoption of an innovation would be slow and some faculty members would unnecessarily reinvent existing educational resources.

As an example of a role played by change agents, I had the experience of working with a faculty member who had a novel idea to "flip" his lectures. He

²⁷ Rogers defines a change agent as an individual or an organization. For this project, I am investigating faculty change agency and am only referring to change agents as individuals.

wanted to record his lectures for students to watch before class meetings so he could work with them on homework-like problems during class sessions. He felt his students would learn more from his guidance on worked problems than listening to him lecture in class, especially if they could still receive the lecture. He asked how the lectures could be recorded and posted online. In fact, several other faculty members at Johns Hopkins had already done the same thing under the mentoring of an engineering faculty member who wrote a guide for “flipped lectures.” The faculty member requesting the consultation would have unnecessarily reinvented a well-researched teaching practice if he had not been connected with a local change agent.

6.1.1 Organizational Incentives and Sorting Mechanisms

For this project, I am investigating how social position affects the likelihood of an instructor becoming a change agent for the educational innovations under study. A significant association between social position and a faculty member’s change agency can be expected to result from the combination of (a) variations in organizational incentives and (b) sorting mechanisms. Sorting mechanisms limit to which college job candidates choose to apply and affect whom colleges decide to hire. Goals, skills, and experience are considered by both candidates and potential employers when exploring person-organization fit (Kristof 1996). Organizational incentives have been shown in prior research to mold members’ behaviors once individuals have been sorted (Loch, Huberman, & Stout 2000; Lacetera & Zirulia 2012).

In considering sorting processes, it is not assumed that a direct causal relationship exists between social position and a faculty member's change agency. Rather, prior experiences and/or characteristics of an individual may affect employment trajectories and change agent tendencies. For example, a graduate student who develops a passion for teaching through teaching assistant opportunities may be more likely to apply for positions at teaching colleges and advocate for teaching best practices once hired. Similar sorting processes also influence the type of faculty position to which a candidate applies and is hired. A candidate with experience conducting research and publishing results is more likely to apply for tenure-track positions and continue to publish once hired.

Once sorted, organizational incentives are likely to exert more direct causal influence on one's change agent tendencies and actions. Incentives act as a mediating or intervening variable between social position and change agency. Incentives include economic and non-economic rewards (Pink 2009, p. 242; Fenker 1977, p. 453). For example, tenure-track faculty promotions at research universities are based on research output. They also often have access to travel funds that enable them to present at conferences. Contingent faculty are less likely to have such benefits. Larger teaching loads also limit the time lecturers can dedicate to writing journal article submissions or conference presentation proposals. Adjunct positions are regularly populated by professionals who work in private industry or other non-academic environments. These individuals are more likely influenced by organizational incentives of their full-time employers rather than colleges where they work part-time.

Incentives also vary by college type. While most colleges publicize the importance of teaching and undergraduate education, incentives at research universities may deter faculty members from spending significant time on their teaching responsibilities. Perceptions of the rigor, or lack thereof, of discipline-based educational research (e.g., physics education research, engineering education research) may also deter faculty members at research-intensive universities from contributing to the literature (Henderson 2011). This can also occur with intra-institution communication channels. Faculty members at research universities may be less likely to be invited (or attend) departmental seminars on teaching issues compared to faculty members at baccalaureate colleges. I worked with a tenured engineering faculty member on a multi-year education research project. Our project partner from another research university traveled to Baltimore to present the final results at the weekly departmental research seminar. Only one faculty member attended the presentation.

6.1.2 Measure Faculty Change Agency

While I cannot measure sorting mechanisms and organizational incentives directly in this study, I do believe I will see their effect in the association between change agency and by social position. My measure of change agency is publishing or presenting on the innovation. I do not limit this measure to peer-review journal publications or conference presentations. Instructors can publish or present in many different venues. Departmental meetings and college publications provide opportunities to publicize teaching practices or resources with local faculty. Respondents were asked, “Did you present, publish or

formally communicate your experience implementing ____ to a public audience?”

Examples of non-scholarly publications submitted by respondents include the following.

- “marketed implementation of PLTL to administration”
- “Internally: faculty seminars, department and college”
- “When I was Chair of Biology, I encouraged wider usage of SALG by Biology faculty to get timely feedback on effectiveness of teaching methods and to incorporate the results into teaching portfolios.”
- “Presented to Core curriculum faculty”
- “Department meeting: fall in service”
- “I presented informally about the SALG at faculty meetings in my department and ...was asked to do the same for a different department.”

6.2 Hypotheses

Considering these sorting mechanisms and differential exposure to incentives and resources, I propose that social position will be associated with an adopter’s likelihood of publishing or presenting. Tenured and tenure-track faculty’s experience and expectations for publishing and presenting their discipline-based research findings, along with access to resources to do so, will lead them to publish and present on their use of teaching practices more frequently than contingent faculty. I believe this is more likely to occur at baccalaureate colleges where the teaching mission is given a higher priority. The

following is a restatement of my hypotheses regarding how social position affects the likelihood that someone will act as a change agent.

Hypothesis 3a: Tenured and tenure-track faculty members will more frequently publish and present in anonymous-search networks on educational innovations they have adopted compared to lecturers and adjunct faculty members controlling for innovation category.

Hypothesis 3b: Teaching incentives at baccalaureate colleges will lead their faculty members to publish and present more frequently in anonymous-search networks on educational innovations than colleagues in the same social position at research universities and associate's colleges controlling for innovation category.

If a significant association is detected between social position and change agency, part of this association will be interpreted as spurious or merely correlational (e.g., resulting from sorting processes) while some association will be interpreted as potentially causal (e.g., organizational incentives operating as mediating pathways between social position and actions consistent with change agency).

6.3 Testing the Hypotheses

Poisson regression will be used to test these hypotheses because the dependent variable is count data in which I expect many of the respondents will report having made no presentations or publications about the innovation under study. These models can be generally expressed as the following.

$$\log[p] = \alpha + \beta_1 I + \beta_2 T + \beta_3 C_{RI} + \beta_4 C_{SR} + \beta_5 C_A + \beta_{23} T * C_{RI} + \beta_{24} T * C_{SR} + \beta_{25} T * C_A$$

where p is the expected value for presenting (publishing) on an educational innovation in an anonymous-search network.

and:

I = innovation category

T = tenured or tenure-track dummy variable (lecturers and adjuncts are reference)

C_{RI} = inter-institutional category of adopter (research-intensive university)

C_{SR} = inter-institutional category of adopter (some-research university)

C_A = inter-institutional category of adopter (associate's college)

Collecting data on faculty members' experiences with three different educational innovations also provides an opportunity to explore how characteristics of the innovation are associated with publication and presentation frequencies. The simplicity or complexity of the innovation may have an impact in several ways. An adopter may not perceive it is worth sharing information about the use of an innovation that can be adopted easily and quickly. Barriers to entry may diminish the likelihood of adoption (Rogers 2003), but they also provide adopters opportunities to tell a more compelling or complex story about how those barriers were overcome. The number of adaptations of an innovation also increases with its complexity; these adaptations can be published as case studies. Adopters may also be less likely to publish on the use of a basic innovation that does not have a significant impact on student learning because they do not have interesting or compelling data to report.

The complexity of an innovation may also shape the community of support that develops around it. Educational innovations may require significant institutional commitments for adoption. A new course management system or classroom design requires staff to manage the resource (e.g., servers, software)

along with user support specialists to help faculty members learn how to use it and troubleshoot issues once they adopt it. These high-support resources can lead to the development of communities of support that span across institutions. Conferences, journals, and online forums can originate from these support communities to help adopters with implementation and maintenance. These communication channels also provide opportunities for individual users to act as change agents by sharing information about the innovation. For example, PLTL has a dedicated annual conference and Google forums site where users can ask questions and share advice specifically about PLTL.

The focus of this project is to explore how social position affects the process of adoption. The data do not facilitate the development of causal explanations, but an exploration of how change agency varies by differences in innovation characteristics will be discussed.²⁸

6.3.1 Overall Patterns of Change Agent Behavior

The dependent variable for this chapter's analysis is publishing or presenting on an educational innovation. While change agents can exert their influence by sharing information through conversations within personal networks, self-reports of these activities are often unreliable. Publishing or presenting on an

²⁸ Additional data would be needed to explore the causal mechanisms of how innovation characteristics affect faculty change agency. This could be done several ways. First, I would choose innovations based on characteristics that I theorized were associated with change agency. For this project, the innovations were chosen based on characteristics I expected were associated with different adoption patterns, not change agency. Another method would be to conduct a real-time, longitudinal study in which adopters were tracked for several years to identify when and why they decided to publish or present (or not). Having data on when people published and presented could be used as a dependent variable in hazard models to test the association with different innovation characteristics as independent variables. Another method would be to conduct a full literature review of publications and presentations on each innovation to identify who is presenting and publishing along with how often they do so.

innovation also requires a more significant commitment than casually passing on information about an innovation. The commitment to publicly publish or present provides a better differentiator between individuals who act as change agents compared to adopters who act as a “linker” that passes information about the innovation through the diffusion network. Rogers defines a change agent as an individual who, “influences clients’ innovation-decisions in a direction deemed desirable by a change agency” (Rogers 2003, p. 366). Based on this definition, a change agent is one who is not simply trying to help a colleague solve a problem, but is an advocate trying to encourage broader adoption of an innovation.²⁹ Publishing and presenting represent measures of change agency that reflect Rogers’ definition and can be supported by documentation.

Participants who indicated they published or presented on the main survey were asked to list up to three citations for publications or presentations they authored. These citations were not limited to peer-review publications or conference presentations. Respondents could list experiences publishing or presenting within the local institution (e.g., faculty newsletters, departmental seminars). Responses were coded into count variables (Table 6.1). The zero count represents only *users* who said they did not publish or present. Non-users were excluded because the process for why non-users do not publish and present

²⁹ Rogers does note that in some cases a change agent may work against diffusion where the innovation is associated with undesirable effects (Rogers 2003, p. 366). For this project, change agent is conceptualized to be an individual who works to expand, not impede, the adoption of the educational innovations described in this study.

is primarily affected by their decision to not adopt.³⁰ They cannot report on the use of an innovation that they never implemented. The influence of social position on the likelihood of adoption is the subject of Chapter 4.

There were clear differences in the proportion of respondents reporting that they published or presented about their use of the innovation. Peer-led Team Learning (PLTL) had a much higher percentage of users who had published or presented on their use of PLTL as compared to CPR or SALG. More than 60 percent of PLTL users met the threshold of change agent. This aligns with the previous discussion about how the complexity of an innovation can facilitate more frequent publishing about an innovation. PLTL is the most complex and resource-intensive innovation in this study. Staff or faculty members must hire undergraduate students as leaders, schedule PLTL sessions, write weekly practice problems, and pay student leaders or supervise them for credit. Each of these is a barrier to entry. Recognizing the challenges of entry or initial adoption, the early adopters of PLTL established a national network of users from multiple institutions through a National Science Foundation (NSF) grant to support members and expand PLTL's use. Early adopters created an institute to train potential adopters. They also host an annual conference so users can share their experiences, results, and modifications of PLTL. The investment to pay for coordinators and student leaders may also lead college administrators to encourage early adopters to publicize their experience with PLTL within the

³⁰ In general, change agents do not have to be users of the innovation. In this study, however, there were almost no cases of respondents who published or presented on the innovation who were not also users. The few exceptions are staff members.

organization to encourage other faculty members to adopt the innovation in the hopes of benefiting from increased efficiencies achieved through economies of scale.

A qualitative review of the citations provided by respondents suggested that adopters were passionate about spreading awareness of PLTL. These included comments like, “various conference seminars between 1999 and 2005 helped me spread the PLTL word.” The PLTL community also received a dissemination grant from NSF that may have encouraged and facilitated a high number of users publishing and presenting at various conferences and workshops.

- “I was the Project Manager for the PLTL National Dissemination grant project funded by NSF from 1999-2006.”
- “I participated in several PLTL workshops where PLTL was disseminated.”
- “[Presented] many times during the [NSF dissemination] grant period.”

SALG had the lowest measure of change agency: 70 percent of users said they did not publish or present. The characteristics of the SALG provide a useful comparison to PLTL. SALG is a survey tool that faculty members can develop in less than 30 minutes by borrowing questions from previously published surveys and then emailing a URL to students. While SALG survey questions may differ between courses, its implementation is standardized through the web-hosting service, and there is not much variation in implementation to report. SALG is also a data collection instrument used to capture student feedback and

perspectives on learning. It is not directly used in instruction. Faculty members use the SALG to collect data about students' opinions of other educational innovations. For example, a faculty member could use the SALG to collect student feedback on their experience learning in a PLTL program. In these situations, a publication or presentation may use data collected from a SALG survey, but the primary focus of the report is on the impact of a different educational innovation (e.g., PLTL).

6.3.2 Modeling Number of Publications and Presentations on Innovations

I assume the dependent variable – publishing or presenting on the innovation – to display a Poisson distribution because the dependent variable is a non-negative, count variable with a large right skew. The expected value and variance of a Poisson-distributed random variable are assumed to both equal the mean. A violation of the Poisson distribution is overdispersion – when the variance is larger than the mean. In these cases, the data can be modeled with a negative binomial model, which is based on the negative binomial distribution that allows for a greater variance than the mean.³¹

The mean and variation for the data collected for each innovation are shown in Table 6.2. From Table 6.2 the mean was very similar to the variance for PLTL. The CPR and SALG distributions displayed evidence of overdispersion. To account for this overdispersion, a comparison of the negative binomial regression to a Poisson regression models was conducted with additional

³¹ Underdispersed data occurs when the variance is less than the mean. This does not typically occur in social science data because it implies the data collected is highly homogeneous (there is little variation). Heterogeneity of responses is more likely, which results in overdispersion. This was the case with the data collected for this project.

evaluative functions in STATA.³² The *countfit* function runs specific models – in this case Poisson and negative binomial regressions – on the same data and suggests which model is more appropriate based on an analysis of the residuals. The *nbvargr* function graphs the observed proportions along with the Poisson and negative binomial probabilities. Based on these comparisons, the negative binomial regression was only significantly different from the Poisson regression model for the SALG innovation. Therefore, the model for the three innovations is different: CPR and PLTL use a Poisson model and SALG uses a negative binomial model. This is not unprecedented. Analysts often select negative binomial regressions because true Poisson distributions are not often observed in social science research. However, "Poisson distributions are far from nonexistent, with some researchers even observing the presence of both Poisson and negative binomial distributions within the same study," (Piza 2012, p. 1).

The benefit of using the negative binomial regression model is that it has an extra parameter to account for the overdispersion ($\mu + \mu^2/r$). The negative binomial results are efficient under overdispersion and the confidence intervals are robust. In addition, the analyst is less likely to falsely assume that coefficients are statistically significant. In addition, the link function is the same for both Poisson regression and negative binomial regression: natural log of the mean $[\ln(\mu)]$. This enables coefficients for the three innovations modeled to be

³² A zero-inflated negative binomial regression was not considered as an alternative to the Poisson regression because the counts for zero were not considered excessive nor generated by separate processes from count values. An example of when the zero-inflated negative binomial regression had been appropriate would have been if users and non-users of the innovation could not be differentiated and an excessive number of zero counts were observed because of the separate process of non-use was the casual mechanism.

compared even though the distribution of the random component is different. In the goodness of fit testing, the coefficients were compared between the Poisson and negative binomial regressions for each innovation. The consistency in the coefficients between the models suggest that my narrative interpretation could compare coefficients between innovations.

6.3.3 Modeling Change Agency

There are two ways I tested the hypotheses. I first measured the association between social position and a measure of the *intensity* of change agency: the number of publications and presentations by an adopter. It is possible, however, that the association is more appropriately modeled as the direction of change agency. Social position may be associated with simply being a change agent as opposed to the frequency of change agent activity. This may be the case for more recent innovations that have not been employed as often as more established innovations. Less complex innovations that cannot be adapted in new ways may also limit how many times a faculty member can present or publish on their use of the innovation. The second test used this alternative measure of change agency. I used logit models with a dichotomous dependent variable that represents whether an adopter published/presented or not. The analysis section describes the difference in findings between these two approaches.

6.3.4 Modeling Estimates for Independent Variables

The independent variables were grouped into three categories as shown in Table 6.3. This categorization reflected the model testing based on 1) the faculty

members' background characteristics, 2) social position variables associated with the hypotheses, and 3) additional variables that were associated with the adopter's experience. Data that were not provided by the respondents were supplemented by conducting web searches (e.g., faculty title and discipline identified through the faculty member's web page). Mean values and standard deviations of the independent variables for each innovation are provided in Table 6.4.

6.4 Results from Modeling Change Agency

Tables 6.5 through 6.7 present the results of the Poisson or negative binomial models. All coefficients are presented in their exponentiated form as incident rate ratios. They are interpreted below from Model 3 for each innovation except as noted. As explained above, the random component for CPR and PLTL is a Poisson distribution and for SALG it is negative binomial.

The key variables testing the hypotheses measured the 1) hierarchy of faculty roles (adjunct instructor to tenured full professor) and 2) research intensity of school as measured by the Carnegie classification (associate's college to research university). Faculty role was modeled as two dummy variables representing 1) tenured or not and 2) tenure-track or not. This was done to see whether there was a different association with the dependent variable for tenured faculty versus non-contingent faculty in general.

6.4.1 CPR

My first hypothesis (3a) is that tenured and tenure-track faculty are more likely to publish and present on their use of the innovation compared to lecturers and adjuncts. The rationale was that tenured and tenure-track faculty have more

experience, pressure, and access to resources that enable them to publish and present at higher rates. There was weak support for this in Model 2 for CPR. The coefficient for the tenured variable was initially significant ($p < 0.05$) when controlling for background characteristics and institution type. The coefficient became insignificant when a dummy variable representing grant funding was added to Model 3. Faculty members who obtain a grant to use CPR increased their incident rate of publishing by 117 percent compared to those with no funding ($p < 0.001$). This did not contradict Hypothesis 3a in that tenured faculty are more likely to win grant funding and this can often include requirements to disseminate findings from the funded project. The grant funding variable likely explains a causal pathway in which faculty position is associated with change agency.

The second hypothesis (3b) is that faculty members at baccalaureate colleges would be more likely to publish and present than peers at other types of colleges. For CPR, the incident rate of publishing and presenting was predicted to be 104 percent higher for faculty members at research universities compared to faculty members at associate's colleges. The coefficient for baccalaureate colleges was not significantly different from associate's colleges. This was opposite the hypothesis' prediction. It appears that sorting processes and/or organizational incentives that operate on faculty members at research universities were associated with higher rates of publishing and presenting in the education domain in addition to their disciplinary research.

A variable representing the number of years since first adoption was also significant with the coefficient being greater than one.³³ The positive coefficient means the probability of publishing increased the earlier the respondent started using the innovation. This is not surprising as more time using the innovation provides more time to collect data and/or report on the experience. The model estimated a 12 percent increase in the incident rate ratio for each additional year of teaching with CPR ($p < 0.01$)

The only background variable coefficient that was significant was academic discipline. Humanities faculty incidence rate of publishing and presentation on the CPR application was 255 percent higher than social science faculty – the reference group – after controlling for other variables. The dummy variables representing science and engineering faculty were combined into a STEM dummy variable because of the low cell counts for engineering. The coefficient for the STEM faculty dummy variable was not significant in any of the models.

6.4.2 PLTL

PLTL also gave partial support for Hypothesis 3a. Non-contingent faculty were predicted to publish more than contingent faculty. For PLTL, the coefficient for non-contingent faculty (i.e., tenured and tenure-track faculty) was significant in the full model ($p < 0.10$; see Model 3). Non-contingent faculty's incident rate of publishing was 78 percent more than lecturers and adjuncts. The coefficient for tenured faculty was also significant ($p < 0.05$). Tenured faculty's incident rate

³³ The variable was reversed coded so that a larger number equates to an earlier adoption (i.e., 2012- year of adoption).

of publishing was 36 percent less than non-tenured faculty. It appears most of the change agent activity was conducted by assistant professors. When faculty position was modeled as a dummy variable for each of the six position categories, only the coefficient for the dummy variable representing assistant professors was significant ($p < 0.10$; model not shown). Assistant professors' incident rate of publishing or presenting on PLTL was 80 percent higher than that of the reference group, lecturers.

The number of years teaching (with or without the innovation) was only significant for PLTL. While the coefficient was consistent across each model, the impact was small. This provides indirect support for the Hypothesis 3a in that veteran faculty were more likely to publish articles and present at conferences. This effect was over and above the amount of time faculty members had used the innovation (i.e., "number of years used" variable). It would be expected that the longer someone has used an innovation, the more time they will have had to collect data and report on their experience. A further exploration of this effect will be provided in the *Discussion* section (6.8) below.

For PLTL, the incident rate of publishing was 53 percent higher for faculty members at research universities compared to those at associate's colleges, controlling for other variables (e.g., faculty position). Dummy variables representing baccalaureate colleges were insignificant. Like CPR, this provides contrary evidence for Hypothesis 3b that faculty members at baccalaureate colleges would be predicted to publish or present the most.

Model 3 estimated grant funding increased the incident rate of publishing or presenting by almost 140 percent compared to those who did not receive a grant ($p < 0.001$). The strong association of grant funding likely originated from the influence of reporting requirements associated with most grants and a correlation with a faculty member's initial commitment to pursue grant funding to support adoption. The number of years using PLTL also had an impact on publishing and presenting. The incident rate increased by 8 percent for every year an adopter used PLTL ($p < 0.05$).

For PLTL, there were no social science and humanities faculty respondents for PLTL.³⁴ The reference group for PLTL was engineering faculty. The model predicts the incident rate of science faculty publishing and presenting on PLTL was almost half the rate of engineering faculty. I believe the decreased rate of science faculty publishing compared to engineering faculty may result from who established the early PLTL community. The original innovators were chemistry faculty and the early spread of PLTL occurred within the chemistry education research community. The amount of publication opportunities in the sciences may have saturated because most individuals using PLTL hailed from the sciences. Engineering faculty – a minority of users – had new perspectives to share and possibly new presentation and publication outlets that had not been

³⁴ This likely occurred because PLTL is a course supplement to help students with solving quantitative problems in a structured way. This does not mean that problem-solving courses do not exist in the social sciences or humanities (e.g., introduction to social statistics). There are just no cases of PLTL diffusing to these disciplines. There are few problem-solving courses in the humanities and social sciences. There were three respondents who indicated they taught an education course. These were dropped because the full response implied PLTL was the course topic presented as an educational method students could use as future teachers (e.g., high school chemistry teacher) as opposed to the instructor employing PLTL as method to help students learn the course content.

previously used (e.g., engineering-focused journals, conferences). Future research could include investigating whether innovations are more likely to spread within discipline-based education communities compared to general faculty populations.

6.4.3 SALG

In testing Hypothesis 3a, the SALG model results were similar to the CPR models. The coefficient for tenured faculty was initially significant. The addition of the variable representing grant funding slightly reduced the tenured faculty coefficient's magnitude, but also increased its standard error so it was no longer significant. Model 3 predicted that obtaining a grant increased the incident rate for publishing or presenting by about 140 percent, which was similar to PLTL ($p < 0.001$). This provided additional support that grant funding was a mediating variable between faculty position and the dependent variable (i.e., tenured faculty were more likely to win grants, and grant funding led to increased publishing and presenting rates). Each additional year of using SALG, increased the incident rate of publishing or presenting by 37 percent ($p < 0.001$). For SALG, the coefficient for institution type was not significant. An interaction term for college type and faculty position was explored but was not significant for any innovation.

6.4.4 How well do the models fit the publication frequency data?

The goodness of fit of the Poisson and negative binomial models was evaluated in several ways. First, initial comparisons of the Poisson regression and negative binomial regression models were conducted using the countfit and nvargr functions in STATA to identify what was likely to be the best approach to

modeling the data. The negative binomial regression model also provided an estimate of the dispersion parameter, α . If this value is significantly different than zero, then it suggests the negative binomial regression model is better than the Poisson regression model. These tests indicated that only the SALG data should be modeled using negative binomial regression.

Nested models were compared using the deviance to conduct a likelihood ratio test. Summary statistics were explored to identify how good the model fit the data. This analysis used likelihood-ratio goodness of fitness statistics to test if the model tested was statistically significant from the saturated model. If the difference between the two models is not statistically significant, then the current model is a good fit for the data. This was not the case for these models. The goodness of fit tests indicated Model 3 in each case was still significantly different from the saturated models. These statistics suggest that influencers not accounted for in the model have a significant impact on estimating publication and presentation counts. Unfortunately, the data collection for this project does not facilitate including additional variables in the model to improve the fit. As such, the coefficients are interpreted with caution and only suggest weak support for the hypotheses as noted above.

Model residuals were reviewed to identify if any observations had an undue influence on the model. The threshold for investigation was if the residual difference between the observed and expected were more than two. For PLTL and CPR, there were very few observations that exceed this threshold. The residuals were often mostly slightly over the threshold (2.00), and upon

investigating the flagged observations in more detail, they were not considered problematic.

6.5 Results from Modeling Becoming a Change Agent or Not

The previous analysis was primarily an investigation of change agent *intensity* as measured by the count of publications or presentations. Because the models' goodness of fit were not good, a second analysis was performed to investigate the association between social position and becoming a change agency. In these models the dependent variable was dichotomous indicating whether the user has published/presented or not. Logit regression was used to investigate the influence of the independent variables on the binary dependent variable.

6.5.1 CPR

For CPR (Table 6.8), the institution type was more associated than faculty position with publishing and presenting. The coefficients for faculty position were not significant. As for institution type, the results again did not support Hypothesis 3b that faculty members from baccalaureate colleges would be most likely to publish. The odds of faculty members at research universities publishing or presenting at least once was almost four times higher than faculty members at associate's colleges. The coefficients for master's universities and baccalaureate colleges were not significant.

Grant funding in the logit models strongly predicted publishing over not publishing like the CPR Poisson regression model. The odds of publishing or presenting at least once were 318 percent higher for faculty members who

received a grant to fund their use of CPR compared to those without grant funding. The coefficient representing how early the respondent first used the innovation was significant with its results in the direction expected. For each additional year since a user adopted CPR the odds of publishing or presenting increased by 17 percent.

6.5.2 PLTL

The PLTL logit models differed from the other two innovations in that the coefficient for tenured faculty was significant (see Table 6.9). Tenured faculty's odds of publishing or presenting were 80 percent less than non-tenured faculty. The coefficient for non-contingent faculty was not significant as it was in the PLTL Poisson regression model (see Section 6.4.2). As with CPR, the coefficient for the institution type variable became significant, which was not the case in the Poisson regression model. The odds of faculty members from research universities publishing or presenting was almost 500 percent more than faculty members at associate's colleges. The odds of faculty members at master's universities publishing or presenting were 300 percent more compared to associate's colleges. The coefficient for baccalaureate colleges was not significant. These results taken together contradict Hypothesis 3b. Grant funding was strongly associated with publishing; PLTL users who receive grant funding increased their probability of publishing by 841 percent.

6.5.3 SALG

The SALG logit regression model interpretations partially supported the hypotheses (see Table 6.10). The odds of tenured faculty publishing or presenting

was 77 percent higher than non-tenured faculty. This was a more specific result than expected as the coefficient for tenure-track faculty dummy variable was not significant. There was no support for institution type predicting a SALG user publishing or presenting at least once. The likelihood of publishing or presenting for a faculty member who received a grant to use SALG was 350 percent higher than users who did not receive a grant. Each additional year of using SALG, led to a 40 percent increased likelihood of publishing or presenting at least once.

6.5.4 How well do the models fit the change agent (or not) models?

Similar goodness of fit tests described above were conducted for the logit models testing change agency. The major change was that collapsing the dependent variable to publish or not improved the goodness of fit as expected. The Pearson and likelihood-ratio goodness of fitness statistics revealed that the models shown above were not statistically significant from the fully saturated model for all three innovations. This result suggests the more robust inferential analysis should be conducted on the logit models. That is, social position and the other independent variables were better predictors of whether a faculty user becomes a change agent as opposed to the intensity of their change agency described by the Poisson and negative binomial regression models.

6.6 Results from Combining Datasets to Compare Results While Controlling for Innovation Category

I conducted a pooled analysis to identify whether the key variables used to test the hypotheses remained significant once the models could control directly for the innovation. This analysis was done by combining the three data sets

together. I then re-ran the negative binomial and logit regression models with additional variables representing each innovation along with interaction terms created between the innovation dummy variables and the social position variables.³⁵ Table 6.11 shows the results for the negative binomial regression model that estimates the change agent intensity (i.e., number of publications or presentations) when controlling for key independent variables. Table 6.12 shows the results for the logistic regression model that measured the association between the key independent variables and the likelihood of publishing or not.

6.6.1 Results from Modeling Change Agent Intensity While Controlling for Innovation Category

The dummy variables representing the innovation were included in Model 1 with the background variables. SALG was the excluded dummy variable. The innovation dummy variables were significant and indicated a higher frequency of publishing for CPR ($p < 0.01$) and PLTL ($p < 0.001$) when controlling for other background characteristics. This is not surprising as SALG had the lowest percentage of users who published or presented (< 30 percent) as shown in Table 6.1 and described in Section 6.3.1, *Overall Patterns of Change Agent Behavior*.

Model 2 added the social position variables. Tenured faculty were predicted to publish more frequently than non-tenured faculty when controlling for the other variables including innovation ($p < 0.10$). This provided support for Hypothesis 3a. Faculty members at research universities were also predicted to

³⁵ *Countfit* and *nbvagr* tests were completed to identify if a Poisson or negative binomial regression model was a better fit because the individual innovation models used both. A negative binomial regression model was a better fit for the combined datasets.

publish or present more frequently than faculty members at associate's colleges. This contradicted Hypothesis 3b because it was instructors at baccalaureate colleges who were predicted to publish more frequently. This contrary finding was similar to the individual innovation analyses conducted for CPR and PLTL innovations above.

The dummy variables representing the CPR and PLTL innovations were still significant and greater than one in Model 2. Model 3 added interaction terms to identify whether any dependencies exist between the various measures of social position and the innovations. None were found. This likely results from low cell counts associated with some of the 10 interaction terms created (five position variables X two innovations). The goodness of fit, as measured by the log likelihood ratio test, was also not significantly improved with the addition of these interaction terms, therefore, these models will not be analyzed.

Model 3 added the variables representing the adoption experience. These include whether or not the adopter received grant support and the number of years she or he used the innovation (i.e., a measure of early adoption). As with the individual innovation analysis above, the coefficients were greater than one and significant (both $p < 0.001$). The number of publications or presentations was predicted to increase the longer someone had used the innovation. Publication and presentation frequencies were also predicted to increase if an adopter received grant support. As in the individual innovation analyses, the significance of the coefficient for the tenured faculty variable disappeared. As stated above, this was

likely because tenured faculty are more likely to obtain grant support than other types of faculty.

What is interesting was that the coefficient for the PLTL dummy variables predicted fewer publications and presentations when the variable representing grant funding and years used were added ($p < 0.05$). I believe this reflected key differences between SALG and PLTL. The PLTL community offers significant grant funding opportunities to assist new faculty members implementing the innovation. In addition, SALG is a much newer innovation that was not available for adoption until 2007 compared to PLTL, which originated in the 1990s. I believe this suggests that the large number of publications and presentations associated with PLTL can be strongly attributed to the support available and its earlier founding compared to an innovation like SALG.

6.6.2 Results from Becoming a Change Agent or Not While Controlling for Innovation Category

The previous findings are reinforced by the logistic regression models (Table 6.12). The same coefficients were significant and in the same direction when comparing Models 1 and 2 from the logistic regression with the previous analysis of change agent intensity. Faculty members were more likely to be a change agent who publishes or presents if they use CPR or PLTL, and if they were tenured and work at research universities. In Model 3, we see the similar results that the likelihood of being a change agent increased with grant funding and the number of years using the innovation ($p < 0.001$). The negative effect of PLTL in Model 3 was not significant in this model, suggesting the advantages of

grant support and years used had a stronger effect on the intensity of one's change agency (i.e., amount of publishing and presentation compared to the decision to be a change agent). The one major change from the negative binomial regression results was that the coefficients for the variables representing master's universities and baccalaureate colleges were significant in Model 3 (both $p < 0.10$). The magnitude of the coefficient was less than that for instructors at research universities, which contradicted Hypothesis 3b.

6.6.3 How well do the models fit the data?

The same goodness of fit tests used in the previous sections were run on the models in this section (i.e., the models estimated using the combined datasets). I used the *countfit* and *nvargr* functions in STATA to test if the negative binomial regression model provided a better estimate of the change agency intensity data than the Poisson regression. It did, which was not a surprise as the SALG data comprised a majority of the combined data set and its models required the use of the negative binomial regression.

The likelihood ratio test of nested models showed that the addition of the grant and years used variables significantly improved the models (Model 3 in both cases). The big change was that the change agent intensity model was not significantly different from the saturated model when the dummy variables representing the innovation category were added. This was not the case when the change agent intensity models were estimated for each innovation separately. The importance of this is that it suggests the models in this section are a good fit for the data. It also suggests that innovation characteristics may be the missing

variables unaccounted for in the change agent intensity model. The summary goodness of fit tests for the logit regression models also demonstrated that the models were not significantly different from the saturated model. This had been the case with the individual innovation models as well.

6.7 Exploring Beyond the Models: Reported Motivation

One way to understand the weak support for the hypotheses is by investigating faculty members' motivation for publishing and presenting. Respondents who reported they published or presented at least once were specifically asked how a list of motivations affected their decision to become a change agent. Respondents reported their answer through a Likert scale ranging from hindrance to enabled. The list of motivations included social norms (e.g., pressures to publish), resources available (e.g., travel funds for conferences), and intrinsic reasons (e.g., personal commitment to improve teaching). These categories were specifically created to investigate some of the possible casual pathways used to motivate the hypotheses, namely access to resources and social norms. Tables 6.13 through 6.15 present a summary of responses. For most of the motivations listed in the survey, a majority of respondents generally reported the item had "no effect." If the motivation did have an effect, it was generally listed as an enabler and not a hindrance.

These data were not used in the models because social position was a better measure of my conceptual framework which was based on sorting mechanisms and organizational incentives. The reported motivations only measure incentives of which I knew I did not have a complete list. In addition,

the responses lacked heterogeneity (i.e., 80-90 percent of respondents chose “did not have an effect” for several choices) and I was concerned low cell counts would prevent the models from converging. Instead, I chose to analyze the reported motivation data with measures of association to explore the relationship with different faculty roles and institution types.

6.7.1 Measuring the Association Between Social Position and Motivators

Most faculty members responded that items listed under social norms and resources were not influential – either positive (i.e., enabler) or negative (i.e., hindrance). Respondents overwhelmingly reported personal commitment to improve teaching was an important incentive. This intrinsic motivation was listed as the most common reason for publishing and presenting across all innovations. Considering the logic about sorting mechanisms discussed earlier in the paper, it would be expected that faculty members at teaching colleges would be more likely to state personal commitment to teaching as a motivation. In addition, faculty members in roles specifically dedicated to teaching – lecturers and adjuncts – may also have higher rates of citing personal commitment to teaching as a motivator.

Kendall-Stuart *Tau-c* and Goodman-Kruskal *Gamma* were used to measure the level of association between the respondent’s social position and reported motivation for publishing. This is indirectly a test of Hypothesis 3a regarding the influence of faculty position. It is a weaker test because it relies on faculty members’ self-reported perceptions and not a direct measure of their behavior. Both of these tests measure the strength of the association between two

ordinal variables through a calculation of the proportional reduction in error. The difference between the two is that *Tau-c* is a more conservative estimate because the *Gamma* calculation does not account for tied pairs (De Muth 2006, p. 447; Frankfort-Nachmias & Leon-Guerrero 2006, p 234-244). As noted above, many respondents chose no effect as their response for many of the motivational choices, thus resulting in a large number of tied responses. I calculated both measures to identify how much the *Gamma* measure overestimated the association. If *Gamma* was close to *Tau-c* – less than 0.05 difference – than the *Gamma* coefficient was used for interpretation.

The range for *Tau-c* and *Gamma* is -1.0 to +1.0 in which the magnitude indicates the strength of the association and the sign indicates the direction (e.g., negative equating to an inverse relationship) (Frankfort-Namias & Leon-Guerrero 2006, p. 230). I used a threshold of 0.2 for the *Tau-c* magnitude as indication that there is at least a moderate relationship between social position and motivation.

6.7.2 Results from Measures of Association

I did not find a moderate relationship between social position and a personal commitment to improve teaching as motivation for publishing or presenting. The measure of association was calculated with several representations for social position: a dummy variable for tenured or not, a dummy variable for non-contingent versus contingent faculty status, and dummy variables representing institution type. Institution type was considered an ordinal

variable because it is based on the amount of research activity at the institution, which I expected to have an inverse relationship with educational change agency.

Although a moderate relationship was not found between social position and personal commitment to improving teaching, there were other relationships found between social position and motivational types. For CPR, there was a moderate inverse relationship between a faculty member's tenured status and his or her motivation to publish to gain status in a professional organization ($Tau-c = -0.26$). Untenured faculty reported status gains as a motivation at higher rates than tenured faculty. This could be interpreted to mean that tenured faculty are less concerned about gaining status than untenured faculty who hope to be promoted to a more prestigious faculty rank. There was also a moderate relationship ($Tau-c = 0.25$) between institution type and the motivation to gain status in a professional organization by publishing. The cross tabulation indicated that only faculty members at research institutions reported being motivated in this way. This may reflect a self-selection by these faculty members into research universities. Faculty members who work at research universities were more likely to be engaged in publishing in professional organizations. There was also a moderate relationship between a faculty member's tenured status and his or her past personal success presenting at conferences ($Tau-c = 0.29$). Tenured faculty report at higher rates that they were motivated by past personal success (i.e., their confidence in presenting their ideas was based on based success). This is an expected spurious association as described at the beginning of this chapter: faculty members who were successful publishing and presenting were more likely

to receive tenure. This is an example of a possible sorting mechanisms effect. There was also a moderate relationship between a faculty member's tenured status and interest in receiving teaching awards ($Tau-c = 0.25$). Seventeen percent of tenured faculty reported they were motivated by winning teaching awards; no untenured faculty members reported being motivated by teaching awards.

For PLTL, several moderate relationships were identified. A moderate relationship was found between institution type and past personal success publishing ($Tau-c = 0.21$). Specifically, faculty members at research universities report being motivated by their past success. Again, this may reflect a self-selection bias as faculty members at research universities likely publish more than faculty members at other types of universities. Their confidence in publishing on teaching innovations may have been driven by their success in navigating publishing on disciplinary research. Faculty members at research universities also reported higher rates of being motivated to gain status in professional organizations through publishing ($Tau-c = 0.25$). There was also a moderate association identified between faculty rank and motivation to gain status within the organization by publishing. Tenured faculty ($Tau-c = 0.24$) reported at higher rates that they were motivated to do so. There were no moderate or strong relationships identified between social position and motivational reports for SALG respondents.

6.8 Discussion

6.8.1 Faculty Role and Change Agency

The analysis above suggest weak, mixed support for my hypotheses. The educated guess that tenured and tenure-track faculty would more frequently publish and present was only found to be true for PLTL, with the models predicting lower rates of publishing for tenured faculty compared to tenure-track faculty. Partial support was found for CPR and SALG. Tenured faculty were found to have higher odds of publishing and presenting than non-tenured faculty (including assistant professors and contingent faculty). The addition of a grant-funding variable to Model 3 reduced the significance of the faculty position coefficient in the CPR and SALG models, suggesting an association between faculty rank and receiving a grant. This was also the case in the models based on the combined datasets that control for innovation category. It suggests that getting grants is the underlining mechanism that explains the relationship between social position and change agency.

6.8.2 Institution Type and Change Agency

A more robust association was found between institution type and change agency, however, the direction contradicted Hypothesis 3b. In the CPR Poisson regression model and the CPR and PLTL logit models, change agency was associated with research universities, not teaching colleges. At research universities, it appears that the sorting processes and organizational incentives that lead faculty members to publish and present on their disciplinary research may also encourage them to publish in the education domain. The association

between publishing and research universities was most pronounced when modeling the dependent variable as a binary: published or not. The coefficients for these models were significant while controlling for faculty position. As such, it would be interesting to explore whether contingent faculty at research universities are publishing and presenting more than peers at institutions with less research activity. If so, was this because organizational incentives targeted at tenured and tenure-track faculty also influenced contingent faculty – directly or indirectly? Do junior faculty – hoping to be promoted or have their contract renewed – mimic the activity of senior faculty to signal their acceptance of general norms about research productivity at the institution?

Summary goodness of fit measures suggest that the data collected were better used at predicting the choice to be a change agent as opposed to how intensely a faculty member embraced the change agent role for individual innovation. When the dependent variable was constructed as a dichotomous variable indicating an adopter had published or presented at least once, the model actually fits the data well. The analysis suggests that future research should explore how an adopter's relationship with the community of support affects the likelihood of becoming a change agent. Faculty that strongly identify with these communities may regularly participate in community activities. Faculty members may also possibly commit to “passionately” advocating for the innovation through new communication channels to expand its use.

6.8.3 Grant Funding and Change Agency

For CPR and SALG, the addition of a grant-funding variable reduced the significance of the faculty position coefficient. Receiving a grant may be the underlining mechanism that explains the relationship between social position and change agency. Tenured and tenure-track faculty are more likely to have experience and success writing funded grant proposals, which in these models predicts higher frequencies of publishing and presenting. The reason faculty members who acquire external funding publish or present more is that funding agencies' typical requirements to disseminate knowledge gained from the project. A trend to investigate would be whether the increased publication and presentation rate of tenured faculty occurs before or after they receive tenure. The data in this study do not permit me to investigate this question.

6.8.4 Variations in Change Agency by Innovation

Considering these results and the wide variations in publication rates across innovations (Table 6.3) suggests that perhaps the frequency of publishing and presenting on an innovation may be more associated with the innovation itself rather than the instructor's social position. This could arise from differences between the innovations and the associated communities of support that create opportunities for publishing and presenting. For example, innovations that can be adapted facilitate writing or presenting about unique case studies. Centralized communities of support establish innovation-specific conferences and publications that provide opportunities for presenting and publishing. There is support for the latter in my analysis of the models controlling for innovation

category. Users of PLTL were predicted to publish or present less than SALG users controlling for years of use and grant support (See Model 3 in Table 6.11). Future research could explore how different characteristics of educational innovations and the structure of support communities may shape change agency patterns among adopters of different innovations.

6.8.5 Possibilities for Future Research

Future research could explore whether innovations diffuse primarily within communication channels and diffusion networks aligned with discipline-based research communities such as chemistry, engineering, and the social sciences. For example, PLTL users in this study were predominantly from the science disciplines with a few engineers. No PLTL user self-identified as a social scientist. PLTL is an approach to help with quantitative problem-solving. Social science departments, like sociology and economics, offer courses that could benefit from the PLTL approach. Students in a social statistics course or microeconomics course could benefit from small-group problem practice sessions. It would be interesting to investigate whether PLTL has not been adopted in non-STEM courses because social science faculty do not identify the relevance of it or because they are unaware of it due to being disconnected from STEM-based diffusion networks.

Another area to explore is how trends in publishing about innovations are associated with adopter phases. Gartners' hype cycle describes how technology innovations experience a peak of inflated expectations in the early stages (Gartner 2013). This peak is then followed by a trough of disillusionment before

acceptance slowly reaches a steady state. In the initial hype phase, potential adopters have a strong need for information about the innovation to educate themselves. This may facilitate early adopters being invited to share information about their experience. For example, in 2012 Massive Open, Online Courses (MOOCs) became a much talked about educational innovation in both higher education and the popular press (Friedman 2012; Young 2012). Conferences organizers actively recruited MOOC providers and instructors to talk about their experience to capitalize on the excitement behind these new teaching approaches. By 2014, interest in MOOCs began to wane (Koenig 2014).

6.9 Conclusions

In summary, there was weak, mixed support for my hypotheses that social position is associated with faculty change agency. Tenured faculty were more likely to publish and present than untenured faculty for CPR and SALG, however this effect was diminished when controlling for grant funding. This attenuation of effect is likely explained by tenured faculty winning more grant funding. Funding agencies often include requirements to disseminate findings from the funded project. The grant funding variable likely explains a causal pathway in which faculty position is associated with change agency. Non-contingent faculty who use PLTL were more likely to publish and present than lecturers and adjuncts. These findings support the hypothesis that tenured and tenure-track faculty would be more likely than contingent faculty to publish and present in anonymous-search networks. Faculty members at research universities were more likely to present and publish than associate's colleges. No difference was found when

comparing faculty members at baccalaureate colleges against faculty members at associate's colleges, which contradicts Hypothesis 3b.

For the data collected, the models describing whether or not a faculty member becomes a change agent displayed a better goodness of fit than the models describing how often they publish or present. Grants provided leverage for not only broadening adoption but encouraging faculty members to act as change agents by publishing and presenting on their experience. The most frequently cited reason for publishing and presenting was a personal commitment to teaching, not access to resources or pressures operating through social norms. Differences in descriptive statistics suggest that innovation characteristics were also an important driver and present an opportunity for future research to explore.

Table 6.1: Publication Numbers of Respondents Who Used Innovation (non-users excluded)

Publication Number	CPR	PLTL	SALG
0	64 (56.64%)	50 (36.23%)	307 (71.40%)
1	21 (18.58%)	34 (24.64%)	64 (14.88%)
2	8 (7.08%)	20 (14.49%)	20 (4.65%)
3+	20 (17.70%)	34 (24.64%)	39 (9.07%)
TOTAL	113	138	430

Table 6.2: Mean and Variance of Publishing and Presenting by Innovation

Innovation	Mean	Variance	# of observations
CPR	0.858	1.337	113
PLTL	1.275	1.427	138
SALG	0.513	0.889	430

Table 6.3: Descriptions of Independent Variables

Variable		Description
<i>Background Characteristics</i>		
Gender		Male is the reference.
Discipline		Dummy variables for each of the four categories: natural sciences, engineering, social sciences, and humanities. The reference group changes in each model because not all 4 groups were represented for each innovation (e.g., PLTL is not used by social scientists or humanists).
Years of teaching		Interval-ratio variable representing years of teaching reported by respondents; ranged (in half year increments) from 0 to 50.
Doctoral Degree		Modeled as a dummy variable representing doctorate or not because a high percentage of respondents listed their terminal degree as a Ph.D. (80% for each innovation).
<i>Social Position</i>		
Faculty role		Faculty role is an ordinal variable that is represented in several ways throughout the models: 1) dummy variable representing non-contingent faculty(tenured and tenure-track). The reference were contingent faculty (lecturer and adjunct) 2) dummy variable representing tenured (e.g., full and associate professors) or not 3) dummy variables representing each of the ordinal categories with lecturers being the reference group
College type		College type is an ordinal variable based on a collapsed version of the Carnegie Classification: research universities, master's universities, baccalaureate colleges, associate's colleges.
Interaction: Faculty role X College type		Created from previous two variables.
<i>Adoption Experience</i>		
Grant funding		Dummy variable with no grant funding as reference.
Years since first use		Respondents listed the year they first used the innovation. This response was reverse coded to represent the number of years since the individual first used the innovation.

Table 6.4: Mean Values of Independent Variables

Variable			CPR n=113	PLTL n=138	SALG n=430
Gender			0.522 (0.501)	0.442 (0.498)	0.591 (0.520)
Science Course			0.796 ³⁶ (0.404)	0.899 (0.303)	0.809 (0.641)
Engineering Course				-	0.055 (0.230)
Humanities Course			0.106 (0.309)	-	0.063 (0.243)
Teaching Years			18.562 (8.749)	23.551 (11.163)	14.733 (9.091)
Doctoral Degree			0.814 (0.391)	0.862 (0.346)	0.847 (0.361)
Non-contingent Faculty	Tenured Faculty	Full Professors	0.389 (0.490)	0.457 (0.499)	0.277 (0.448)
		Associate Professor	0.248 (0.434)	0.261 (0.441)	0.307 (0.462)
	Untenured Faculty	Assistant Professor	0.150 (0.359)	0.130 (0.338)	0.233 (0.423)
Lecturers		0.159 (0.367)	0.138 (0.346)	0.123 (0.329)	
Contingent Faculty					
Adjunct Faculty			0.053 (0.225)	0.014 (0.120)	0.060 (0.239)
Research University			0.336 (0.474)	0.478 (0.501)	0.312 (0.464)
Master's University			0.239 (0.428)	0.205 (0.409)	0.365 (0.482)
Baccalaureate College			0.115 (0.320)	0.094 (0.293)	0.209 (0.407)
Associate's College			0.309 (0.464)	0.217 (0.414)	0.114 (0.318)
Grant Funding			0.142 (0.351)	0.746 (0.437)	0.148 (0.355)
Years Since First Use			7.151 (3.267)	8.746 (2.864)	1.826 (1.214)

³⁶ Science and engineering courses were combined into a STEM variable for CPR because of the low cell count for engineering faculty.

Table 6.5: Incident Rate Ratios from Poisson Regression of Publishing and Presenting on CPR Controlling for Social Position and Adoption Experience

	Model 1 Background Characteristics	Model 2 Social Position	Model 3 Adoption Experience
Intercept	0.254*	0.174*	0.104**
Gender	0.860	0.893	0.909
STEM course ³⁷	2.325	2.653+	1.897
Humanities Course	4.118*	6.172**	3.553*
Years Teaching	0.992	0.987	0.986
Doctoral Degree	1.604	1.156	0.933
Tenured		1.989*	1.389
Tenure-track		0.925	1.179
Research University		2.026*	2.043*
Master's University		1.598	1.531
Baccalaureate College		1.016	1.087
Grant Years Used			2.170*** 1.122**
Log Likelihood	-148.86	-144.28	-134.42
n	113	113	113

*** p<0.001, **p<0.01, *p<0.05, + p<0.10

³⁷ Science and engineering faculty were combined into a STEM faculty variable because of low cell counts for engineering faculty. Only 2 engineering faculty responded to the survey.

Table 6.6: Incident Rate Ratios from Poisson Regression of Publishing and Presenting on PLTL Controlling for Social Position and Adoption Experience

	Model 1 Background Characteristics	Model 2 Social Position	Model 3 Adoption Experience
Intercept	0.975	0.655	0.203*
Gender	1.080	1.097	1.063
Science Course	0.598*	0.645 ⁺	0.591+
Years Teaching	1.025***	1.025**	1.017*
Doctoral Degree	1.115	0.916	0.922
Tenured		0.789	0.638+
Tenure-track		1.620	1.784+
Research University		1.388	1.526+
Master's University		1.390	1.460
Baccalaureate College		1.173	1.401
Grant			2.364***
Years Used			1.084*
Log Likelihood	-200.28	-195.24	-187.06
n	138	138	138

*** p<0.001, **p<0.01, *p<0.05, + p<0.10

Table 6.7: Incident Rate Ratios from Negative Binomial Regression of Publishing and Presenting on SALG Controlling for Social Position and Adoption Experience

	Model 1 Background Characteristics	Model 2 Social Position	Model 3 Adoption Experience
Intercept	0.383**	0.387*	0.171***
Gender	0.806	0.823	0.856
Science Course	0.959	0.945	0.943
Engineering Course	1.043	0.982	0.959
Humanities Course	0.939	1.045	1.296
Years Teaching	1.025*	1.012	1.015
Doctoral Degree	1.096	1.091	0.998
Tenured		1.626+	1.445
Tenure-track		0.794	0.794
Research University		1.275	1.304
Master's University		0.968	1.078
Baccalaureate College		1.007	1.023
Grant			2.395***
Years Used			1.373***
Log Likelihood	-408.00	-405.97	-392.27
n	430	430	430

*** p<0.001, **p<0.01, *p<0.05, + p<0.10

Table 6.8: Odds Ratios from Logit Regression of Publishing and Presenting on CPR Controlling for Social Position and Adoption Experience

	Model 1 Background Characteristics	Model 2 Social Position	Model 3 Adoption Experience
Intercept	0.120*	0.055*	0.027*
Gender	0.646	0.674	0.657
STEM Course	4.225+	5.723*	4.048
Humanities Course	7.988*	13.526*	8.950+
Years Teaching	0.996	0.977	0.969
Doctoral Degree	2.626+	1.236	0.911
Tenured		2.822	2.086
Tenure-track		1.067	1.439
Research University		4.238*	4.874*
Master's University		2.354	2.343
Baccalaureate College		1.156	1.288
Grant			4.179*
Years Used			1.167*
Log Likelihood	-73.54	-69.78	-64.92
n	113	113	113

*** p<0.001, **p<0.01, *p<0.05, + p<0.10

Table 6.9: Odds Ratios from Logit Regression of Publishing and Presenting on PLTL Controlling for Social Position and Adoption Experience

	Model 1 Background Characteristics	Model 2 Social Position	Model 3 Adoption Experience
Intercept	6.900	2.864	0.168
Gender	1.421	1.615	1.764
Science Course	0.093*	0.110*	0.198
Years Teaching	1.049**	1.057**	1.056*
Doctoral Degree	0.663	0.424	0.412
Tenured		0.526	0.186*
Tenure-track		1.941	3.096
Research University		3.129*	5.644**
Master's University		2.757+	3.989+
Baccalaureate College		1.629	3.446
Grant			9.414***
Years Used			1.077
Log Likelihood	-82.40	-79.61	-67.53
n	138	138	138

*** p<0.001, **p<0.01, *p<0.05, + p<0.10

Table 6.10: Odds Ratios from Logit Regression of Publishing and Presenting on SALG Controlling for Social Position and Adoption Experience

	Model 1 Background Characteristics	Model 2 Social Position	Model 3 Adoption Experience
Intercept	0.268**	0.282**	0.117***
Gender	0.914	0.918	0.920
Science Course	0.987	0.973	0.997
Eng Course	1.569	1.471	1.390
Humanities Course	1.078	1.207	1.465
Years Teaching	1.012	0.996	0.998
Doctoral Degree	1.134	1.211	1.081
Tenured		2.022*	1.767+
Tenure-track		0.794	0.792
Research University		1.297	1.479
Master's University		0.894	1.090
Baccalaureate College		1.117	1.236
Grant			3.479***
Years Used			1.394***
Log Likelihood	-261.602	-251.92	-237.93
n	430	430	430

*** p<0.001, **p<0.01, *p<0.05, + p<0.10

Table 6.11: Incident Rate Ratios from Negative Binomial Regression of Publishing and Presenting Controlling for Social Position, Adoption Experience, and Innovation

	Model 1 Background Characteristics	Model 2 Social Position	Model 3 Adoption Experience
Intercept	0.251*** (0.085)	0.208*** (0.078)	0.174*** (0.062)
Gender	0.919 (0.112)	0.932 (0.114)	0.956 (0.109)
Science Course	1.377 (0.402)	1.372 (0.400)	1.197 (0.330)
Eng Course	1.765 (0.654)	1.649 (0.611)	1.634 (0.565)
Humanities Course	1.594 (0.596)	1.712 (0.639)	1.583 (0.555)
Years Teaching	1.019** (0.007)	1.013+ (0.007)	1.010 (0.007)
Doctoral Degree	1.203 (0.215)	1.019 (0.213)	0.951 (0.187)
CPR	1.577** (0.258)	1.609** (0.266)	0.843 (0.195)
PLTL	2.014*** (0.317)	2.082*** (0.331)	0.581*** (0.155)
Tenured		1.396 ⁺ (0.250)	1.201 (0.205)
Tenure-track		0.950 (0.211)	0.993 (0.209)
Research University		1.514* (0.307)	1.581* (0.299)
Master's University		1.278 (0.260)	1.331 (0.255)
Baccalaureate College		1.194 (0.279)	1.248 (0.275)
Grant			2.259*** (0.318)
Years Used			1.123*** (0.034)
Log Likelihood	-758.112	-753.561	-729.877
n	671	671	671

*** p<0.001, **p<0.01, *p<0.05, + p<0.10

Table 6.12: Odds Ratios from Logit Regression of Publishing and Presenting on SALG Controlling for Social Position, Adoption Experience, and Innovation

	Model 1 Background Characteristics	Model 2 Social Position	Model 3 Adoption Experience
Intercept	0.142*** (0.065)	0.093*** (0.047)	0.069*** (0.037)
Gender	1.007 (0.167)	1.023 (0.172)	1.015 (0.177)
Science Course	1.700 (0.642)	1.729 (0.659)	1.461 (0.572)
Eng Course	3.621* (1.821)	3.314* (1.696)	2.679+ (1.390)
Humanities Course	1.908 (0.937)	2.146 (1.065)	1.942 (0.999)
Years Teaching	1.020* (0.009)	1.011 (0.011)	1.009 (0.011)
Doctoral Degree	1.261 (0.302)	0.927 (0.261)	0.837 (0.244)
CPR	1.915** (0.426)	2.084** (0.48)	1.035 (0.348)
PLTL	3.586*** (0.804)	3.874*** (0.901)	0.714 (0.284)
Tenured		1.604+ (0.388)	1.362 (0.344)
Tenure-track		0.964 (0.288)	1.019 (0.316)
Research University		2.302*** (0.645)	2.710* (0.797)
Master's University		1.598+ (0.451)	1.785+ (0.529)
Baccalaureate College		1.651 (0.525)	1.827 (0.608)
Grant			4.025*** (0.910)
Years Used			1.154*** (0.051)
Log Likelihood	-417.372	-410.170	-384.872
n	678	678	678

*** p<0.001, **p<0.01, *p<0.05, + p<0.10

Table 6.13: Motivating Influencers for CPR³⁸

Variable	Hindered		No Effect		Enabled	Total
Institutional incentives to publish	0 0%	0 0%	36 80.00%	3 6.67%	6 13.33%	45 100%
Prof Org incentives to publish	0 0%	0 0%	39 86.67%	4 8.89%	2 4.44%	45 100%
Past personal success publishing	0 0%	1 2.22%	34 75.56%	4 8.89%	6 13.33%	45 100%
Institutional incentives to present	1 2.22%	0 0%	24 53.33%	11 24.44%	9 20.00%	45 100%
Prof Org incentives to present	0 0%	1 2.22%	36 80.00%	7 15.56%	1 2.22%	45 100%
Past personal success present	0 0%	0 0%	14 31.11%	18 40.00%	13 28.89%	45 100%
Travel Resources available	2 4.44%	1 2.22%	22 48.89%	7 15.56%	13 28.89%	45 100%
Desire to gain status at your institution	1 2.22%	0 0%	22 48.89%	17 37.78%	5 11.11%	45 100%
Desire to gain status within your prof org	0 0%	1 2.22%	29 64.44%	13 28.89%	2 4.44%	45 100%
Personal commitment to improve teaching	0 0%	0 0%	4 8.89%	12 26.67%	29 64.44%	45 100%
Desire for teaching awards	2 4.44%	0 0%	38 84.44%	3 6.67%	2 4.44%	45 100%
Annual review	1 2.22%	1 2.22%	23 51.11%	14 31.11%	6 13.33%	45 100%
Other	1 2.22%	0 0%	36 80.00%	1 2.22%	7 15.56%	45 100%
Total	8 1.37%	5 0.85%	357 61.03%	114 19.49%	101 17.26%	585 100%

³⁸ Four respondents who indicated they published terminated the survey before completing the questions on what motivated them to publish. That is why n=45 instead of n=49.

Table 6.14: Motivating Influencers for PLTL

Variable	Hindered		No Effect		Enabled	Total
Institutional incentives to publish	0 0%	0 0%	42 50.60%	16 19.28%	25 30.12%	83 100%
Prof Org incentives to publish	0 0%	1 1.20%	55 66.27%	14 16.87%	13 15.66%	83 100%
Past personal success publishing	0 0%	0 0%	48 67.83%	18 21.69%	17 20.48%	83 100%
Institutional incentives to present	0 0%	1 1.20%	42 50.60%	25 30.12%	21 25.30%	83 100%
Prof Org incentives to present	1 1.20%	2 2.41%	59 71.08%	10 12.05%	11 13.25%	83 100%
Past personal success present	0 0%	2 2.41%	26 31.33%	33 39.76%	22 26.51%	83 100%
Travel Resources available	4 4.82%	2 2.41%	33 39.76%	26 31.33%	18 21.69%	83 100%
Desire to gain status at your institution	2 2.41%	3 3.61%	32 38.55%	30 36.14%	16 19.28%	83 100%
Desire to gain status within your prof org	2 2.41%	2 2.41%	45 54.22%	24 28.92%	10 12.05%	83 100%
Desire for teaching awards	2 2.41%	5 6.02%	53 63.86%	14 16.87%	9 10.84%	83 100%
Personal commitment to improve teaching	0 0%	0 0%	2 2.41%	17 20.48%	64 77.11%	83 100%
Annual review	1 1.20%	3 3.61%	29 33.94%	32 38.55%	18 21.69%	83 100%
Other	0 0%	0 0%	79 95.18%	1 1.20%	3 3.61%	83 100%
Total	12 1.11%	21 1.95%	539 49.95%	260 24.10%	247 22.89%	1,079 100%

Table 6.15: Motivating Influencers for SALG

Variable	Hindered		No Effect	Enabled		Total
Institutional incentives to publish	0 0%	1 0.83%	72 59.50%	25 20.66%	23 19.01%	121 100%
Prof Org incentives to publish	3 2.48%	1 0.83%	80 66.12%	14 11.57%	23 19.01%	121 100%
Past personal success publishing	3 2.48%	0 0%	63 52.07%	37 30.58%	18 14.88%	121 100%
Institutional incentives to present	2 1.65%	1 0.83%	59 48.76%	39 23.97%	30 24.79%	121 100%
Prof Org incentives to present	3 2.48%	0 0%	75 61.98%	23 19.01%	20 16.53%	121 100%
Past personal success present	5 4.13%	0 0%	39 32.23%	47 38.84%	30 23.79%	121 100%
Travel Resources available	6 4.96%	7 5.79%	52 42.98%	28 23.14%	28 23.14%	121 100%
Desire to gain status at your institution	1 0.83%	0 0%	61 50.41%	40 33.06%	19 15.70%	121 100%
Desire to gain status within your prof org	2 1.65%	0 0%	68 56.20%	35 28.93%	16 13.22%	121 100%
Personal commitment to improve teaching	1 0.83%	0 0%	4 3.31%	27 22.31%	89 73.55%	121 100%
Desire for teaching awards	4 3.31%	0 0.00%	89 73.55%	22 18.18%	6 4.96%	121 100%
Annual review	1 0.83%	4 3.33%	57 47.50%	35 29.17%	23 19.17%	120 100%
Other	3 6.67%	0 0%	30 66.67%	4 8.89%	8 17.78%	45 100%
Total	34 2.27%	14 0.94%	749 50.07%	366 24.47%	333 22.26%	1,496 100%

VII. Social Position and Influence in Diffusion Networks

The first two analytic chapters explored how social position is associated with the likelihood of adopting (see Chapter 4) and abandoning (see Chapter 5). Chapter 6 explored how social position is associated with change agency. This chapter explores the connection between these chapters by investigating how influence is structured by the relationships between potential adopters and those disseminating information about the innovation. Specifically, I am interested in the *relative* social position of disseminators compared to the potential adopter.

My work in a teaching and learning center has given me a vantage point to observe how relative social position plays a role. Over several years I have heard faculty members comment, “That educational resource may work there (name of teaching/community college), but it won’t work here at Johns Hopkins (i.e., a research-intensive university).” This opinion shows that social position is associated with interest in or adoption of educational resources and practices. It does not explicitly tell us why, however. Employing a sociological view and systematic analysis can help unpack this statement.

7.1 Change Agents and Disseminators

For this chapter, I name anyone sharing information about the innovation a “disseminator.” This conceptualization is related to, but broader than, the concept of change agent investigated in the previous chapter. Rogers defines change agents as individuals who actively promote an innovation with the goal of increasing its adoption (Rogers 2003, p. 366). Change agents are not simply

sharing information about the innovation, but proactively advocating for it. Information is passed through social networks by more than just change agents. Professors may share information in response to a request for help from a colleague. They may also informally mention their use of the innovation during a conversation in the hall or at a departmental meeting. Disseminators are not necessarily formal advocates for the innovation so they are not all considered change agents. Change agents are considered a subgroup within the broader category of disseminators.

My reason for expanding the analysis from change agents to disseminators is that I am interested in whom potential adopters name as influential. This would include anyone sharing information about the innovation, not just change agents. More specifically, I want to investigate whether potential adopters are more likely to be persuaded to adopt by faculty members who have a similar or higher rank and/or work at a similar- or higher-status institution. Is the relative social position between disseminator and potential adopter associated with adoption rates? This relative social position can be described by the 1) the structural organization of existing relationships within and across groups and 2) norms that influence how power and status are assigned and are used to influence members' behaviors. I will explore both in building toward this chapter's central hypothesis.

7.1.1 Structural Organization of Relationships

The relative social proximity of actors can facilitate or hinder the diffusion of an innovation (Granovetter 1973; Burt 2000). Information is more likely to flow between two individuals who have a previous connection. This occurs not

only for individuals but institutions as well, especially those within the same geographic proximity (Whittington, Owen-Smith, & Powell 2009). It is not surprising that diffusion networks are correlated with personal relationships within an institution or across professional organizations (Frank, Zhao, & Borman 2004). In higher education, these relationships map onto the organization of instructors by faculty roles and disciplinary areas. The growth of disciplinary-based education research (DBER) is an example of how education diffusion networks develop from these relationships. "DBER combines discipline-specific expert knowledge, challenges of learning and teaching in that discipline, and the science of learning and teaching" (Singer, Nielson, & Schweingruber 2012, p. 2). DBER initiatives spread within discipline-specific communities (e.g., biology, physics) through the networks originally created by professional societies to connect faculty members by common research interests (p. 170).

Within a college, faculty relationships are influenced by academic position. There is usually an expectation that tenure-track junior faculty are mentored – formally and informally – by tenured senior faculty (Tierney & Bensimon 1996). Faculty members with research responsibilities collaborate on research (Creamer & Lattuca 2005; Dickens and Sagaria 1997). Adjuncts tend to have weak ties to the organization (Gappa & Leslie 1993) and are not always fully assimilated into the institution (Grieve & Worden 2000). Their short-term contracts limit their ability to develop relationships with other faculty members and participate in committee assignments.

Relationships between colleges can also be associated with faculty positions. Tenured and tenure-track faculty are likely to develop relationships with their peers through professional organizations dedicated to research. Hitchcock, et al. (1995) found that junior faculty's professional success was correlated with greater numbers of relationships to faculty members at other institutions. Lecturers, if they are given the support to engage in external professional development opportunities, are more likely to connect through organizations focused on teaching, such as the Professional and Organizational Development Network in Higher Education or the Educause Learning Initiative.³⁹ I am not suggesting that relationships do not exist between contingent and non-contingent faculty groups, but that they are less common than within group connections.

7.1.2 Power and Status Differentials

In addition to considering how the organization of personal relationships shapes diffusion, the power and status differentials of those relationships need to be considered. We can think of this influence as opinion leadership. Rogers defines opinion leadership as “the degree to which an individual is able to influence other individuals’ attitudes or overt behaviors informally in a desired way with relative frequency” (Rogers 2003, p. 27). In general, opinion leaders tend to be more cosmopolitan, have higher socioeconomic status, and be seen as more innovative (Rogers 2003). While Rogers states that opinion leadership is

³⁹ The Professional and Organizational Development Network in Higher Education is devoted to improving teaching and learning in higher education. The Educause Learning Initiative community is designed to facilitate the sharing of ideas and innovations among higher education professionals committed to advancing learning through IT innovation.

not a function of one's position (p.27), I disagree with this statement in the context of higher education.

Higher education is marked by clear hierarchies of faculty position and institution type as previously noted. There are reasons why junior faculty in less powerful positions are more likely to adopt ideas or suggestions from more senior faculty than vice versa. Contingent faculty are typically hired on time-limited contracts. Decisions to renew are typically decided by senior faculty member in the department or school. Contingent faculty may adopt the suggestions of senior faculty to signal their respect or acceptance of teaching norms at the institution. This same logic likely applies to tenure-track faculty whose professional advancement is determined by tenured faculty. It is through these power dynamics that social position plays a more causal role in shaping who is identified as influential. Power differentials may lead to higher diffusion rates if a charismatic opinion leader in a senior position can use his or her influence to encourage adoption. It can also slow diffusion processes because the flow of information about the innovation tends to occur in one direction. This unidirectional flow can also occur across institutions.

Additionally, the nature of degrees awarded and competitiveness of students attracted to different types of schools lead to a hierarchy of schools. This hierarchy is highly correlated with the research activity at colleges. Research-intensive universities dominate school rankings and media coverage. Faculty members may be more likely to adopt teaching practices pioneered or used at more prestigious research universities because of the perceived status of the

institution. For example, Johns Hopkins consulted with Washington University in St. Louis on the adoption of Peer-led Team Learning (PLTL). Many other schools were using it, but the faculty members at the university leading the adoption chose to consult with a peer institution instead of a school like Indiana University – Purdue University of Indianapolis (IUPUI) where one of the key founders of PLTL works.⁴⁰

Power dynamics also operate within the organization, which can hinder local diffusion. Micropolitics within a department or school may cause faculty members to discount or reject their peers' recommendations because they do not want to legitimize them (Datnow 2000). Faculty members may also want to foster a reputation for being innovative by implementing an educational resource from a colleague from another institution that is new to the local institution. Beyond power dynamics, flaws related to local implementation are more readily observed by colleagues that may discourage adoption. For example, a new in-class voting system that does not work correctly with the institution's wireless network system may be discussed at faculty meetings or mentioned by students to other faculty members. Knowledge of these problems may discourage faculty members from adopting their peer's "flawed" resource.

⁴⁰ IUPUI is categorized as a research university (high research activity) in the Carnegie Classification. In my work with faculty and administrators at Johns Hopkins, however, I am often asked to make comparisons with our "peers," which typically is defined as schools in the Ivy Plus Consortium or the Consortium on Financing Higher Education (COFHE). The Ivy Plus includes the eight Ivy League schools and Stanford, MIT, New York University, and the University of Chicago; Johns Hopkins is not a member. The COFHE schools include 31 universities and liberal arts colleges consistently ranked as the most prestigious (e.g., Princeton University, Rice University, University of Chicago, Swarthmore College, Johns Hopkins). The example demonstrates that colleges consider prestige and reputation when choosing institutions to model. I recognize the peer group example is smaller than the Carnegie Classification categories, however, I use the Carnegie Classification in my analysis because it would be impossible to map the peer reference groups each institution defines for itself.

7.2 Hypothesis

In summary, previous research suggests adopters may be influenced by disseminators based on existing relationships that map onto organizational structures that are associated with faculty roles and institution type. I anticipate that adopters are more likely to be influenced by individuals perceived to have the same or higher status. Status is defined by faculty rank or institution type. I expect that the effect of status will be more evident within colleges because faculty members are more likely to interact across different ranks within a college. When faculty members interact with colleagues outside the organization, organizational structures will likely dictate interactions with someone of a similar institution and faculty type (e.g., tenured faculty from research universities sharing ideas at a conference). As such, my hypothesis is that status differentials between adopters and disseminators will be more pronounced across faculty ranks than across institution types (see Figure 7.1).

Hypothesis 4 - Faculty members will more frequently cite instructors from the same institutional category than from the same faculty rank as an influential source of information about an educational innovation.

I differentiated between social-exchange and anonymous-search networks in previous chapters. Anonymous-search networks are those in which the adopter does not communicate personally with the person publishing or presenting information. It is the adopters receiving the information who are anonymous, not the source of information. The adopters usually can identify the author of a

website or article. Conference presenters are even more easily identified.

Therefore, I do not differentiate between social-exchange and anonymous-search networks in stating the hypothesis.⁴¹

7.3 Testing the Hypothesis

I modified the categories for faculty rank and institution type to fit this chapter's analysis. A concern with using the social position categories featured in previous chapters is that 1) respondents would not remember the specific rank of the disseminator, especially when one was influenced through an anonymous-exchange network (e.g., speaker at a conference) and 2) most faculty members are not sufficiently familiar with the Carnegie Classification to be able to identify the difference between categories (e.g., research universities and master's universities).⁴²

Another concern is that traditional faculty ranks and Carnegie classification categories used in the previous chapters have a ceiling and floor effect. A full professor could not choose an instructor with a higher specific rank and an adjunct could not choose an instructor with a lower position. I am interested, however, in the association between relative social position that is defined in part by status and power. Full professors can be department chairs or hold named professorships to which other faculty members assign higher status. Therefore, my measure of relative faculty rank and institution type is defined by

⁴¹ While the association between social position and opinion leadership is hypothesized to operate similarly within the two networks, the lack of social interaction will make it more difficult for adopters to remember or state the social position of those that influenced them through anonymous-search networks.

⁴² Faculty members may be able to identify the Carnegie Classification category of their own institution, but are less likely to identify the category for a range of other institutions at which the disseminator could work.

the perspective of the respondent as noted below. This measure seems appropriate in that many full-professor respondents identified influential disseminators as holding a “higher rank.” The following lists the options presented to respondents for describing the faculty rank and institution type of the person who most influenced them. Respondents chose their answers separately for each component.

Faculty Rank Options	Institution Type Options
<ul style="list-style-type: none"> • Higher-ranked faculty • Same or similar-ranked faculty • Lower-ranked faculty • Staff • No one • Don’t remember 	<ul style="list-style-type: none"> • Higher-status institution • Same or similar-status institution • Lower-status institution • No one/Not a college • Don’t remember

I combined the responses for “No one” and “Don’t remember” for both components. Don’t remember is essentially missing data. I assumed that if a respondent could not remember the status or rank of the disseminator then this status or rank had not been a major influence, which was similar to being influenced by no one (i.e., both influences are absent of status).

The results in this section include respondents that I define as “potential adopters.” Some of these individual eventually used the innovation at least once, others never used the innovation despite registering for an account or expressing

interest in obtaining information about the innovation.⁴³ The disseminators identified by these respondents were not assumed to always encourage potential adopters to use the innovation. Rogers notes that influential individuals can be advocating for or against the innovation (Rogers 2003, p. 27). While it is likely that most people identified as influential were advocating for the innovation, some may have been dissuasive because of the potential adopter's specific situation. For example, a faculty member using clickers in a large lecture class may dissuade a colleague from using clickers in a small seminar class where direct conversation is highly valued.

7.4 Results of Exploring Whom is Identified as Influential

I examined the social positions of the most influential disseminators identified by the potential adopters who responded to the survey. The disseminators' social positions are described in bivariate tables based on the relative faculty rank and relative institutional status. The hypothesis predicts that respondents will more likely choose a disseminator of the same institutional status than same faculty rank. Tables 7.1 - 7.3 display the results.

7.4.1 CPR

The descriptive patterns for CPR appear to be inconsistent with what Hypothesis 4 states. Potential adopters overwhelmingly chose disseminators of a higher status for both the faculty role and institution type (Table 7.1). Forty

⁴³ Users may register for an account without using it because they may need to create a user profile to pilot it. For example, a faculty member curious about the SALG survey may register for an account to create a test survey to understand how the systems works and identify what questions are available. After this pilot phase, the registered user may choose to implement it or not in his or her course. I surveyed every person who registered for an account, regardless of whether they implemented it with their students or not.

percent of respondents said the most influential disseminator hailed from a higher-status college. Almost 33 percent of respondents said the most influential disseminator was a higher-ranked faculty member. This was the mode, followed closely behind by faculty members from the same or similar rank (31 percent). The hypothesis predicted that respondents would more frequently choose someone of a similar-institutional status than the same faculty rank. The percentage of respondents choosing no one for each component was relatively high: 28 percent and 23 percent for institution type and faculty rank, respectively.

7.4.2 PLTL

The results for PLTL (Table 7.2) appear to be more consistent with the hypothesis than CPR. Almost 63 percent of respondents (91 of 145) identified the person who most influenced them as coming from the same or similar-status college. The next most common choice was higher-status college (19 percent). Forty-five percent of respondents said the most influential person held a higher rank, 37 percent chose same or similar-status rank. The number of respondents reporting that no one influenced them was much lower than for CPR: seven percent and nine percent for institution type and faculty rank, respectively.

7.4.3 SALG

The SALG responses were also consistent with the hypothesized effect. Fifty-three percent of respondents chose disseminators from the same or similar-status college. The next most common category was no one (26 percent). The choices for the disseminator's faculty rank followed the trends of the previous innovations. The most frequent choice was a faculty of a higher rank (31

percent). The next most common choice was a faculty member of the same or similar rank (24 percent). This was followed closely behind by no one (22 percent). For all three innovations, very few respondents chose a disseminator from lower faculty rank or institutional status. The values range from one to six percent.

7.4.4 Cases of No One Influencing the Adopter

While the data suggest the importance of considering the rank and status of disseminators, the data also documented that a large number of faculty members adopted SALG and CPR in isolation or did not remember the status and rank of the person who influenced them. About 20 percent of SALG and CPR respondents reported no one influenced them. For PLTL, the frequency drops to six percent. This variation likely reflects characteristics of the innovation. CPR and SALG are freely available and not complicated to adopt. Because they are web-based, they are more easily accessible for either piloting or adopting. PLTL requires institutional support – either by paying or assigning credit to undergraduate peer leaders. Implementation is also not trivial in that it requires scheduling classrooms, writing problem sets, and often coordinating across sections. PLTL may require more persuasion through the involvement of a disseminator to encourage new faculty members to adopt it. The next section explores whether potential adopters are more likely to implement an innovation if they engage with a disseminator as opposed to adopting in isolation.

7.4.5 Comparing Differences in Whom Users versus Non-users Identify as Influential

Are there differences in whom users and non-users identify as influential? I became specifically interested in this question upon noting the large numbers of CPR and SALG respondents who reported they did not remember who influenced them or that no one influenced them. I am able to explore this question because the survey respondents include anyone who expressed interest in learning more about the innovation. They did not necessarily have to adopt. For CPR and SALG, I created my survey population from a list of users who registered for an account, not those who adopted. For PLTL, the population included those who registered for a workshop on PLTL, registered for information on the PLTL website, or contacted the founders or leaders for more information.

Users' and non-users' choices for the relative faculty rank of the disseminator are primarily differentiated by the proportions reporting "no one" and "higher rank" (see Tables 7.4 - 7.6). For both CPR and SALG, respondents who reported that no one influenced them were much less likely to adopt. Thirty-six percent of CPR non-users and 31 percent of SALG non-users said no one influenced them. For users the frequency was 24 percent for CPR and 16 percent for SALG. When higher-ranked disseminators are reported, we see the opposite trend; users report higher-ranked faculty more frequently. For CPR, 27 percent of non-users report being influenced by a higher-ranked faculty member and 37 percent of users report the same. For SALG, the frequencies are 26 percent for non-users and 37 percent of users. There were very few non-users for PLTL so

the data are not described here. While the PLTL survey population included users and non-users, very few respondents reported not adopting (5 out of 142). For this reason, PLTL was not included in this analysis.

The differences were not as wide between users and non-users in reporting the institutional status of the most influential person (see Tables 7.7 - 7.9). For CPR, 29 percent of non-users and 21 percent of users reported they were not influenced by anyone. For SALG, the results were 33 percent for non-users and 22 percent of users. Thirty-eight percent of CPR non-users reported being influenced by someone from a higher-status institution. The frequency was 43 percent for users. For SALG, the frequencies were 13 percent for non-users and 16 percent for users.

7.4.6 Comparing Disseminator's Influence by Respondent's Social Position

The previous section provided descriptive statistics to illuminate the frequency with which respondents identified different categories for the relative social position of their most influential disseminator. I used multinomial logit models to explore the odds of a potential adopter choosing a disseminator from a specific, relative social position as the most influential. Multinomial logit models are an extension of the basic, binary logit model in that they describe the odds of a response in one category instead of another, but the multinomial logit model can simultaneously account for respondents choosing from among more than two options (Agresti 1996). The purpose for using multinomial logit models was to compare who respondents chose as most influential (e.g., higher-ranked faculty at higher-status universities versus similar-ranked faculty at the same-status

institution) while controlling for various characteristics of the respondents (e.g., user versus non-user, tenured faculty versus untenured faculty, years of teaching). The dependent variable categories refer to the relative social position of the disseminator compared to the potential adopter. These models can be generally expressed as the following.

$$\log(p_j/p_J) = \beta_0 + \beta_j F + \beta_j C + \beta_j I$$

where $\log(p_j/p_J)$ is the log odds of a potential adopter naming a disseminator in position j compared to a baseline category as the most influential.

and:

F = Faculty rank of potential adopter

C = Institutional category of potential adopter

I = innovation category

I did not include variables controlling for social-exchange and anonymous-search networks because they hypothesized effect was not predicted to be affected by the source of information (see Section 7.2 – *Hypothesis*).

The relative social position of the disseminator compared to the potential adopter is comprised of two components: relative faculty rank and relative institution status. I modeled the dependent variable in three different ways for each innovation.

- 1) Include both components of relative faculty rank and institutional status as direct test of Hypothesis 4: $J = 8$ categories (1. same institution status-different faculty rank, 2. same institutional status -

same faculty rank, 3. different institutional status-different faculty rank, 4. different institutional status-same faculty rank, 5. no one/don't remember for both components, 7. same faculty rank-unknown institutional status, 7. same institution status-unknown faculty rank. 8. different faculty rank or institutional status-unreported opposite category).

- 2) Modeling only faculty rank $J = 5$ (higher-rank faculty, same-rank, lower-rank, no one, staff, innovation founder)
- 3) Modeling only institutional status $J = 4$ (higher status, same status, lower status, no one)

Table 7.10 provides a description of each independent variable included in the models, and Table 7.11 provides the mean values of the independent variables used in the models for each innovation.

7.4.7 Data Results When Modeling the Influence of Relative Social Position

None of the multinomial logit models converged when the dependent variable represented all eight categories created by intersecting relative faculty rank and institution status (Set 1 above). This likely occurred because of the low number of responses for several categories. For SALG and PLTL, almost 90 percent of the responses fell into four of the eight categories for the dependent variable. This prevents me from conducting a direct test of the hypothesis.

Because the first set of models did not converge, I ran separate multinomial logit models in which the dependent variable represented either relative faculty rank (including staff and the innovation founder) or institutional

status. This was done for each innovation. I chose to separate the categories because the components of social position – faculty rank and institution type – had independent effects in the analyses discussed in the first three analytic chapters.

The second and third set of models, unfortunately, did not reveal any compelling patterns that would provide strong support or contrary evidence for the hypothesis (see Tables 7.16 - 7.18). None of the hypothesized coefficients in the model for CPR relative faculty rank were significant (see Table 7.16). For PLTL, the incident rate of choosing a same-ranked faculty member as the most influential over a higher-ranked faculty member is 77 percent lower for faculty at research universities ($p < 0.05$). None of the other hypothesized coefficients were significant (see Table 7.17). For SALG, different hypothesized coefficients were significant (see Table 7.18). The incident rate ratio of choosing no one over a higher-ranked faculty member is 63 percent lower for respondents from master's colleges compared to associates colleges ($p < 0.01$). These same respondents were also 46 percent less likely to choose same or similar- ranked faculty compared to higher-ranked faculty. Faculty from research universities and baccalaureate colleges (but not from master's colleges) are more likely to choose staff over higher-ranked faculty compared to faculty from associate's colleges. The models in which the dependent variable represented relative institutional status also displayed no patterns for which coefficients were significant (models not shown).

The only consistent finding was that the number of years the respondent taught was significant across the models predicting the most influential disseminator's relative faculty rank. Faculty members with more experience are more likely to report that the most influential disseminator is someone of lower or similar rank (See Tables 7.16 - 7.18). This variable is significant after controlling for the respondent's position. This could imply that the longer someone has taught the more open they are to being influenced by someone of lesser status. They may feel less of a need to follow more senior faculty.

7.5 How Disseminators are Influential

There are many ways a disseminator can be influential. Providing a clear argument based on data for why an educational innovation improves student learning can compel other faculty members to adopt it. My hypothesis follows from the presumption that social norms and power dynamics within and across schools would influence potential adopters to use an innovation. The results above show an association between relative social position and adoption. Specifically, SALG users are more likely to be influenced by someone than non-users. Non-users more frequently cite being influenced by no one. The results also show that CPR and SALG potential adopters are more often influenced by disseminators with higher faculty rank. Is this merely associational or is there a causal effect of the disseminators' relative social position? To explore this I conducted a qualitative analysis of comments respondents shared about how the most influential disseminators persuaded them. Respondents answered the question, "How was s/he [the most influential disseminator] influential?" The

following describes how many respondents answered the questions for each innovation.

- CPR – 126 out of 170 respondents
- PLTL – 120 out of 145 respondents
- SALG – 218 out of 809 respondents

7.5.1 Preparing the Data

I started my analysis by reading all of the comments to generate a list of categories used to code the comments. The categories included the following.

- Position – the respondent cited how the position of the disseminator influenced their decision to adopt. In no case did respondents describe how they were dissuaded from adopting. Example comment: “It was important to see that PLTL was being used at a research university very similar to mine.”
- Experience – the disseminator shared persuasive information (e.g., student learning gains, features of the innovation) in which the comment did not indicate any aspect of the disseminators’ relative social position as influencing the respondent. Example: “That person's positive experience with it and the data presented on how it helped students think more critically.”
- Helped – the disseminator provided support to the respondent as she or he implemented the innovation for the first time. Example: “[The disseminator] helped me with technical problems and issues.”

- Aware – the respondent became aware of the innovation from the disseminator. Example: “He's a heat seeker when it comes to technology and we share finds all the time.”
- Required – the respondent cited they were required to use the innovation. Example: “Department head required all faculty members to use SALG instrument on class evaluation.”
- Grant – the respondents cited how a grant program made them aware of the innovation or that grant-funding supporting the development of the innovation gave it credibility. Example: “...the fact that it was funded by a National Science Foundation (NSF) grant and no fee charge for usage gave me credibility.”

I read all of the comments a second time to code each comment with the categories above. After coding the data, I read all the comments a third time to verify my coding. Multiple codes could apply to each comment. Some comments were not tagged with any codes. For example, comments that simply named the position of the person who was most influential did not receive a code (e.g., “My graduate advisor”).

I used probit and logit models to check whether any biases existed between who responded and who did not to the open-ended question. I created a dependent variable for whether someone entered a comment about how the most influential person impacted their decision to adopt or not. I conducted both probit and logit regression analyses using the key independent variables used in this chapter: measures of respondent’s faculty rank and institution type. None of the

coefficients in the models were significant which suggests that the responses were not biased by my categorization of social position.

7.5.2 Analysis of Respondent Comments

A quantitative summary of the coding by innovation is provided in Tables 7.13 - 7.15. CPR and PLTL respondents overwhelmingly commented that the disseminator was influential because of the persuasive information they provided. Over 50 percent of the CPR comments indicated the disseminator provided results or descriptions of the innovation that influenced the respondent's decision. An example comment was, "The presenter was influential because information was provided about the process for using CPR and how the system was beneficial in showing improvements in the writing process for students at other institutions." For PLTL and SALG, the frequency was over 30 percent. Providing information was the modal response for PLTL as it was for CPR.

Some respondents commented that the disseminator made them aware of the innovation ($n = 105$ across all three innovations). "We met by chance at the _____ Conference. He referred me to pltl.org." "Awareness" was the most frequently cited influence for the SALG responses ($n = 70$). The disseminator may have also provided convincing data that influenced the potential adopters' decision, but not all the comments indicated that. Those that did were coded with both categories (i.e., "awareness" and "information provided").

7.5.2.1 How Disseminators' Social Position Influences Adoption

It is not surprising to find so many respondents describing how they were persuaded to adopt based on the results and experiences of others who

implemented the innovation. My hypothesis should not be interpreted as ignoring this rational decision making process. The hypothesis was meant to suggest how relative social position may also act as an influence. There was clear evidence of this. For CPR and PLTL, the disseminator's position was the second most frequent cited influence. For all three innovations, just under 20 percent of the comments referenced how the disseminator's position was influential. It is through these data that we see the nuance of how a disseminator's social position can influence potential adopters.

7.5.2.1.1 Examining Relative Institution Status

I start with examples of how faculty members come to adopt from similar-status institutions ($n = 7$). Comments reflected decisions to adopt based on an assumed compatibility of the innovation based on the institution type of previous adopters. "The fact that it had developed at a comparable institutions was helpful to know." Another respondent concisely shared, "similar student demographic." There were multiple references to considerations of institutional compatibility, but only one case of faculty rank used to evaluate the innovation's compatibility. "She was a faculty member too and because I was able to relate to her due to her position, I saw the potential of using it for my courses too."

These comments on institutional matching suggest some patterns consistent with the hypothesis: instructors are more likely to name a disseminator from a similar-status school than same faculty rank. It is indirect because these comments demonstrate *how social position is used to evaluate whether the innovation is a match*. I developed my hypothesis based on an expectation that

faculty members would more likely name a disseminator from similar-status colleges *because of the social networks they engage in*. The most direct support of the hypothesis was a comment in which a respondent said, “I tend to discuss pedagogy with faculty at institutions similar to my own.”

While these statements are consistent with the hypothesis, there were also instances of respondents commenting that they were influenced by a higher-status college ($n = 6$).

- “Being associated with University of Wisconsin-Madison didn't hurt.”
- “Teachers College was ahead of my college in the use of online education.”
- “The program [CPR] was run out of UCLA.”

The more prestigious reputation of the disseminators' college may not only influence a potential adopter, but be used by that adopter to justify its use with others. One respondent shared how she or he was able to use the status of other institutions in discussing the implementation with administrators. “Being able to tell my administration that even students at MIT and UCLA have challenges with content writing made it more respectable for me to address this problem with my own students without seeming to condescend or put them down.”

7.5.2.1.2 Examining Relative Faculty Rank

Respondents shared how they were influenced by higher-ranked faculty. As I discussed in the hypothesis development, junior faculty may reflect their acceptance of social norms to senior faculty by copying the senior faculty's

teaching practices. This comment implies this dynamic between a senior faculty and recent hire. “[S/he] was a more advanced faculty member a[t] the institution that I just had accepted a position.” This communication of expectations by senior faculty and acceptance by junior faculty is more explicit in this comment. “[S/he] described how the SALG could be included for tenure and promotion.” The interaction between faculty members are not always positive and sometimes show the power differentials associated with different ranks. One respondent stated she or he was, “pressured to use SALG by senior faculty member to advance their own agenda.” This comment gives evidence of Portes’ and Landolt’s concept of negative social capital (1996). Specifically, this is an example of a senior faculty member restricting a junior faculty members’ freedom to control how they teach.

The influence of faculty rank can be less direct in that potential adopters are not trying to signal respect by adopting, but assign value to the innovation based on the reputation of the individual. Examples of this type of association include the following.

- “His status as a successful scientist was somewhat influential.”
- “I know one of the authors of the article by name/reputation and that lent additional credibility.”
- “Director of the Learning and Teaching program and an ed researcher-a good double.”
- “I have known her for years and respect her work.”

I define social position by faculty rank and institution type. There is also a structure of faculty relations based on disciplinary expertise. Respondents also shared how the disseminator's disciplinary expertise persuaded them to adopt ($n = 18$). One respondent commented that the disseminator is the, "Director of our center for teaching and learning. He knows his stuff!"

7.5.2.2 Other Influences in the Diffusion Process

The previous descriptions show the various causal pathways in which the relative social position between disseminators and potential adopters influences the diffusion of educational innovations. Sometimes credibility or awareness came from other organizations like granting agencies ($n = 20$). NSF was mentioned several times. One PLTL respondent said, "The fact they had NSF money led credibility to the program." A similar comment was made by a SALG respondent. "I checked the SALG website and the fact that it was funded by NSF grant and no fee charge for usage gave me credibility." Even more emphatic was this comment. "When the NSF suggests that you use something in order to improve your grant, you do it!" This demonstrates the power of granting agencies to influence the teaching practices of faculty.

NSF's influence is that it can imply a requirement to adopt. There were 36 comments in which faculty members stated they were explicitly required to use the innovation (see Tables 7.13 - 7.15 for breakdown by innovation). "[My] Department head required all faculty members to use SALG instrument on class evaluation." The expectation to adopt can also occur as faculty members are assigned existing courses that have pre-defined teaching resources or strategies

that are expected to be used. “The decision to use PLTL had been made, and the faculty member quit, so I took over the program.” Despite these examples, the fact that only 36 out 663 responses (less than 5 percent) shows that top-down mandates to use these innovations were not a main driver of diffusion.

An interesting, unexpected result was respondents who said they were influenced to adopt as graduate students by their faculty mentors ($n = 5$). This frequency suggests that dissemination plans should strongly consider how graduate student training can seed the diffusion of educational innovations. This is extremely relevant for graduate student professional development programs and organizations like the Center for the Integration of Research, Teaching, and Learning (CIRTL). CIRTL is a network of 22 R1 research universities committed to training STEM graduate students on pedagogical best practices so they are better prepared to be effective teachers when they obtain their first faculty position.⁴⁴ The impact of faculty members on graduate students can also be applied to new faculty members. There were two cases of a new faculty member sharing the importance of mentoring by a senior faculty member. One example is a respondent who wrote, “She was my informal mentor and really helped me survive the first few quarters teaching. She was influential because she really cared about the students and their learning and she was very supportive.”

7.6 Discussion

I expected that status differentials would be more prevalent along faculty rank than institution type. The data suggest mixed results regarding this

⁴⁴ CIRTL also expects these graduate students to be more effective researchers as well because they will have to spend less time developing their teaching skills as new faculty.

hypothesis. The PLTL and SALG patterns are consistent with the hypothesis in that respondents more often chose someone from a different faculty rank than a different status institution. The CPR patterns, however, are inconsistent with the hypothesis in that respondents more often chose disseminators from different status institution than different faculty rank. One clear trend is that when respondents chose someone from a different faculty rank or institutional status, the rank and status were higher. The next section explores these trends in more detail.

7.6.1 Focusing on the Relative Status of the Disseminator's Institution

CPR respondents more frequently reported the most influential disseminator hailed from an institution of higher status. This outlier may reflect the uniqueness of the population I surveyed. Problems with the CPR user database only permitted me to survey CPR administrators at each institution. As such, most of these respondents were the first person to register for a CPR account at their institution. They are more likely to have been influenced by someone from another college. In addition, the CPR tool was developed at UCLA, which is a large research university with a good reputation. The responses for institution type may frequently reflect the specific reputation of UCLA. Of the six open-comments that reflected how a higher-institutional status college influenced their decision, four of those were for CPR. Each of these four comments referenced the status of UCLA.

PLTL and SALG respondents reported the most influential disseminators more frequently came from the same institution or similar-ranked institution.

While there were two cases of respondents commenting that they were influenced by someone from a higher-status college, most shared that they were influenced by someone from a similar-status institution. One respondent even commented that when he discussed pedagogical strategies with instructors from other schools, his discussion partners tended to come from similar schools. If diffusion is often facilitated through weak ties, then these data suggest that weak ties across institutions tend to link similar types of colleges (Granovetter 1973).

7.6.2 Considering Faculty Rank

What is clear is that potential adopters were more likely to name the most influential disseminator as someone with a higher rank. This was the mode for all three innovations. Is this because respondents want to signal respect for senior faculty because of promotion concerns, trust senior faculty's experience more, or tend to be lower rank faculty who have more options for picking senior faculty? These are not likely the best explanations because full professors were the largest response group for each innovation, and they often chose disseminators with a higher rank despite being categorized as a senior faculty member themselves. It may be the status is important on its own.

Potential adopters rarely categorized the disseminator as a faculty member of lower status, regardless of whether that is defined by faculty rank or institution type. Staff (i.e., non-faculty) were also rarely selected as the most influential. The frequency did not exceed seven percent for any innovation. This may suggest that faculty members do not value the input of staff or that staff are not adequately trained to provide support to faculty members adopting new innovations. These

results suggest that change agents advocating for an innovation may be more effective in increasing adoption by recruiting disseminators and opinion leaders of higher rank.

A significant percentage of respondents (20 percent) also said they were influenced by no one. There was some evidence for CPR and SALG that non-users (i.e., those who never adopted) were more likely to cite “no one” than users. This provided evidence that those who can identify the source of information, whether through social-exchange or anonymous-search networks, were more likely to adopt. Additional support for this association was seen in the PLTL data. Respondents were much less likely to cite no one influenced them (six percent) and the adoption rates were the highest of the three innovations. This may reflect the different characteristics of the innovations. SALG and CPR are hosted online so it is much easier for a potential adopter to pilot it without interacting with anyone. PLTL is a classroom-based innovation. Potential adopters would need to visit a college or course that was using it to see it in action. PLTL also has a very large support community that hosts conferences and its own journal. Potential adopters have more opportunities to engage with change agents who actively advocate for the PLTL at other institutions.

7.6.3 First Source of Information

Another area to explore is what are the sources of information faculty members report becoming aware of the innovation. Tables 7.13 - 7.15 provided frequency distributions of the first source of information through which respondents reported becoming aware of each innovation. For PLTL and SALG,

faculty members at the home institution were the mode. Over 40 percent of PLTL respondents and 35 percent of SALG respondents reported their first source of information was a faculty member at their home institution. The mode for CPR was conference. Almost a third of respondents said they first learned about CPR at a conference (31 percent). Another eight percent of respondents said they learned about CPR through a workshop. This is likely a reflection of the population of respondents. CPR respondents are primarily the administrators for the use of CPR at their college and generally the first adopter at the institution so they would be more likely to learn about it through external sources. While it is not surprising that the CPR respondents were more likely to choose anonymous-exchange networks more frequently, why did respondents list faculty at the same institution more frequently than faculty at another institution? Perhaps, there are non-users who were aware of the innovation and shared it with others. Another explanation could be that the administrator was not the first user, but took over the responsibility of the first user after she or he left the institution or decided not to use the tool anymore.

Faculty at the same institution were the second most frequent source cited (19 percent) by CPR respondents. For PLTL, faculty at another institution were the second most frequent cited source (19 percent). This frequency was about the same as the combined categories of conferences and workshops (22 percent). This may reflect the strong community network that was used to diffuse the innovation. PLTL users worked collaboratively and proactively to encourage peers within and across institutions to adopt PLTL through personal networks and

formal events. For SALG, the second most frequent source was conferences (15 percent) with faculty at other institutions cited about half as often (eight percent). About three percent of SALG respondents reported learning about the innovation from a workshop.

While both PLTL and SALG received funding from the NSF, only SALG respondents reported the NSF made them aware of SALG's existence. This was not an option listed on the survey, but almost 2.5 percent of respondents listed the NSF under the "Other" option. Respondents explained that the SALG tool was listed in NSF requests for proposals and that NSF program directors suggested its use. This suggests the NSF is an important disseminator in diffusion networks.

CPR and SALG both had recognizable leaders who worked hard to spread awareness of the educational resource. Arlene Russell led the development and dissemination of CPR. Stephen Carroll was an early user of SALG who took over its oversight. A small percentage of respondents cited them as the first source of information: Arlene Russell (three percent) and Stephen Carroll (five percent). These individuals can be seen as influential, but having limited reach.

Conferences were consistently listed most frequently among the anonymous-search networks. Why were websites and journal articles, which are more accessible, not listed more frequently? My interpretation is that awareness of an innovation is more likely the result of a push of information to the potential adopter rather than a request (or pull). First awareness, by definition, means a potential adopter is not aware the item previously existed and, therefore, does not know to search for it. Potential adopters may have a problem for which they

search for a solution. However, if someone is searching for an assessment survey, there are hundreds of options available that reduce the probability that they will discover the SALG tool in a web search. Conferences provide a space in which groups of individuals come together around a common topic (e.g., disciplinary research, educational topics) and share ideas. Change agents drive the agenda of conferences in many cases by applying to talk on their experience using an educational innovation. It is the presenters and conference organizers who choose the presenters. They influence what resources attendees will discover by attending. Stephen Carroll, the program director for SALG, talks at dozens of conferences a year to raise awareness of the SALG. His advocacy has directly influenced awareness of thousands of people. The power of conferences is that they provide attendees an opportunity to learn about many, diverse resources in a short amount of time. Change agents are more likely to reach potential adopters who were not specifically looking for a particular solution and, therefore, help the innovation break out of closed communities of users.

The importance of push over pull in first awareness also explains why social-exchange networks are listed more frequently than anonymous-search networks for first awareness. Individuals talking to their colleagues about their work is more likely to lead to awareness than a potential adopter searching for it anonymously.

If conferences are an important link in raising awareness, are they equally accessible to all? Contingent faculty may be less likely to attend conferences because of the lack of travel support. This would be most acute for adjuncts.

There is evidence of this in the data. Contingent faculty cite conferences and workshops as the first source of information 50 - 75 percent less often than the rate of tenured and tenure-track faculty (table not shown).

7.7 Conclusion

The data reveal that diffusion is influenced by the relative social position between the potential adopter and disseminator. I hypothesized that instructors would be more likely to be influenced by faculty from a different faculty rank than an institution with different status. The data for PLTL and SALG is consistent with this statement but the finding was directional, which was not hypothesized. Influence was more often associated with higher faculty rank, not lower. The same was the case for CPR. The CPR data were not consistent with the hypothesis because respondents also characterized the influential disseminators as hailing from higher-status institutions more often than higher-ranked faculty positions.

A significant number of SALG and CPR respondents said no one influenced them and non-adopters chose this option more frequently than adopters. This suggests the positive impact social-exchange networks can have on potential adopters. Innovation support communities are an example of a social-exchange network that can increase the likelihood of potential adopters using the innovation. Developing a large community advocating for the innovation can amplify this affect. PLTL has the largest, most coordinated support community of the three innovations studied. PLTL respondents were the

least likely to state that no one influenced them. Respondents also had the highest rate of adoption.

Qualitative data provided insight into how the differences in the relative social position of potential adopters and disseminators influences diffusion patterns. Potential adopters interpret institutional status in several ways. Some respondents described how institutional status was used as a cue to the compatibility of the innovation for their institution. Others described how the status of the institution could be used to justify implementing the innovation to senior administrators. Respondents explained why they were influenced by higher-ranked faculty. Senior faculty act as mentors advising new or junior faculty on teaching resources to use. There was also evidence of this occurring with graduate students. Respondents also admitted to adopting as a way to signal their acceptance of teaching norms. More senior faculty, especially administrators like department heads, may require the use of specific educational innovations.

Social position may not be the dominant influence on potential adopters. Respondents more often described how disseminators influenced them through data on how student learning gains could be improved or assisted in the implementation process. However, there was clear evidence that relative social position had an impact. Change agents and innovators should consider this when creating a diffusion plan.

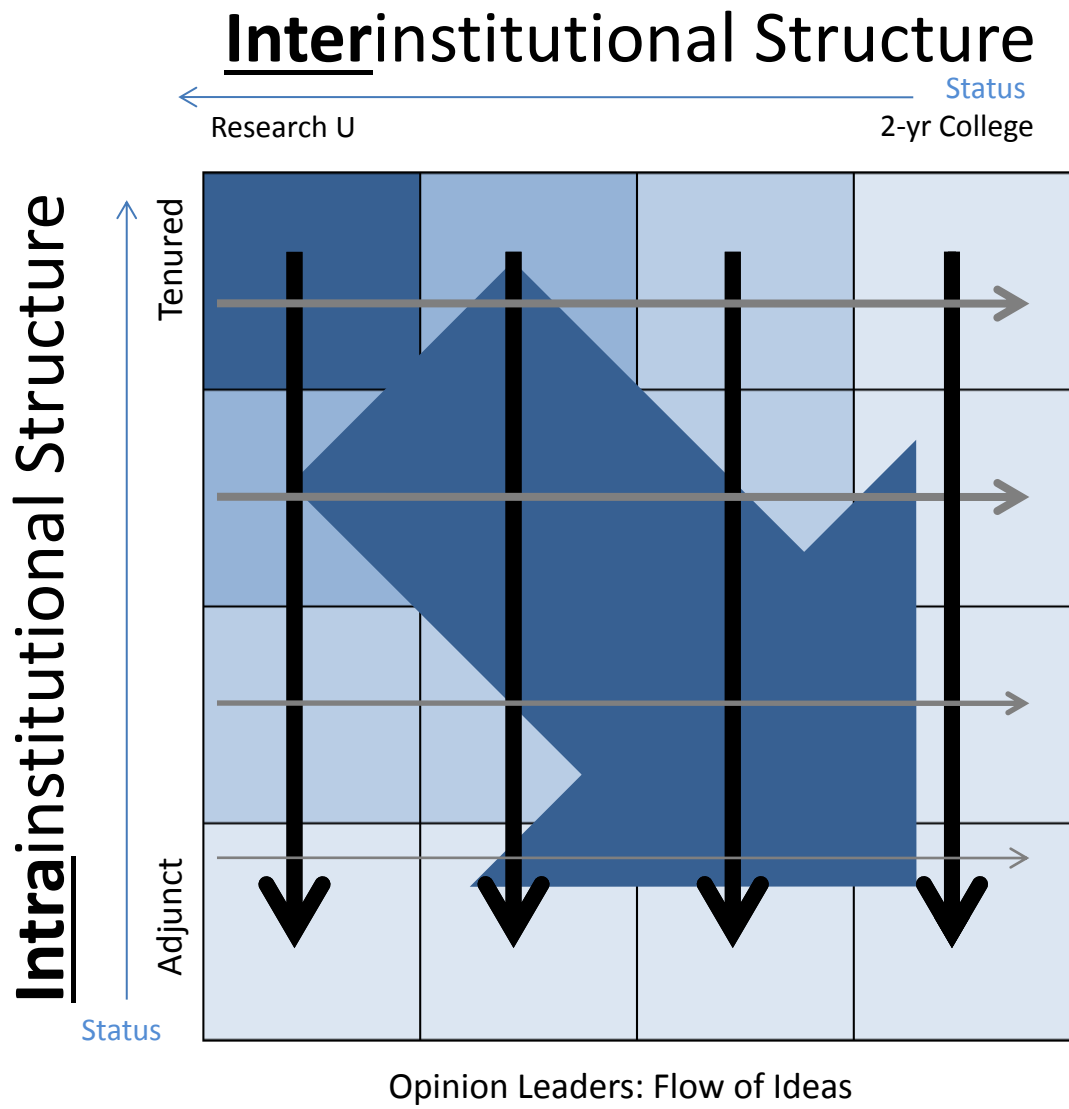


Figure 7.1: Hypothesized Patterns of Opinion Leadership in Persuasion/Decision-Making Stages in which Within-College, Between-Faculty-Rank Diffusion Dominates

Table 7.1: CPR Top Influence Counts

	Higher ranked	Same Ranked	Lower Ranked	Staff	No one	Missing	TOTAL
Higher-Status College	34 (20.00%)	18 (10.59%)	2 (1.18%)	5 (2.94%)	7 (4.12%)	2 (1.18%)	68 (40.00%)
Same- or Similar-Status College	18 (10.59%)	28 (16.47%)	1 (0.59%)	1 (0.59%)	1 (0.59%)	0 (0%)	49 (28.82%)
Lower-Status College	2 (1.18%)	5 (2.94%)	2 (1.18%)	0 (0%)	0 (0%)	0 (0%)	9 (5.29%)
No one / Do not remember	1 (0.59%)	1 (0.59%)	0 (0%)	0 (0%)	37 (21.76%)	0 (0%)	39 (22.94%)
Missing	1 (0.59%)	0 (0%)	0 (0%)	0 (0%)	2 (1.18%)	2 (1.18%)	5 (2.94%)
TOTAL	56 (32.94%)	52 (30.59%)	5 (2.94%)	6 (3.53%)	47 (27.65%)	4 (2.35%)	170 (100%)

Table 7.2: PLTL Top Influence Counts

	Higher ranked	Same Ranked	Lower Ranked	Staff	No one	Missing	TOTAL
Higher Status College	18 (12.41%)	8 (5.52%)	0 (0.00%)	1 (0.69%)	0 (0%)	0 (0%)	27 (18.62%)
Same or Similar-Status College	38 (26.21%)	40 (27.59%)	5 (3.45%)	7 (4.83%)	1 (0.69%)	0 (0%)	91 (62.76%)
Lower Status College	5 (3.45%)	2 (1.38%)	2 (1.39%)	0 (0%)	0 (0%)	0 (0%)	9 (6.21%)
No one / Do not remember	1 (0.69%)	2 (1.38%)	0 (0%)	1 (0.69%)	9 (6.21%)	0 (0%)	13 (8.97%)
Missing	1 (0.69%)	1 (0.69%)	0 (0%)	0 (0%)	0 (0%)	3 (2.07%)	5 (3.45%)
TOTAL	63 (43.45%)	53 (36.55%)	7 (4.83%)	9 (6.21%)	10 (6.90%)	3 (2.07%)	145 (100%)

Table 7.3: SALG Top Influence Counts

	Higher ranked	Same Ranked	Lower Ranked	Staff	Stephen Carroll	No one	Missing	TOTAL
Higher-Status College	61 (7.54%)	20 (2.47%)	1 (0.12%)	16 (1.98%)	7 (0.87%)	5 (0.62%)	0 (0%)	110 (13.60%)
Same- or Similar-Status College	175 (21.63%)	155 (19.16%)	23 (2.84%)	34 (4.20%)	30 (3.71%)	5 (0.62%)	3 (0.37%)	425 (52.53%)
Lower-Status College	4 (0.49%)	5 (0.62%)	2 (0.25%)	1 (0.12%)	2 (0.25%)	0 (0%)	0 (0%)	14 (1.73%)
No one / Do Not Remember	10 (1.24%)	13 (1.61%)	2 (0.25%)	20 (2.47%)	9 (1.11%)	152 (18.79%)	2 (0.25%)	208 (25.71%)
Missing	2 (0.25%)	3 (0.37%)	1 (0.12%)	1 (0.12%)	4 (0.49%)	19 (2.35%)	22 (2.72%)	52 (6.43%)
TOTAL	252 (31.15%)	196 (24.23%)	29 (3.58%)	72 (8.90%)	52 (6.43%)	181 (22.37%)	27 (3.33%)	809 (100%)

Table 7.4: Comparison of CPR Users and Non-users Choices of Most Influential Disseminator – Faculty Rank

	Non-user	User	TOTAL
No One	20 (36%)	27 (24%)	47 (28%)
Staff	3 (6%)	3 (3%)	6 (4%)
Lower-Rank Faculty	1 (2%)	4 (4%)	5 (3%)
Same-Rank Faculty	16 (29%)	36 (32%)	52 (31%)
Higher-Rank Faculty	15 (27%)	41 (37%)	56 (34%)
TOTAL	55 (100%)	111 (100%)	166 (100%)

Pearson $\chi^2 = 4.192$ df = 4 p < 0.381

Table 7.5: Comparison of CPR Users and Non-users Choices of Most Influential Disseminator – Institution

	Non-user	User	TOTAL
No One	16 (29%)	23 (21%)	39 (24%)
Lower Status	2 (4%)	7 (6%)	8 (5%)
Same Status	16 (29%)	33 (30%)	49 (30%)
Higher Status	21 (38%)	47 (43%)	68 (41%)
TOTAL	55 (100%)	110 (100%)	165 (100%)

Pearson $\chi^2 = 1.733$ df = 3 p < 0.630

Table 7.6: Comparison of PLTL Users and Non-users Choices of Most Influential Disseminator – Faculty Rank

	Non-user	User	TOTAL
No One	1 (20%)	9 (7%)	10 (7%)
Staff	0 (0%)	9 (7%)	9 (6%)
Lower-Rank Faculty	0 (0%)	7 (5%)	7 (5%)
Same-Rank Faculty	2 (40%)	51 (36%)	53 (37%)
Higher-Rank Faculty	2 (40%)	61 (45%)	63 (45%)
TOTAL	5 (100%)	137 (100%)	142 (100%)

Low cell counts violate Pearson χ^2 assumption

Table 7.7: Comparison of PLTL Users and Non-users Choices of Most Influential Disseminator – Institution

	Non-user	User	TOTAL
No One	2 (50%)	11 (8%)	13 (29%)
Lower Status	0 (0%)	9 (7%)	9 (7%)
Same Status	2 (50%)	89 (65%)	91 (65%)
Higher Status	0 (0%)	27 (20%)	27 (19%)
TOTAL	4 (100%)	136 (100%)	140 (100%)

Low cell counts violate Pearson χ^2 assumption

Table 7.8: Comparison of SALG Users and Non-users Choices of Most Influential Disseminator – Faculty Rank

	Non-user	User	TOTAL
No One	111 (31%)	70 (16%)	181 (23%)
Staff	38 (11%)	34 (8%)	72 (9%)
Stephen Carroll	25 (7%)	27 (6%)	52 (7%)
Lower-Rank Faculty	14 (4%)	15 (4%)	29 (4%)
Same-Rank Faculty	74 (21%)	122 (29%)	196 (25%)
Higher-Rank Faculty	93 (26%)	159 (37%)	252 (32%)
TOTAL	355 (100%)	427 (100%)	782 (100%)

Pearson $\chi^2 = 32.306$ df = 5 p < 0.001

Table 7.9: Comparison of SALG Users and Non-users Choices of Most Influential Disseminator – Institution

	Non-user	User	TOTAL
No One	114 (33%)	94 (22%)	208 (27%)
Lower Status	7 (2%)	7 (2%)	14 (2%)
Same Status	177 (52%)	248 (60%)	425 (56%)
Higher Status	44 (13%)	66 (16%)	110 (15%)
TOTAL	342 (100%)	415 (100%)	757 (100%)

Pearson $\chi^2 = 11.249$ df = 3 p < 0.010

Table 7.10: Descriptions of Independent Variables

Variable	Description
<i>Background Characteristics</i>	
Gender	Male is the reference.
Discipline	Dummy variables for each of the four categories: natural sciences, engineering, social sciences, and humanities. The reference group changes in each model because not all 4 groups were represented for each innovation (e.g., PLTL is not used by social scientists or humanists).
Years of teaching	Interval-ratio variable representing years of teaching reported by respondents; ranged (in half year increments) from 0 to 50.
Doctoral Degree	Modeled as a dummy variable representing doctorate or not because a high percentage of respondents listed their terminal degree as a Ph.D. (80% for each innovation).
<i>Social Position</i>	
Faculty role of <u>potential adopter</u>	Faculty role is an ordinal variable that is represented in several ways throughout the models: 1) dummy variable representing non-contingent faculty(tenured and tenure-track). The reference were contingent faculty (lecturer and adjunct) 2) dummy variable representing tenured (e.g., full and associate professors) or not 3) dummy variables representing each of the ordinal categories with lecturers being the reference group
College type of <u>potential adopter</u>	College type is an ordinal variable based on a collapsed version of the Carnegie Classification: research universities, master's universities, baccalaureate colleges, associate's colleges.
Interaction: Faculty role X College type	Created from previous two variables.
<i>Adoption Experience</i>	
Years since first use	Respondents listed the year they first used the innovation. This response was reverse coded to represent the number of years since the individual first used the innovation.

Table 7.11: Mean Values of Independent Variables

Variable			CPR n = 170	PLTL n = 144	SALG n = 809
Gender			0.500 (0.501)	0.465 (0.501)	0.595 (0.520)
Science Course			0.765 (0.446)	0.868 (0.340)	0.712 (0.453)
Engineering Course				0.097 (0.297)	0.059 (0.236)
Social Science Course			0.047 (0.212)	-	0.138 (0.341)
Humanities Course			0.129 (0.337)	-	0.075 (0.264)
Teaching Years			17.597 (9.156)	22.640 (10.993)	14.756 (9.235)
Doctoral Degree			0.806 (0.397)	0.861 (0.347)	0.826 (0.380)
Non-contingent Faculty	Tenured Faculty	Full Professors	0.382 (0.487)	0.474 (0.498)	0.290 (0.454)
		Associate Professor	0.206 (0.406)	0.243 (0.430)	0.246 (0.431)
	Untenured Faculty	Assistant Professor	0.200 (0.401)	0.146 (0.354)	0.253 (0.435)
		Lecturers	0.135 (0.343)	0.146 (0.354)	0.126 (0.332)
Contingent Faculty					
Adjunct Faculty			0.076 (0.267)	0.028 (0.165)	0.084 (0.278)
Research University			0.318 (0.467)	0.479 (0.501)	0.337 (0.473)
Master’s University			0.247 (0.433)	0.215 (0.412)	0.355 (0.479)
Baccalaureate College			0.129 (0.337)	0.090 (0.286)	0.188 (0.391)
Years Since First Use			4.756 (4.308)	8.382 (3.307)	0.969 (1.270)

Table 7.12: Results of Categorizing Potential Adopters' Comments About How the Most Influential Disseminator was Persuasive

	CPR <i>n</i> = 126	PLTL <i>n</i> = 120	SALG <i>n</i> = 217
Position influential	21 (16.7%) ⁴⁵	19 (15.8%)	40 (18.4%)
Provided information	65 (51.6%)	43 (35.8%)	66 (30.4%)
Helped implement	14 (11.1%)	17 (14.2%)	4 (1.8%)
Made aware	16 (12.7%)	19 (15.8%)	70 (32.3%)
Grant Program	1 (0.8%)	9 (7.5%)	10 (4.6%)
Required to Use	5 (4.0%)	9 (7.5%)	22 (10.1%)

⁴⁵ The sum of responses per category do not add to the number of comments (*n*) because comments could have multiple or no codes applied to it.

Table 7.13: First Source of Information – CPR

	Count	Percent
Faculty at same institution	33	19.41%
Faculty at other institution	19	11.18%
Staff	5	2.94%
Arlene Russell (founder)	5	2.94%
<i>Conference</i>	52	30.59%
Workshop	14	8.24%
CPR Website	14	8.24%
Journal article	6	3.53%
Non-Journal publication	2	1.18%
Professional Organization	4	2.35%
Don't Remember	16	9.41%
Missing	0	0%
TOTAL	170	100%

Table 7.14: First Source of Information – PLTL

	Count	Percent
<i>Faculty at same institution</i>	64	44.14%
Faculty at other institution	27	18.62%
Staff	7	4.83%
Conference	17	11.72%
Workshop	15	10.34%
Journal article	4	2.76%
Non-Journal publication	1	0.69%
Professional Organization	4	2.76%
Other (description not provided)	1	0.69%
Don't Remember	3	2.07%
TOTAL	145	100%

Table 7.15: First Source of Information – SALG

	Count	Percent
<i>Faculty at same institution</i>	290	35.85%
Faculty at other institution	64	7.91%
Staff	44	5.44%
Stephen Carroll (director)	38	4.70%
Conference	121	14.96%
SALG Website	60	7.41%
Journal article	17	2.10%
Non-Journal publication	9	1.11%
Professional Organization	38	4.70%
National Science Foundation	19	2.35%
Workshop	25	3.09%
Don't Remember	75	9.27%
Missing	9	1.11%
TOTAL	809	100%

Table 7.16: Incident Rate Ratios for Relative Faculty Rank of CPR Respondent's Choice for Most Influential Disseminator

	Model 1 Background Characteristics	Model 2 Social Position	Model 3 Adoption Experience
No One			
Intercept	0.785+	1.054	1.436
Gender	0.482	0.507	0.527
STEM Course	0.448	0.472	0.591
Humanities Course	1.037	0.978	1.077
Years Teaching	1.039	1.040	1.041
Doctoral Degree	1.115	0.779	0.746
Tenured		0.654	0.666
Tenure-track		2.195	2.125
Research University		1.637	1.779
Master's University		1.806	1.861
Baccalaureate College		1.344	1.303
Years Used			
Staff			
Intercept	0.296+	0.085+	0.144
Gender	0.116	0.116	0.121+
STEM Course	0.558	0.664	0.993
Humanities Course	2.106	1.725	2.140
Years Teaching	0.969	0.997	0.999
Doctoral Degree	1.186	2.297	2.003
Tenured		0.611	0.640
Tenure-track		0.428	0.408
Research University		0.495	0.588
Master's University		0.744	0.765
Baccalaureate College		0.646	0.618
Years Used			
			1.000
Lower-ranked Faculty			
Intercept	0.000	0.000	0.000
Gender	0.945	1.393	1.343
STEM Course	231,931	1,333,205	248,768

Humanities Course	516,003	3,300,764	691,487
Years Teaching	1.162**	1.137*	1.149*
Doctoral Degree	0.737	0.420	0.429

Tenured		3,064,869	764,660
Tenure-track		0.000	0.000
Research University		4.605	5.321
Master's University		3.139	3.479
Baccalaureate College		0.000	0.000

Years Used

Same or Similar-ranked Faculty

Intercept	0.361	0.335	0.383
Gender	1.438	1.446	1.470
STEM Course	0.889	0.775	0.880
Humanities Course	0.752	0.673	0.731
Years Teaching	1.093***	1.083**	1.084**
Doctoral Degree	0.790	0.758	0.739

Tenured		1.451	1.483
Tenure-track		1.414	1.381
Research University		0.733	0.777
Master's University		1.709	1.762
Baccalaureate College		0.521	0.519

Years Used

*** p<0.001, **p<0.01, *p<0.05, + p<0.10

Table 7.17: Incident Rate Ratios for Relative Faculty Rank of PLTL Respondent's Choice for Most Influential Disseminator

	Model 1 Background Characteristics	Model 2 Social Position	Model 3 Adoption Experience
No One			
Intercept	0.000	0.000	0.000
Gender	1.819	1.669	1.510
Science Course	2,016,615	1,130,000	4,982,788
Years Teaching	1.130***	1.161**	1.161**
Doctoral Degree	2,853,412	6,75,000	3,950,000
Tenured		0.470	0.451
Tenure-track		0.193	0.217
Research University		7,223,047	4,034,879
Master's University		5,673,549	3,297,639
Baccalaureate College		2,590,000	1,590,000
Years Used			1.000
Staff			
Intercept	0.000	0.000	0.000
Gender	1.484	3.243	3.375
Science Course	4,637,503	4,380,000	6,760,000
Years Teaching	0.918	0.870*	0.897
Doctoral Degree	0.378	0.219	0.417
Tenured		8.651	11.198
Tenure-track		1.040	0.483
Research University		3.756	4.198
Master's University		0.000	0.000
Baccalaureate College		0.000	0.000
Years Used			1.360*
Lower-ranked Faculty			
Intercept	0.000	0.000	0.000
Gender	0.300	0.379	0.404
Science Course	0.454	0.486	1.138
Years Teaching	1.114**	1.080	1.082
Doctoral Degree	1,989,718	8,563,929	3,713,552

Tenured	1,230,000	6,485,534
Tenure-track	0.614	0.619
Research University	0.475	0.689
Master's University	0.000	0.000
Baccalaureate College	0.572	0.679
Years Used		1.207

Same or Similar-ranked Faculty

Intercept	0.000	0.246	0.592
Gender	0.300	0.771	0.731
Science Course	0.454	0.961	0.952
Years Teaching	1.114**	1.089***	1.090***
Doctoral Degree	0.199	1.031	1.009

Tenured	1.707	1.719
Tenure-track	1.027	1.014
Research University	0.241*	0.232*
Master's University	0.317+	0.308
Baccalaureate College	0.131	0.133

Years Used	1.000
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*** p<0.001, **p<0.01, *p<0.05, + p<0.10

Table 7.18: Incident Rate Ratios for Relative Faculty Rank of SALG Respondent's Choice for Most Influential Disseminator

	Model 1 Background Characteristics	Model 2 Social Position	Model 3 Adoption Experience
No One			
Intercept	1.762	2.949	4.176
Gender	1.067	1.092	1.096
Science Course	0.589+	0.522	0.643
Engineering Course	1.609	1.335	1.544
Humanities Course	0.848	0.876	1.001
Years Teaching	1.075***	1.060***	1.056***
Doctoral Degree	0.663+	0.663	0.655
Tenured		1.381	1.470
Tenure-track		1.201	1.239
Research University		0.652	0.642
Master's University		0.366**	0.369**
Baccalaureate College		0.690	0.715
Years Used			1.000***
Staff			
Intercept	0.174	0.150	0.205
Gender	0.778	0.772	0.782
Science Course	0.667	0.610	0.698
Engineering Course	0.427	0.341	0.373
Humanities Course	0.798	0.758	0.824
Years Teaching	1.053**	1.031	1.027
Doctoral Degree	1.088	0.793	0.774
Tenured		2.088+	2.194*
Tenure-track		1.029	1.058
Research University		5.358*	5.296*
Master's University		3.104	2.462
Baccalaureate College		4.297+	4.425+
Years Used			1.000*
Lower-ranked Faculty			
Intercept	0.501	0.084	0.107

Gender	0.999	0.975	0.982
Science Course	1.236	1.203	1.327
Engineering Course	0.000	0.000	0.000
Humanities Course	1.087	0.968	1.031
Years Teaching	1.126***	1.105***	1.102***
Doctoral Degree	0.747	0.602	0.588
Tenured		3.818+	3.947+
Tenure-track		0.394	0.401
Research University		1.222	1.217
Master's University		2.425	2.457
Baccalaureate College		1.518	1.555
Years Used			1.000

Same or Similar-Ranked Faculty

Intercept	0.160+	0.307	0.336
Gender	0.918	0.948	0.960
Science Course	1.608	1.478	1.490
Engineering Course	2.314+	1.903	1.896
Humanities Course	1.766	1.850	1.886
Years Teaching	1.083***	1.067***	1.067***
Doctoral Degree	1.025	0.839	0.816
Tenured		1.314	1.320
Tenure-track		2.119*	2.174*
Research University		0.867	0.880
Master's University		0.531+	0.542+
Baccalaureate College		0.579	0.584
Years Used			1.000

Stephen Carroll

Intercept	0.282	0.364	0.457
Gender	0.609	0.584+	0.589+
Science Course	1.307	1.321	1.450
Engineering Course	2.108	2.252	2.291
Humanities Course	1.478	1.446	1.544
Years Teaching	1.112***	1.098***	1.096***

Doctoral Degree	0.612	0.565	0.553
Tenured		1.797	1.856
Tenure-track		0.679	0.693
Research University		1.144	1.140
Master's University		1.587	1.603
Baccalaureate College		0.879	0.897
Years Used			1.000
*** p<0.001, **p<0.01, *p<0.05, + p<0.10			

VIII. Conclusion

This project investigated processes that shape or influence how educational innovations diffuse through higher education. I first explored how patterns of use, defined by adoption and abandonment, are associated with a potential user's social position and the networks of information one consults to learn about an innovation. I then investigated who provides the information populating these networks, and how this change agency is associated with a person's social position. Last, I explored whether potential adopters filter information based on the social position of the change agent.

The patterns of use investigation attempted to answer the following research questions: *What networks of information do faculty members use to learn about an educational innovation they may adopt? How do these networks influence the likelihood of a faculty member adopting and eventually abandoning the innovation?* I redefined Rogers' (2003) concept of communication channels with a sociological perspective to define these communication systems as social-exchange and anonymous-search networks. *Social-exchange networks* are existing or newly-created person-to-person relationships purposefully used to communicate information about an innovation in which the sender, receiver, and timing of exchange are known within the networks. These include face-to-face and electronic communications. *Anonymous-search networks* transmit information about an innovation without involving direct, person-to-person communication (sharing information through websites or journal articles).

I conducted this project by creating quantitative case studies of three educational innovations: Calibrated Peer Review (CPR), Peer-led Team Learning (PLTL), and Student Assessment of Learning Gains (SALG) instrument. I worked diligently with the user support communities for each innovation to identify a list of all faculty members in the United States who became aware of each innovation. I surveyed these individuals about what sources of information influenced them – social-exchange and anonymous-search networks – along with their experience and motivation for publishing or presenting as a change agent. These data were combined with user logs when available and web searches when needed to create comprehensive case studies analyzed for each innovation.

8.1 Summary of Findings

8.1.1 Patterns of Adoption

Instructors who rely more heavily on social-exchange networks over anonymous-search networks are more likely to adopt. It matters less what initial source of information a potential adopter consults than whether she or he eventually utilizes a social-exchange network. In general, the likelihood of adoption increases if the potential adopter consults a social-exchange network at any point in the persuasion stage. The likelihood of adoption continues to increase as the potential user consults additional social-exchange networks. Only for one innovation, SALG, did consulting a social-exchange network as the initial information source lead to higher rates of adoption.

I expected that the strength of the association between social-exchange networks and the likelihood of adopting would be diminished in certain situations.

Specifically, I expected it would be weaker for 1) tenured and tenure-track faculty and 2) faculty at research universities. The findings were weak and mixed. I had expected the diminished association would have characterized the broader group of non-contingent faculty that included both tenured and tenure-track faculty, but this was not the case. The effect was only seen for tenured faculty for CPR and SALG. For the PLTL case study, the effect was the opposite. The positive association between social-exchange networks and the likelihood for adoption was stronger for tenured faculty. This likely stems from the unique characteristics of PLTL compared to the other innovations. For complex innovations that require significant institutional support, tenured faculty may be more likely to garner administrative support compared to faculty members in less prestigious and more contingent positions.

I also expected to find that the likelihood of adopting would be lower for tenured and tenure-track faculty at research universities as compared to others. There was no support for this, but partial contradictory evidence. For PLTL, tenured faculty at research universities (as opposed to both tenured and tenure-track faculty at research universities) were more likely to adopt than instructors in other positions and/or institution types. The effect is likely driven by tenured faculty who, as explained above, are more likely to acquire the support needed to implement PLTL at their colleges.

8.1.2 Patterns of Abandonment

Overall abandonment rates were low. This is partially due to the method by which abandonment was measured. Respondents had to report that they, “Do

not plan to use it again.” There were a number of respondents who had not used an innovation in several years who reported they may or definitely will use it again. It is not clear whether these individuals will actually do so, which may indicate that a faculty member’s commitment to use an innovation may be more likely to fade than to suddenly end. Do teaching practices get dropped in the trashcan or are they left forgotten on the shelf to collect dust? A future study could interview faculty members about teaching practices they have not recently used to identify why they have not continued to use them and their likelihood for doing so in the future to identify how users transition into a state of abandonment. Change agents would be interested in this information because instructors who slowly lose interest in an innovation over time could be supported in a way to maintain their interest and enthusiasm for using the educational resource.

I expected that instructors would be more likely to abandon an innovation if they were influenced by anonymous-search networks rather than social-exchange networks. My rationale was that the social pressures that lead an instructor to adopt will also lead him or her to persist in using it. The findings were the opposite. In general, faculty members who were more influenced by social-exchange networks to adopt were more likely to abandon the innovation compared to adopters who were influenced by anonymous-search networks. It may be that the social influence that increases the likelihood of adoption is removed by the person sharing information (or no longer has an effect) after the instructor adopts. Another reason may be that potential adopters feel pressure to adopt or make decisions that are less objective or rationally considered compared

to instructors who are guided more independently through anonymous-search networks.

The negative relationship between social-exchange networks and abandonment was not affected by the institution at which an instructor worked nor his or her faculty role. The absence of this effect is likely explained, at least partially, by the low abandonment rates overall. It is hard to measure a discernable effect on these controlling variables when so few respondents actually abandon each innovation.

8.1.3 Patterns of Change Agency

My next research question asked: *How does a faculty member's social position affect his or her decision to become an advocate for an educational innovation by publishing or presenting information through communication channels?* CPR and SALG tenured faculty author more publications or presentations than non-tenured faculty. However, when a measure for grant funding was added to the model, the coefficient for faculty position dropped to non-significance. I believe the positive association between being a tenured faculty and becoming a change agent is mediated through grant funding. That is, tenured faculty may be more likely to win grant funding and funding agencies may be more likely to require grant winners to publish and present on their experience. Grants may increase dissemination by not only directly supporting adoption, but also encouraging faculty members to act as change agents who publish and present on their experience.

When considering institution type, faculty members at research universities published and presented more articles compared to faculty members at other types of colleges. This could mean that the strong organizational incentives at research universities that encourage faculty members to publish in their disciplinary scholarship also indirectly encourage them to publish on educational innovations they employ. Support for this explanation was seen in the reported motivation by respondents. In general, the most frequently cited reason for publishing and presenting was a personal commitment to teaching. However, there was a moderate positive association between being motivated to gain status in professional organizations and being a faculty member at research universities. This association was not found with faculty from other types of institutions.

Differences in descriptive statistics suggest that innovation characteristics were also an important driver in the frequency of publications and number of adopters who become change agents. PLTL, which has a large community of support and is a complex innovation to adopt, had the highest rates of change agency. SALG, which has the lowest barriers to adopt and smallest community of support, had the lowest levels of change agency. Future research should explore how the likelihood of adopters becoming change agents is affected by innovation characteristics such as complexity, which provides opportunities to report on adaptations, and the structure of the user-support community, which may be associated with the density and intensity of publication outlets.

8.1.4 Patterns of Influence

The data reveal that diffusion patterns were influenced by the relative social position between the potential adopter and disseminator. PLTL and SALG instructors were more likely to be influenced by instructors from a different faculty rank than by someone from an institution with different status than one's own as hypothesized. However, the findings were more specific than expected. Potential adopters are more likely to be influenced by faculty members of a higher rank, not lower rank. The same was the case for CPR. CPR respondents also reported being influenced by someone from a higher-status institution more often than a similar-status or the same institution. This likely reflects the unique population of CPR respondents who were primarily the first adopters at their college and would have been influenced by someone from outside their institution. In general, it appears that faculty members of higher status – whether that is defined by rank or institutional status – are more influential in diffusion networks.

A significant number of SALG and CPR respondents said no one influenced them (approximately 20 percent). Not surprisingly, non-adopters chose this option more frequently than adopters. PLTL respondents were the least likely report no one influenced them, which suggests the extensive reach and strong influence of the PLTL community of support – an example of a dominant social-exchange network that exists to disseminate information about the innovation.

Qualitative data provided insight into how the differences in the relative social position of potential adopters and disseminators influences diffusion patterns. Potential adopters interpret the institutional status of the person that influenced them in several ways. Some respondents described how the institutional status was used as a cue to the compatibility of the innovation for their institution. Others described how the status of the institution could be used to justify implementing the innovation to senior administrators.

Respondents also explained why they were influenced by higher-ranked faculty members. Senior faculty act as mentors advising new or junior faculty on teaching resources they might use. There was also evidence of this occurring with graduate students. Respondents also admitted to adopting an instructional practice or method as a way to signal their acceptance of teaching norms to more senior faculty. There is even evidence of more authoritarian processes acting on potential adopters, such as when administrators, especially department heads, require the use of specific educational innovations.

8.2 Limitations of this Research Study

8.2.1 Differences in Response Rates

The strength of this research project is the development of three case studies based on extensive surveys with moderately high response rates. However, there are limitations to consider. First, while the overall response rates were about 50 percent, the response rates were significantly lower for SALG non-users (about 22 percent). I conducted a test for biased responses between respondents and non-respondents using institutional type as a controlling variable

(see Appendix C). No strong evidence of bias was found. It would have been helpful to conduct this analysis on other independent variables, but institution type was the only variable I had for both respondents and non-respondents.

8.2.2 Comparing Different Populations

A second limitation was that the CPR population was not exactly comparable to the PLTL and CPR population. After I began this project, I was informed that I would not be able to get a list of all CPR users. I was able to obtain a list of the administrators for each institution with at least one CPR account that had been activated. Often these administrators were the first people to adopt CPR at their colleges, therefore, this population is better described as the early adopters at each institution. While the CPR population was not exactly the same as the other groups, it did provide an opportunity to analyze the data with a third comparative perspective. My interpretations in Chapters 4 - 7 account for this difference in populations.

Another limitation is that it is almost an impossible task to capture a list of everyone who ever became aware of the educational innovations. It is unrealistic to think even a large team of researchers could document every hallway conversation, informal exchange before meetings, or email communication in which someone became knowledgeable of a broadly-diffused innovation. For this reason, I defined awareness in a way that allowed me to clearly describe each population in a standardized way. Awareness was defined by an instructor formally collecting information on the innovation. For CPR and SALG, I used account registrations on the respective websites to define awareness. For PLTL, I

used registration logs for conferences or workshops along with email requests to community leaders. That said, someone could have requested information through a social-exchange network that was undocumented (e.g., emailing a colleague who had used the innovation). This is most likely the case for PLTL, which is not a technological innovation with centralized registration records. I believe this is one of the reasons why the PLTL data was characterized by significantly higher adoption rates (i.e., there was potentially a pro-adoption bias in the construction of the population).

Future studies should consider the challenge of constructing a population of potential adopters for non-technological innovations. This would likely best be done by tracing the evolution of an innovation from its birth so the researchers can work closely with the initial innovators and change agents to track who communicates with whom about the innovation. These longitudinal studies, however, are difficult to complete – not just because they take time, but because it is difficult to identify at the inception which innovations will successfully propagate.

8.2.3 Changes in Institutional Affiliation

In creating the life histories of instructors in each population, I did not capture how respondents' institutional affiliations changed over time. As explained in Chapter 2, I made this decision because I worried my response rates would decrease as the survey became longer. I assumed that institutional affiliation did not change frequently (unlike faculty role). Also when someone changes institutions it does not necessarily mean the type of institution I am

modeling changes (e.g., a professor moving from one associate's college to another). That said, future research that could account for this change would have the advantage of measuring whether institutional change, even within the same institutional category, impacts adoption and why. This institutional change could have an effect on the likelihood of adoption for different reasons. First, the instructor would be immersed in a new social-exchange network that provides opportunities to become aware of the resource. Another factor could be differences in institutional characteristics that influence the potential adopter's decisions.

8.2.4 Measuring Abandonment

As mentioned above, measuring abandonment is difficult. When does a faculty member realize she or he is no longer going to use a teaching resource again? From my data, it appears that instructors may stop using an innovation but may not believe they have truly abandoned it. The case of “fading interest” makes it difficult to identify when someone abandons an innovation. For this survey, abandonment was defined by the respondent reporting they, “do not plan to use it again.” Future studies could consider trying to use different measures of abandonment, such as a standard time of inactivity.⁴⁶

8.2.5 Common Origins: Chemical Education Community

An inadvertent limitation of this project was that I chose three innovations that arose from the chemical education community despite learning about each

⁴⁶ As described in Chapter 5, I was unable to do this in the present study because some users had only recently adopted. In addition, SALG was a relatively new development. I was not comfortable defining abandonment based on a standard time of inactivity for the analyses.

from faculty members in different disciplines: engineering, humanities, and the natural sciences. Future studies should attempt to study the diffusion of innovations that originated from different educational communities. This is becoming more relevant with the growth of disciplinary-based education research (Singer, Nielson, & Schweingruber 2012), which has led to the development of dissemination networks within traditional research communities (e.g., physics education research community, chemical education groups).

8.2.6 Reliability of Reports

A final limitation of this study is that it relies on respondents' memories. This is more of a concern for early adopter respondents who first implemented the innovation 10 or 15 years ago and may have difficulty remembering their adoption experience.

8.3 Research Implications

This section will describe the implications of the findings. Innovators, change agents, and granting agencies funding dissemination activities may benefit from the recommendations based on this project's analysis. In addition, I suggest how this project's findings engage with the sociology of work research on organizational conflict and the potential relevance of the findings for primary and secondary education systems.

8.3.1 Social Isolation and Lack of Awareness

This study did not rely on random samples of all faculty members in the American higher education system. However, adjuncts were clearly missing in the analysis. The percentage of faculty respondents who were adjuncts was less

than 10 percent for all three innovations (see Table 4.2). For CPR and SALG, the second lowest response rate occurred for lecturers. For PLTL, lecturers response rate was only slightly higher than assistant professors. Clearly contingent faculty are underrepresented considering they make up 68 percent of all faculty members at colleges in the United States (American Association of University Professors 2010). Change agents need to account for this potential social isolation when developing dissemination plans

Social isolation can occur by choice, but also by the structure of social relations (Granovetter 1973). Some people have fewer opportunities to learn because of whom they are, or are not, connected to. Isolation is dependent on not only the density of an individual's relational network (i.e., number of relations), but also "network idiosyncrasies" (i.e., where someone is located in the network) (Abrahamson & Rosenkopf 1997). Strang and Meyer (1992) suggest that connections among influencers and potential adopters is cultural in addition to relational. That is, it is not enough for the connection to be made, but also actors must have a shared cultural understanding of their roles so that a potential adopter is more likely to be receptive to adopting. Strang and Meyer's work is typically theorized at the institutional level, but this is still relevant at the person-level.

Change agents should be aware of how cultural mismatch or isolation acts as a barrier to their diffusion goals. They need to look for ways to bridge structural holes in social systems they are targeting for adoption. In addition to being diligent in identifying potential adopters, change agents must also account for cultural differences when developing their dissemination plans. This would be

extremely important when developing international dissemination plans because cultural differences will be more acute.

8.3.2. Granting Agencies Role in Diffusing Innovations

Some granting agencies, like the National Science Foundation (NSF), specifically fund dissemination activities. The early PLTL community received one of four *Systemic Changes in the Undergraduate Chemistry Curriculum* grants from NSF in 1995 specifically to increase the rate of adoption (Gafney &Varma-Nelson 2008, p. 10). This had a large impact on developing the user support community that led to broad adoption. Granting agencies should also be aware of how they can indirectly contribute to innovation diffusion beyond direct funding.

As my analysis in Chapter 6 suggests, granting agencies play an important role in encouraging faculty members to act as change agents. Faculty members who received grant funding to support the implementation of an innovation were more likely to publish or present on their experience than were other faculty members. This tendency was found across all three innovations. Granting agencies should encourage faculty members who are funded to adopt new educational innovations to share their experience with others as part of the funding requirements.

Granting agencies can also indirectly support adoption by recommending innovations previously funded by those agencies. In Chapter 7 I described how instructors were influenced to adopt the SALG instrument because it was mentioned in several NSF programs' requests for proposals. Faculty members

take recommendations from granting agencies seriously. Funding groups should leverage this when publishing request-for-proposals.

8.3.3 Discipline-based Education Innovation

The 21st century has seen a growth of discipline-based education research as a recognized field (Singer, Nielson, & Schweingruber 2012). As noted above, the three case studies created for this project originated from the chemical education community. This is an example of a discipline-based education research community that is well-established with a dense network of connections. Future groups developing dissemination strategies should consider the role these communities play while accounting for their unique characteristics that facilitate the dissemination of teaching best practices. For example, physics education research groups are often located within physics departments themselves, not within education departments or schools (e.g., University of Colorado at Boulder, University of Illinois at Urbana-Champaign). This facilitates the dissemination of physics education research principles to traditional physics researchers who teach. In addition, the *American Journal of Physics* has a dedicated section for physics education research. This also makes the education research more accessible to faculty members who conduct traditional physics research from different colleges. There are also multiple conferences and organizations that network these groups and individual instructors together (e.g., American Association of Physics Teachers, Physics Education Research Conference), which help to spread ideas between departments and colleges.

8.3.4 Choosing to Innovate or Adopt

Granting agencies and change agents advocating for broad innovation adoption should also be aware of pro-innovations biases that may distort the diffusion process. In Chapter 6 I document that change agents reported most frequently that they were motivated by a commitment to improve teaching and learning. Being motivated, however, does not mean a potential change agent gets the opportunity to publish or present. Conference organizers and journal editors are more likely to publish the results of an innovator than a late adopter. In addition, more prestige is given to innovators than adopters. A colleague shared that, “more credit is given, at least in education research, for coming up with a new idea.”

In Chapter 2, I describe how faculty members respond to organizational incentives that likely influences who publishes or presents. If organizational incentives encourage faculty members to publish and present, but journal editors and conference organizers are more likely to accept publications and presentations about novel inventions or innovation adaptations, then there may exist conflicts that undermine adoption fidelity. Adopters aspiring to be change agents may be motivated to adapt their implementation experience to improve their chances of getting a report on the experience accepted for presentation or publication in the future.

Innovation advocates need to understand the pressures on adopters to adapt. Understanding this social influence would be of interest to organizations that fund dissemination strategies. It will help them understand external pressures

that lead to adaptations that could threaten the cohesion of diffusion initiatives and communities of support.

8.3.5 Competitive Adaption

Innovation adaption may not only result from change agents motivated to publish or present but also occur as a result of fragmentations of diffusion networks. Micropolitics within an institution often lead instructors to look outside the organization for innovations as opposed to adopting from a colleague (Menon & Pfeffer 2003; Menon, Thomson, & Choi 2006; Datnow 2000). Political tensions do not just exist within colleges, but also across them. Competition within professional organizations can also become acute and lead to divisions in communities of support.

The PLTL organization experienced a split several years ago in which one community leader decided to start a new group dedicated to PLTL. The PLTL International Society was incorporated in 2012. In discussions with community members, it appears this split was motivated by political tensions, not functional reasons (e.g., targeting new potential adopter groups, diffusing an adaption of the original innovation). The purpose of both groups is similar: support the propagation of PLTL. Both act on this mission in similar ways. They host their own websites, plan their own conferences, and manage their own publication outlets. Change agents and granting agencies need to be aware of how group cohesion and micropolitics within communities of support dedicated to innovations inhibits or facilitates the diffusion process.

8.3.6 Intersections with Sociology of Work Research

Competitive adaptations points to the importance of considering organizational conflict when discussing innovation diffusion. There is a rich history of research in the sociology of work domain that directly relates to my interest in educational innovation diffusion. Likewise, studying how educational innovations are adopted can provide insight into processes that describe how employees maintain autonomy, informally resist administrative control, and manage competing responsibilities at work. In this section, I describe how the research I have conducted relates to research on labor dynamics.

8.3.6.1 Instructor's Job Insecurity, Autonomy, and Agency

There is a long history of sociological research documenting how autonomy at work and overall job security lead to stronger feelings of personal control (Kohn & Schooler 1983; Schieman & Plickert 2008). However, economic shifts are leading to increased job insecurity in many industries (Kallenberg 2011). This is evident in higher education by the significant growth of contingent faculty as a proportion of all faculty members in colleges and universities within the United States. Over two-thirds of faculty members in the United States are now classified as contingent (American Association of University Professors 2010).

How does a lack of job security impact classroom-based decision making? A feeling of job insecurity could lead faculty members to work harder and adopt new teaching methods out of a sense of competition. It may also have the opposite effect by negatively impacting instructors' agency. These individuals

may be less willing to take risks in pioneering the adoption of new teaching methods on campus for fear of violating local norms or having a failed implementation lead to poor course evaluations. Glavin (2013) found evidence for the latter in that increased job insecurity is associated with decreased decision-making and sense of personal control. This study analyzed panel data sampling workers from a broad range of industries.

In general, college instructors have more personal control over how to manage their classrooms than someone working in a hierarchical bureaucracy. The structure of faculty roles provides an experimental group that provides for a good measure of employees' sense of job security. Tenured faculty have some of the highest levels of job security among all professionals. Contingent faculty working on short-term contracts likely have some of the least. Studying college faculty adoption patterns provides an environment in which autonomy and personal control are easily measureable (i.e., the adoption of new teaching practices) and controls for job security are clearly mapped to the hierarchy of faculty positions.

8.3.6.2 Instructor's Resistance to Change

Related to research on job insecurity, the sociology of work field has a long history of investigating job solidarity and resistance among workers (Silver 2003; Akkerman, Born, & Torenvlied 2013). With the increase of contingent faculty in American higher education, colleges and universities have become a new battle ground for worker solidarity. This was seen recently in Wisconsin where faculty collective-bargaining rights were stripped away, sparking large

number of protests in the state capital of Madison (Phelps 2011). Top-down, external mandates are also impacting how faculty members teach. State lawmakers are increasingly trying to exercise more oversight of public colleges through their control of state funding (Kelderman 2011). Senior administrators are under increasing pressure to adopt performance-based accountability standards in response to accreditation agencies (Alexander 2000) and research suggesting colleges are not having a significant impact on student learning (Arum & Roksa 2011).

Research on how educational innovations diffuse in higher education could provide insight into whether instructors' control of classroom practices is being eroded. If this is the case, studying how faculty members resist centralized mandates as a likely barrier to adoption would be of interest to researchers studying labor struggles. My project focused on the interaction among instructors. Research on centralized, mandated diffusion processes must account for the role of senior administrators. They are often responsible for responding to external forces influencing college instruction and negotiating faculty acceptance (or pushing against faculty resistance) of new teaching practices and policies. It would be important to consider how the concept of change agent needs to be adapted, if at all, when applying it to senior administrators playing this mediating role.

8.3.6.3 Overworked Instructors

Another area of potential interaction with my findings is how faculty adoption of teaching practices overlaps with the sociology of work literature on

how “overworked” employees develop strategies to respond to increasing job responsibilities (Moen et al. 2013). Schieman, Whitestone, and Gundy (2006) describe the increasing pressures on professionals as the “stress of higher status,” which leads to inter-role conflicts (e.g., work-family balance). General perceptions exist, however, that faculty careers are immune to these burdens because college professors experience little stress in jobs characterized by long breaks and few demands (Adams 2013).

While flexibility and autonomy are great benefits of faculty positions, significant pressures do exist. Contingent faculty do not typically realize the benefits of high-status faculty positions; many work at multiple colleges to make a living wage. Tenure-track and tenured faculty are also under significant pressures. Federal funding for research continues to decline (adjusted for inflation). As proposal acceptance rates decline (Howard & Laird 2013), faculty members must write more proposals to maintain support for their research. Coupled with state funding cuts, colleges must identify new funding sources. Public universities have begun admitting more out-of-state students to address budget gaps (Kingkade 2012). This can lead to increases in the number of students instructors must teach and/or increases in the number of contingent faculty hired. Engaging the sociology of work literature could be useful for identifying how shrinking resources and increasing demands impact instructors’ teaching practices. Specifically, it would be helpful to explore previous research that investigates how workers assess and address competing demands on the job. Sociology of work researchers could benefit from studying higher education

because it is an institution in which the structure of its core employees is changing (i.e., a shift towards contingent faculty) along with the responsibilities demanded of them.

8.3.7 Translating Findings to Primary and Secondary Education Systems

My research investigates how educational innovations diffuse in higher education. It is natural to consider how these findings relate to education systems more broadly. I am hesitant to make formal, specific predictions as to how the entire projects' findings relate to primary and secondary education systems because my conceptualization of college faculty's social position does not apply directly to K-12 teachers. First, teacher positions in K-12 schools are less hierarchical than faculty positions in higher education. Tenure exists for school teachers in public schools, but it is typically conferred after working for several years as opposed to relying more heavily on performance-based measurements like tenure decisions in higher education. The categories of school teachers are also relatively flat regarding a formal status hierarchy. There are different types of educators within a school that provide specialized services (e.g., reading specialists, speech pathologists, classroom teachers), but there are fewer formal differences in status associated with pay and job stability like higher education (e.g., full professor, associate professor, assistant professor). In K-12 schools, status hierarchies are typically associated with teachers who move into administrative roles (e.g., department heads, assistant principals, principals).

My other measure of a faculty member's social position was based on institutional type. I used this measure of social position because I expected social

norms associated with institutional characteristics, specifically research activities, would affect teaching practices. This method of defining institutional type does not translate to K-12 schools. Primary and secondary school teaching practices are typically shaped by the local and regional influences (Arum 2000). In the public sector, curricula is typically mandated by a central administration.

For these reasons I am not prepared to apply my findings based on social position to K-12 schools. However, that is not to say that social position is not relevant. It is just that social position will need to be conceptualized on other factors that influence social capital in educational systems including the structure of information channels along with the development and influence of teaching norms. Institutional characteristics would likely be defined by public versus private institutions and neighborhood environments. Teacher roles that may likely have an impact may be better defined by their subject area or administrative responsibilities (if they have any).

My findings on the effect of networks are what I believe are most relevant to the K-12 systems. School teachers who learn about new teaching practices and resources through social-exchange networks may be more likely to adopt than those who rely on anonymous-search networks. In considering how these findings could apply to K-12 schools, the sources that make up these networks would need to be reconsidered. For example, most K-12 teachers do not read peer-reviewed journal articles about the effectiveness of the latest teaching resources. This information is likely filtered through the professional development opportunities they are often required to attend. In some ways, these events can be

similar to teaching conferences that college faculty attend. The difference from conferences is that the information is not typically presented by the original authors. In addition, requirements to attend workshops may introduce a perception of coercion that leads K-12 teachers to resist or ignore the workshop topics.

The structure of social-exchange networks is also likely different in K-12 systems. In Chapter 2 I described how college faculty connect through professional organizations and research networks. These relationships can facilitate information about teaching resources across institutions. How are inter-school relationships within K-12 schools established? Public schools within a district or region may have more formal inter-institutional connections dedicated specifically to teaching than colleges because of bureaucratic structures that administer K-12 schools. These school-to-school networks may facilitate connections between institutions, but they also affect the nature of them because of the organizational control that is embedded in them. For example, which individuals develop relationships between schools likely reflect bureaucratic rules and divisions of labor. The content of those interactions are also likely influenced by bureaucratic regulations. Actors within the system have agency, but how information about educational innovations spread may be more influenced by the organizational control of social-exchange networks than in higher education. Again, this may lead teachers to resist mandated changes. How does this type of resistance manifest itself and what can we learn from it to understand how it translates to higher education?

Neo-institutionalists suggest evidence of this resistance is seen in stalled or partially enacted educational reforms (Meyer & Rowan 1977). Through decoupling processes schools are able to respond symbolically to mandates while teachers maintain classroom autonomy. This autonomy is not complete. Diamond (2007) found evidence that teachers were affected by the high-stakes testing movement. Teachers adopted new content in response to tests, and in a limited way, new pedagogical strategies. Coburn (2004) suggests that teachers exercise their agency by maintaining local control through “bounded autonomy.” Teachers are impacted by broader reform movements, often accepting the rationale and adapting them to fit within their local context. They adapt the innovations based on their previous experiences and current classroom milieu. Because of this bounded autonomy, broader movements evolve over time.

This is one area of research that should be explored as colleges enter an era in which more mandates are likely to affect them. In the past year the White House has pushed colleges to adopt new guidelines to combat sexual harassment (Sander 2014) and improve access to disadvantaged students (Field 2014). Understanding how K-12 schools enact decoupling strategies may be useful for investigating how colleges respond to these external pressures. I recognize that these White House examples do not directly impact college faculty’s teaching practices, but it does potentially have an impact on their job responsibilities that indirectly impacts their instructional responsibilities.

8.4 Future Areas of Research

The previous section suggested potential implications of my dissertation findings. These included recommendations for practitioners along with how my findings could inform the work labor researchers studying organizational conflicts and education researchers focused on primary and secondary education systems. This section will describe areas for future research inspired by the findings along with broader research questions I began to consider after commencing this study.

My findings suggest that social position and social networks have an impact on adoption patterns. I am interested in exploring in more detail the issue of social isolation described above. As the percentage of contingent faculty grows, will it be more difficult to implement change if more faculty members are loosely coupled to the institution.

My findings also suggest that innovation characteristics must be considered when developing diffusion models or dissemination strategies. I would like to investigate in more detail what innovation characteristics have the biggest impact on diffusion. These characteristics include the structure of user support communities established to support others and advance the innovations adoption.

I am also interested in how teaching innovations disseminate to new disciplinary clusters. Who is filling the structural holes that facilitate the information flow about innovations housed within network clusters aligned with specific disciplines (Burt 1992)? For whom are there incentives or disincentives to be the sort of change agent who seeks to cross disciplinary boundaries? It is

likely that the education researchers play an important role, but what about teaching and learning staff? The latter group was surprisingly absent in much of the analysis (i.e., few respondents mentioned the influence of teaching and learning staff). I would be interested in why staff are not playing a more prominent role (if this is the case as the data suggest). Burt (1992) describes the benefits of filling this need (e.g., information access, opportunity exposure, information control) so staff members stand to gain from bridging structural holes. The group also benefits. The new information channels opened up are a form of social capital that benefits newly connected groups (Burt 2000).⁴⁷

One question I have begun to consider is whether there are differences in diffusion patterns based on the country of origin for an innovation. I have noticed in my position at a teaching and learning center that broadly-diffused resources tend to originate in the United States. I recognize that I may be biased because I work at an American university, but anecdotal evidence suggests some support for this observation. When researching resources for instructors, my web searches rarely identify resources from other countries. I have also noticed that the presentation lists for international education conferences rarely list educational resources with broad adoption that originate from countries other than the United States.

⁴⁷ Helping to generate social capital within a community can also be factor in the construction of leadership, a potential benefit to those who bridge structural holes. Spillane, Hallett, & Diamond (2003) found that K-12 teachers identified as leaders by their peers were partially named because of their role developing a school's social capital. This social capital was defined by the individual's role in sharing information (i.e., establishing information channels) and generating trust in the community.

I discussed this observation with several attendees at an international science education conference and they agreed. One senior administrator from Canada commented that in his country it is difficult to obtain grant funding for education research from federal granting agencies, let alone funding for dissemination activities. Another faculty member mentioned how presentations by individuals from other countries were not “high quality or interesting... [These presenters] discuss practice, but not rigorous research.” This discerning participant wanted credible data providing evidence of impact before adopting. I know my own colleagues sometimes use a presenter’s country as a proxy for the quality of a presentation. When two presentation titles sound equally interesting, a choice is made based on the presenter’s institution or country of origin.

Are diffusion patterns influenced by the United States’ hegemony in higher education? If so, what would be reasons for broadly-used education resources predominantly originating from the United States? There are a number of possible explanations that if studied could also provide insight into sociological processes.

8.5 Conclusions

My hope is that my findings and conceptual approach will inform both social science theory and educational practice. Regarding the latter, my findings suggest who might be the most influential and what the methods for interacting with potential adopters are most effective. Why is this important? Higher education is under growing pressure to reform and respond to accountability measures based on student outcomes. Meanwhile, the science of learning field

continues to mature in a number of disciplines. Reform initiatives should be properly guided by these findings. In addition, translating educational best practices from the science of learning field to the classroom on a broad scale will be difficult. This dissertation can inform diffusion strategies with a unique sociological perspective.

For example, my work is different, but complementary, to the *Increase the Impact* initiative led by Jeffrey Froyd, Renee Cole, and Charles Henderson, who received NSF support for this program. Its goal is to, “promote the successful propagation of effective curricular materials and teaching and learning strategies” (Henderson, Froyd, Cole, Khatri, & Stanford 2013). The strength of this initiative is that it encourages innovators to strategically plan for dissemination in the early stages of development. The resources and strategies provided focus on innovation and potential adopter characteristics along with the environmental context of those individuals. Their recommendations also include a suggestion to use personal networks to disseminate ideas.

The sociological insight of my work suggests how to refine their recommendations. For example, the propagation options document suggests multiple ways faculty members can disseminate ideas (Henderson, Froyd, Cole, Khatri, & Stanford 2014). These include conference presentations, journal publications, and leveraging existing instructor development communities. They have listed potential options; I have researched which are most likely to lead to adoption. My research would suggest how to prioritize the choices, that is,

putting a higher priority on the instructor development communities over journals publications.

My findings also suggest types of faculty members to recruit for dissemination activities. More senior faculty from more prestigious institutions tend to be more influential. Of course, my findings are for broadly diffused innovations. The *Increase the Impact* group reminds innovators to consider the intended audience. Educational innovations designed for specific types of curricula or institutions may need to consider more focused strategies that attempt to recruit change agents unique to the target community.

My work has not only practical implications for diffusing educational practices in higher education, but can inform social science theory. There is a large body of research on diffusion of innovations that spans multiple disciplines including the social sciences. My work contributes to how social capital contributes to the spread of innovations in the education domain. Specifically, my results provide insight into how social networks create opportunities for organizations and change agents to indirectly influence potential adopters through the social capital that inheres in university communities and inter-institutional organizations. Likewise, in considering structural holes that must be bridged to ensure ideas spread to new groups, my findings describe what type of faculty fill these roles in the higher education system.

My findings suggest that more robust theories are needed to understand how educational innovations diffuse among colleges and universities. My study focused on the role of faculty members, but the impact of other actors should also

be considered including administrators, staff and most important students. As students are treated more as clients in higher education, institutions are more likely to listen to student demands. Likewise, students feel more empowered to exert their own agency to suggest how they want their courses taught based on their experiences in other classrooms.

Higher education diffusion models should simultaneously account for innovation characteristics. My data clearly showed that diffusion patterns and change agency were related to the characteristics of the innovation. These characteristics include the structure of user support communities that develop around these innovations. Therefore, understanding how both the agency of the systems actors and the characteristics influence each other and ultimately drive change would be useful. My work provides an exciting opportunity on which to begin to refine and develop these models. I hope my work does more than contribute to this understanding, but inspires other social science researchers to adopt this field of study. We too can be change agents that contribute to the improvement of higher education.

Appendix A: Survey Questions (Calibrated Peer Review Survey)

Thank you for taking this survey.

The purpose of this dissertation research is to explore how several educational methods, in this case Calibrated Peer Review (<http://cpr.molsci.ucla.edu/>), diffuse among faculty and across colleges. All respondents will be entered into a drawing for the following prizes: eight \$25 Amazon gift cards and one \$100 gift card.

If you decide to participate, you will answer questions asking where you have taught, how you learned about Calibrated Peer Review, and what sources (colleagues, websites, etc.) influenced you when deciding whether to use it or not. You will also be asked about whether you published or presented on your experience. The survey can be completed in as little as 10 minutes with only 2 questions requesting written responses. Your participation is completely voluntary, and you may quit at any time without penalty.

There is minimal risk to participants. No sensitive personal information will be collected. Your responses will be kept confidential. When research results are reported, responses will be aggregated (added together) and described in summary.

If you have questions or concerns about this research, please contact:

Mike Reese
Sociology Doctoral Student
Johns Hopkins University
410-516-4192
mreese@jhu.edu

You may also contact the faculty member supervising Mr. Reese's work: Dr. Stephen Plank, Associate Professor, Johns Hopkins University (410-516-7633 or splank@jhu.edu)

Whom to contact about your rights in this research, for questions, concerns, suggestions, or complaints that are not being addressed by the researcher, or research-related harm:

Homewood Institutional Review Board (HIRB)
AMR 007
Johns Hopkins University
3400 N. Charles St.
Baltimore, MD 21218 Phone Number: 410-516-6580
Fax Number: 410-516-0150

Please print or save a copy of this page for your records.

Please click the "Submit" button at the bottom of the page when you finish.

1. At which college or university are you currently teaching (if on sabbatical/leave, please list full-time employer)?

2. Use this space to enter your institution if it was not listed among the previous choices (optional).

Awareness of Calibrated Peer Review

3. When did you first become aware that the Calibrated Peer Review instrument existed (<http://cpr.molsci.ucla.edu/>). List semester and year if possible.

4. How confident are you of the previous date?

- ☐ Don't remember
- ☐ Somewhat confident
- ☐ Confident
- ☐ Very confident

5. Please select the category from the dropdown menu below that best describes the FIRST SOURCE OF INFORMATION from which you became aware of Calibrated Peer Review?

- ☐ Faculty at the institution where you worked when you first became aware of the innovation
- ☐ Faculty at other institutions
- ☐ Higher education staff other than faculty
- ☐ Professional Organization
- ☐ Website
- ☐ Journal article
- ☐ Non-journal publication
- ☐ Conference
- ☐ Don't remember
- ☐ Other, please specify below.

6. Use this space to describe your previous answer if you chose "other" (optional).

Sources of Information

7. After you first became aware of Calibrated Peer Review, how influential were ALL OF THE FOLLOWING SOURCES of information in convincing you to try it?

	Somewhat Important	Important	Very Important	Not at all
Faculty at the institution where you worked when you first became aware of the innovation	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Faculty at other institutions	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Higher education staff other than faculty	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Professional Organization	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Website	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Journal article	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Non-journal publication	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Conference	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Other?	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

8. Please provide detail for "other" category in previous question if you rated it 2-5 (optional).

9. Think of the person who influenced you the most either through direct communication or information s/he published or presented. Please choose a category that best describes that individual's JOB POSITION.

- ☐ Higher-ranked faculty position
- ☐ Similar-ranked faculty position
- ☐ Lower-ranked faculty position
- ☐ Staff member
- ☐ Don't remember/anonymous
- ☐ No one influenced me

10. Think of the person who influenced you the most either through direct communication or information s/he published or presented. Please choose a category that best describes that individual's INSTITUTION OF EMPLOYMENT.

- ☐ Higher-status college
- ☐ Similar-status college
- ☐ Lower-status college
- ☐ Not a college or university
- ☐ Don't remember/anonymous
- ☐ No one influenced me

11. How was s/he influential? Describe how his/her position and/or institution lend credibility to the information provided to you, if at all.

12. Did you receive grant funding to help you implement Calibrated Peer Review at any point?

- ☐ Yes
- ☐ No

Use of Calibrated Peer Review

13. List the courses by descriptive title, such as "Intro Chemistry I," you have taught in which you used Calibrated Peer Review and your role in that course (e.g., lead instructor, guest lecturer, co-instructor, support staff).

14. Please use the following matrix to estimate how many of your course assignments/exercises used Calibrated Peer Review during each of the academic years listed below (academic year is considered to run from August 1- July 31). Add across courses if you used the instrument in multiple courses in one year.

	0	1	2	3	4 or more	Don't remember	Did not teach that year
2011-2012	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
2010-2011	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
2009-2010	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
2007-2008	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
2006-2007	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
2005-2006	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
2004-2005	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
2003-2002	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
2002-2001	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
2001-2000	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Future Plans to Use Calibrated Peer Review

15. What statement below best describes your plans for using Calibrated Peer Review in the future?

- ☐ Do not plan to use it again
- ☐ May use it again when appropriate
- ☐ Definitely use it when appropriate

Sharing Your User Experience

* 16. Did you present, publish, report, or formally communicate your experience implementing Calibrated Peer Review to a public audience? (If you answer "yes," you will be asked 2 more questions on the next page about your experience.)

- ☐ Yes
- ☐ No

Your Professional History and Work Environment

17. How often do you discuss teaching responsibilities with your colleagues?

	Never	Rarely	Occasionally	Frequently
Department chair/ deans/administrators	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Tenured faculty	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Untenured, tenure- track faculty	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Full-time lecturers/instructors	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Part-time instructors/adjuncts	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

18. What is the highest degree you earned?

- ☐ Doctorate (Ph.D., M.D., J.D., Ed.D, etc)
- ☐ Masters (M.S., M.A., M.Ed., MPH, etc.)
- ☐ Bachelors (B.S., B.A., etc.)
- ☐ Associates
- ☐ Other, please specify

19. How many years have you taught in higher education? Include classes taught as the lead instructor when you were a graduate student, but do not include years as a teaching assistant supporting a faculty.

20. Please list the years you held the following positions along with the institution at which you worked (list multiple institutions per line as needed). If you prefer, please enter a link (URL) to your CV in the "other" category below or email it to mreese@jhu.edu.

- ☐ Tenured Professor _____
- ☐ Tenured Associate Professor _____
- ☐ Untenured Associate Professor _____
- ☐ Untenured Assistant Professor _____
- ☐ Full-time Sr. Lecturer, Lecturer, Instructor (non-tenure track) _____
- ☐ Part-time Adjunct Faculty, Lecturer, Instructor _____
- ☐ Other (please list) _____

21. What is your gender?

- ☐ Male
- ☐ Female
- ☐ I identify as (optional)...

22. To help us contact all users of Calibrated Peer Review, please list the name and email addresses (if known) of any other faculty you know using it (optional). All information will remain confidential.

23. Please enter your email address to be entered into the drawing for the Amazon gift card. All data collected will remain confidential.

24. Would you like to be notified of presentations or publications based on this research project (optional). Again, all information will remain confidential.

- ☐ Yes (be sure to include your email address in previous question)
- ☐ No

Prev

Submit

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(These questions are presented to those who answered “Yes” to question 16)

25. On the previous screen you indicated that you presented, published, reported, and/or formally communicated your experience implementing Calibrated Peer Review to a public audience. Briefly list the following information for each event (if more than 3, list the 3 you think were most influential in motivating other instructors to consider using it)?

- Presentation/Publication Title
- Communication Vehicle (journal title, conference, department meeting, etc.)
- Date (Month and Year)
- Audience Description

--

26. How much did each of the following influence your decision to publish, present, report, or formally communicate your teaching experiences with others?

	Hindered		No Effect	Enabled	
Formal incentives at your institution to publish peer-reviewed research	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Formal incentives at your institution to publish peer-reviewed research	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Formal incentives in your professional organizations/discipline to publish peer-reviewed research	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Personal success previously publishing research	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Formal incentives at your institution to present research at conferences	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Formal incentive in your professional organizations/disciplines to present research at conferences	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Personal success in previously presenting at conferences	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Resources available for travel at your institution	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Desire to gain status within your institution	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Desire to gain status within your professional organization/discipline	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Personal commitment to improving teaching	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Teaching awards or recognition at your institution	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Annual performance review	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Other - please list below	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

27. List other sources that influenced you to share your experience below.

Prev

Submit

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Appendix B: SALG Population Email Invitations (Examples)

High Use Email Invitation

Dear <@first_name@>,

We're contacting you today about the Student Assessment of Learning Gains (aka "The SALG" – a free course evaluation tool available from www.salgsite.org). From a report we just ran, it looks like you've had <@usage@> <@custom@>

You can access our short survey through the link at the end of this email. All respondents will be entered into a drawing for the following prizes: eight \$25 Amazon gift cards and one \$100 gift card. If you only had 5 minutes to go through just the multiple choice questions, your input would still be helpful to us.

The user survey has three main foci.

1. getting your feedback on the SALG and your experience with it
2. investigating how information about the SALG is shared among faculty and which sources are most influential
3. helping us understand more about your current needs and interests in learning assessment

As part of this user research, we're working with Mike Reese, a sociology doctoral student from Johns Hopkins. His research explores the spread of educational innovations among faculty in higher education. Most of the questions in the survey relate directly to his dissertation research so he'll be especially grateful for any time you spend completing this.

If you have any questions, please respond to this email and it will be received by all of us.

Stephen Carroll, Principal Investigator
Melissa Ganus, User Research & Outreach
Mike Reese, Doctoral Student in Sociology

If you don't have questions, please click the link below to start the survey.

Very grateful for your time,
Stephen, Melissa & Mike
on behalf of the SALG Team

Low Use Email Invitation

Dear <@first_name@>,

We're writing today about your past use of the Student Assessment of Learning Gains (aka "The SALG"), a free course evaluation tool funded by NSF and available from www.salgsite.org. From a report we just ran, it looks like you've had <@usage@>

You can access our short survey through the link at the end of this email. All respondents will be entered into a drawing for the following prizes: eight \$25 Amazon gift cards and one \$100 gift card. If you only had 5 minutes to go through just the multiple choice questions, your input would still be helpful to us.

The user survey has two main foci.

1. getting your feedback on the SALG and your experience with it
2. investigating how information about the SALG is shared among faculty and which sources are most influential

As part of this user research, we're working with Mike Reese, a sociology doctoral student from Johns Hopkins. His research explores the spread of educational innovations among faculty in higher education. Most of the questions in the survey relate directly to his dissertation research so he'll be especially grateful for any time you spend completing this.

If you have any questions, please respond to this email and it will be received by all of us.

Stephen Carroll, Principal Investigator
Melissa Ganus, User Research & Outreach
Mike Reese, Doctoral Student in Sociology

If you don't have questions, please click the link below to start the survey.

Very grateful for your time,
Stephen, Melissa & Mike
on behalf of the SALG Team

Non-users Email Invitation

Dear <@first_name@>,

We're writing today about your past use of the Student Assessment of Learning Gains (aka "The SALG"), a free course evaluation tool funded by NSF and available from www.salgsite.org.

<@first_name@>, you have an inactive, unused SALG account linked with the email address <@email@>. It appears from our records that you signed up with this email address to try out the SALG <@custom@>, but something stopped you from collecting any student responses.

Today we want to tap your interests in improving the quality of student learning assessment. In the survey we're hoping you can complete, we want to know more about your current learning assessment usage and how you learned about the SALG even if you don't remember. "Cannot remember" is a valid response on several questions and would help us identify the usefulness of different sources of information. We also want to hear from staff members who registered on the SALG site, but do not teach their own classes. Even if you have not logged into the SALG site more than once, we would get value from your responses to any of the questions in this survey. If you have been actively using the SALG from another email address, please reply to this message to let us know which other address you are using.

Specifically, we're contacting users like you for two purposes:

1. We are working with Mike Reese, a doctoral student from Johns Hopkins, whose dissertation research focuses on how information about educational innovations like the SALG spread between faculty and staff in higher education.
2. We are actively working to improve the quality and ease-of-use of the SALG, and would love your input on what you need in learning assessment tools in general.

The survey can take less than 5 minutes to complete if you need to skip the open-ended questions. You can access the survey through the link at the end of this email. All respondents will be entered into a drawing for eight \$25 Amazon gift cards and one \$100 gift card.

If you have any questions, please reply to this email. It will be received by all of us, and one of us will get back to you as promptly as possible.

If you don't have questions, please click the link below to start the survey.

Very grateful for your time,
Stephen, Melissa & Mike
on behalf of the SALG Team
Stephen Carroll, SALG Principal Investigator
Melissa Ganus, SALG User Research & Outreach
Mike Reese, Doctoral Student in Sociology

Appendix C: Checking for Biased Responses

I attempted to survey the entire population of those who became aware of each innovation. This was done through various data gathering activities including the review of user logs, conference records, journal publications, and snowball sampling. While I had a comprehensive list of potential adopters, not everyone responded to the survey. This means the coefficients for the variables in the models run are not descriptive of a complete enumeration of some known population. Thus, I chose to interpret them as being derived based upon a sample drawn from the population.

I used probit and logit models to check for biased responses. I created a new dependent variable for whether someone responded or not. I then conducted a probit and logit regression analysis using a key independent variable to see whether there was unbalanced response rates across groups. The only variable for which I could easily (and comprehensively) obtain data for non-responders was the institution type. This was done by truncating the respondents' email address to isolate the school domain name. A similar process was used for institution-specific data downloaded from the Carnegie Foundation for the Advancement of Teaching (Carnegie Foundation for the Advancement of Teaching 2010). This download included the institution name, Carnegie Classification, and primary website URL. The website URLs were truncated to isolate the core domain name (e.g., deleting "www." before "jhu.edu"). I then created lookup tables in Excel to match the Carnegie Classification for responders and non-responders for each of the innovations.

For all three innovations, the institution type variable was not significant suggesting there was no bias in response rates by institution type. Unfortunately, I was unable to conduct the same analysis for faculty role. This would have required conducting web searches on faculty role for over 2,500 non-respondents, many of whom are no longer affiliated with an institution (e.g., adjunct faculty).

Appendix D: History of the SALG Tool and Official Release in 2007

The following history of the SALG tool was provided by Dr. Stephen Carroll to Michael Reese on a phone call on June 12, 2013.

SALG was created in 1997 as a paper and pen instrument for a chemistry course at the University of Colorado, Boulder. Sue Lottridge, a graduate student at the University of Wisconsin, was tasked in 1999 with migrating it to an online instrument to test its functionality as a web-based survey. This was done with Microsoft Active Server Pages as part of her master's thesis project. The purpose was only to pilot it. No advertising was done, but faculty members at other universities found and used it.

No one was responsible for maintaining it. Over time the server architecture decayed because no updates were made to it. Sue Lottridge would troubleshoot database problems on a voluntary basis when asked, but not the front end (e.g., user interface). There was also no server support.

NSF funds were acquired in 2005 to revamp the tool. During this time it was discovered the database had been hacked and answers for two questions had been merged. It was not a major problem because individual users could download survey data and manually separate merged data if needed. However, the development team decided to reconstruct the SALG website from scratch because of security concerns.

The new website was launched in 2007 and it was a complete redevelopment. "It was truly a new tool," Stephen Carroll said. The original

instrument had five questions, several of which had no theoretical basis. It was also chemistry specific. The new SALG instrument was discipline independent, included new questions, and changed the ordering and grouping of questions.

No user accounts from the old system were migrated over. This was partly motivated by the database corruption problem. Stephen Carroll said, "We started over. No transition support was given to old users. It was a new instrument."

The SALG team launched the new website with a major promotional effort. They printed and mailed 40,000 brochures to faculty instructional support centers around the United States. They aggressively attended conferences (e.g., disciplinary conferences, education and assessment conferences, and teaching conferences) to present on and advertise the SALG instrument.

Appendix E: Peer Instruction

Peer Instruction (PI) was pioneered by Eric Mazur at Harvard University in his Introduction to Physics Course. PI uses a think-pair-share approach in which the instructor asks students conceptual questions to which they respond individually (e.g., hand raises, in-class voting technology). Based on the frequency of correct responses, the instructor either continues to the next topic or requests students debate their answer with a neighbor who believes a different answer is correct before submitting a response again. This inquiry-based teaching method replaces the traditional lecture in most cases. The instructor may occasionally lecture to clarify conceptual ideas for students (Mazur 2009, p. 10-11).

Eric Mazur created a database of 2,700 potential adopters of Peer Instruction. The contact information is generated from two sources. First, the database includes email addresses for anyone who has contacted him about Peer Instruction (e.g., email questions, speaking requests). He also provides free support materials on his website. Individuals must submit their email address before downloading the materials. These email addresses are added to the database.

Dr. Mazur was eager to partner with me and asked me to work with his post-doctoral fellow, Julie Schell, who was leading the Peer Instruction

initiative.⁴⁸ I worked with the Peer Instruction team for over a year to obtain the contact information. The team ultimately decided that they were not comfortable providing me a list of names. They offered to send my survey invitation with a broadcast message they were already planning to send to the Peer Instruction community asking members to verify their email address. This decision occurred after I began surveying the other innovation populations. I received 108 responses from this invitation. Unfortunately, the team was only willing to send one reminder email. This generated another 57 responses. The response rate was so low (165 out of about 2,700 contacts or approximately 6 percent) that I decided not to use the data in my quantitative analysis. Comments to free-response questions were included in my qualitative analysis in Chapter 7's exploration of how faculty members said they were influenced by their peers.

⁴⁸ Dr. Mazur research group is very large. It includes approximately 30 undergraduate researchers, graduate students, and post-docs who support both his physics scholarship and his education research that includes work on peer instruction.

Appendix F: Respondent's Reports of How Influential Various Sources of Information Were By Innovation

Table F.1 – Number of CPR Respondents Reporting Level of Influence of Various Sources

Source	Not at All	Somewhat Influential	Influential	Very Influential	Total
Faculty at the Same Institution	117 (68.82%)	16 (9.41%)	15 (8.82%)	22 (12.94%)	170 (100%)
Faculty from a Different Institution	69 (40.59%)	29 (17.06%)	44 (25.88%)	28 (16.47%)	170 (100%)
Staff Member	131 (77.06%)	18 (10.59%)	11 (6.47%)	10 (5.88%)	170 (100%)
Professional Organization	129 (75.88%)	24 (14.12%)	11 (6.47%)	6 (3.53%)	170 (100%)
Website	78 (45.88%)	32 (18.82%)	40 (23.53%)	20 (11.76%)	170 (100%)
Journal Article	120 (70.59%)	20 (11.76%)	23 (13.53%)	7 (4.12%)	170 (100%)
Non-journal Publication	146 (85.88%)	12 (7.06%)	9 (5.29%)	3 (1.76%)	170 (100%)
Conference Presentation	84 (49.41%)	15 (8.82%)	32 (18.82%)	39 (22.94%)	170 (100%)

Table F.2 – Number of PLTL Respondents Reporting Level of Influence of Various Sources

Source	Not at All	Somewhat Influential	Influential	Very Influential	Total
Faculty at the Same Institution	51 (35.17%)	16 (11.03%)	27 (18.62%)	51 (35.17%)	145 (100%)
Faculty from a Different Institution	39 (26.9%)	29 (20%)	32 (22.07%)	45 (31.03%)	145 (100%)
Staff Member	93 (64.14%)	22 (15.17%)	16 (11.03%)	14 (9.66%)	145 (100%)
Professional Organization	97 (66.9%)	29 (20%)	10 (6.9%)	9 (6.21%)	145 (100%)
Website	104 (71.72%)	24 (16.55%)	9 (6.21%)	8 (5.52%)	145 (100%)
Journal Article	87 (60%)	30 (20.69%)	17 (11.72%)	11 (7.59%)	145 (100%)
Non-journal Publication	110 (75.86%)	15 (10.34%)	15 (10.34%)	5 (3.45%)	145 (100%)
Conference Presentation	71 (48.97%)	21 (14.48%)	22 (15.17%)	31 (21.38%)	145 (100%)
PLTL Workshop	67 (46.21%)	12 (8.28%)	24 (16.55%)	42 (28.97%)	145 (100%)

Table F.3 – Number of SALG Respondents Reporting Level of Influence of Various Sources

Source	Not at All	Somewhat Influential	Influential	Very Influential	Total
Faculty at the Same Institution	394 (49.62%)	78 (9.82%)	113 (14.23%)	209 (26.32%)	794 (100%)
Faculty from a Different Institution	505 (63.6%)	106 (13.35%)	97 (12.22%)	86 (10.83%)	794 (100%)
Staff Member	603 (75.94%)	54 (6.8%)	75 (9.45%)	62 (7.81%)	794 (100%)
Professional Organization	609 (76.7%)	52 (6.55%)	77 (9.7%)	56 (7.05%)	794 (100%)
Website	454 (57.18%)	132 (16.62%)	137 (17.25%)	71 (8.94%)	794 (100%)
Journal Article	659 (83%)	61 (7.68%)	50 (6.3%)	24 (3.02%)	794 (100%)
Non-journal Publication	737 (92.82%)	20 (2.52%)	23 (2.9%)	14 (1.76%)	794 (100%)
Conference Presentation	524 (65.99%)	41 (5.16%)	82 (10.33%)	146 (18.39%)	794 (100%)
Students	743 (93.58%)	23 (2.9%)	19 (2.39%)	9 (1.13%)	794 (100%)

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MICHAEL J. REESE, JR.

+ Address: 109 Park Dr. Catonsville, MD 21228

+ Email: mreese@jhu.edu

+ Phone: 410.788.3972

EMPLOYMENT

2002 - present	Johns Hopkins University	Baltimore, MD
Associate Director, Center for Educational Resources		
2001 – 2002	Johns Hopkins University	Baltimore, MD
Senior Information Technology Specialist, Center for Educational Resources		
2000 – 2001	Caliber Learning	Baltimore, MD
Program Designer		
2000 – 2001	University of Maryland	Baltimore, MD
Independent Consultant		
1998 – 2000	Booz-Allen, & Hamilton	Mclean, VA
Senior Consultant		
1993 – 1995	Baltimore Gas & Electric	Baltimore, MD
Co-op Student		

EDUCATION

2010 - 2014	Johns Hopkins University	Baltimore, MD
Ph.D., Sociology		
2006 – 2010	Johns Hopkins University	Baltimore, MD
M.S., Sociology		
2000 - 2001	University of Maryland	University College, MD
Graduate Certificate, Foundations of Distance Education		
1996-1998	University of Virginia	Charlottesville, VA
M.Ed., Instructional Technology		
1990 – 1995	Virginia Tech University	Blacksburg, VA
B.S., Electrical Engineering		
Minors in Mathematics & Sociology		

PEER-REVIEWED PUBLICATIONS

1. Magana, Alejandra, Michael Falk, and Michael Reese, Jr. (2013). "Introducing Discipline-Based Computing in Undergraduate Engineering Education." *ACM Transaction on Computing Education*, 13 (4): Article 16.
<http://dl.acm.org/citation.cfm?id=2534971>
2. Hufnagel, Todd and Michael Reese. (2013). "Deepening Conceptual Understanding in an Introductory Material Science Course Through Active learning Strategies." *In Proceedings of the 120th ASEE Annual Conference & Exposition*. Atlanta, GA. June 23-26, 2013.
<http://www.asee.org/public/conferences/20/papers/5999/download>
3. Magana, Alejandra, Michael Falk, Michael Reese, Jr., and Camilo Vieira. (2013). "Materials Science Students Perceptions and Usage Intentions of Computation." *In Proceedings of the 120th ASEE Annual Conference & Exposition*. Atlanta, GA. June 23-26, 2013.
<http://www.asee.org/public/conferences/20/papers/7450/view>
4. Jia Sun, Orla Wilson, Michael Reese, Byung J. Jung, Thomas Dawidcyk, Mingling Yeh, Bal M. Dhar, Bhola N. Pal, Phylcia Trottman, Ian McCue, Lily Berger, G. Ross Blum, Erik Heinemann, David McGee, Jonah D. Erlebacher, and Howard E. Katz. (2009). "Hands-on Preparation and Testing of Solution-Processed Semiconductor Devices in the Undergraduate Classroom." *Journal of Materials Education*, 31(5-6): 271-284.
5. Reese, Michael, Joan Freedman, and Peter Fröhlich. (2009). "Playing Together: Establishing an Interdisciplinary, Interinstitutional Gaming Initiative." *In Proceedings of New Media Consortium Annual Conference Proceedings*. Monterey, June 2009. <http://wp.nmc.org/proceedings2009/papers/gaming-initiative/>
6. Reese, Michael and Ron Levy. "Assessing the Future: E-Portfolio Trends, Uses, and Options in Higher Education." (Research Bulletin, Issue 4). Boulder, CO: EDUCAUSE Center for Applied Research, 2009.
<http://net.educause.edu/ir/library/pdf/ERB0904.pdf>
7. Pearlman, Rebecca and Michael Reese. "Using Digital Field Assignments to Assess Learning in the Sciences." *In Proceedings of Education, Innovation, and Discovery: The Distinctive Promise of the American Research University*, pp 87-90. Washington, DC. November 2008
8. Hall, V. Macie, Don Juedes, Michael Reese, and Ann Woodward. (2006). "Visual Resources, Educational Technologies, & Teaching: A Collaborative Faculty Support Model." *Visual Resources Association Bulletin* 33 (2): 37-55.
<http://jhir.library.jhu.edu/handle/1774.2/33426>

9. Magana, Alejandra, Michael Falk, Camilo Vieira, Oluwatosin Alabi, Sylvain Patinet, and Michael Reese Jr. "Characterizing Undergraduate Materials Science and Engineering Students' Experiences with Integration of Modeling and Simulation into Core Courses." *Submitted for Publication in 2014.*

INVITED CONFERENCE PRESENTATIONS - Education

1. Reese, Michael and Jane Greco. (2014). *Promoting Chemical Education Research on Campus Through Effective Partnerships*. International Conference on Chemistry Education. Toronto, ON
2. Greco, Jane and Michael Reese. (2014). *A New Curricular Pathway to Prepare Students with Advanced Placement Credit for Organic Chemistry*. International Conference on Chemistry Education. Toronto, ON
3. Tifft, Kathryn E., Michael Reese, and Emily J. Fisher. (2014). *Effects of In-Class Group Problem Sessions on Group Studying*. ASM Conference for Undergraduate Educators. Boston, MA.
4. Magana, Alejandra, Michael Falk, and Michael Reese. (2013). *Materials Science Students' Perceptions and Usage Intentions of Computation*. American Society of Engineering Education Annual Conference. Atlanta, GA.
5. Hufnagel, Todd and Michael Reese. (2013). *Deepening Conceptual Understanding in an Introductory Material Science Course Through Active Learning Strategies*. American Society of Engineering Education Annual Conference. Atlanta, GA
6. Reese, Michael and Meiyun Chang-Smith. (2013). *Teaching an Online, Synchronous Class Across Multiple Institutions*. American Association of Physics Teachers. Portland, OR.
7. Jones, Jasmine, Alejandra J. Magana, Michael Falk, Michael J. Reese, and Camilo Vieira. (2013) *Students' Perceptions of Discipline-Based Computational Learning Experiences*. Poster session presented at the Summer Undergraduate Research Fellowship (SURF) Symposium, Purdue University, West Lafayette, IN.
8. Reese, Michael J. (2012). *Academic Integrity Mashed Up*. New Media Consortium Annual Conference. Boston, MA.
https://www.youtube.com/watch?v=3VRi2_TU3eo&list=PL2017353A95DC7ADA
9. Reese, Michael J. (2012). "Designing to Learn, Designed for Fun: An Undergraduate Video Game Development Course." American Society of

Engineering Education Annual Conference. San Antonio, TX.

10. Reese, Michael J. & Reid Sczerba. (2011). *Classroom Collaboration: Putting Design into Action*. New Media Consortium Annual Conference. Madison, WI.
11. Reese, Michael J. (2011). *Bridging the Macro and Micro World... with Blender and Some Legos!* New Media Consortium Annual Conference. Madison, WI.
<http://www.youtube.com/watch?v=IsaJx7dBpUs&t=9m23s>
12. Reese, Michael J. (2009). *Learning and Playing Together: An Interinstitutional, Interdisciplinary Gaming Course*. Flattening the Classroom: Building Collaborative Learning Environments Conference. EDUCAUSE Learning Initiative Online Conference.
13. Freedman, Joan and Michael J. Reese. (2009). *Playing Together: Establishing an Interdisciplinary, Interinstitutional Gaming Initiative*. New Media Consortium Annual Conference. Monterey Bay, CA.
14. Reese, Michael J. and Glenn Johnson. (2009). *Assessing Impact: e-Portfolios in Higher Education*. Mid-Atlantic Regional Educause Conference. Philadelphia, PA.
15. Reese, Michael J. and Rebecca Pearlman. (2008). *Using Digital Field Assignments to Assess Learning in the Sciences*. Reinvention Center Fourth National Conference. Washington, DC.
16. Juedes, Donald, Michael J. Reese, Ann Woodward, and Virginia M. Hall. (2008). *Sparking Innovative Teaching: A Collaboration to Promote Visual Resources*. Catalyst for Creativity Conference. New York, NY.
17. Freedman, Joan and Michael J. Reese. (2008). *Vietnam Remembered: A Lecture/Lab Course*. New Media Consortium Annual Conference. Princeton, NJ.
18. Reese, Michael J., Regina Galasso, and Ann Deleon. (2008). *The City as Laboratory*. Building Bridges in the City and Beyond: Languages, Communities, and Cultures Conference. Baltimore, MD.
19. Reese, Michael J. and Richard Shingles. (2007). *Digital Field Assignments: Course Projects for the Net Generation*. Educause National Conference. Seattle, WA.
20. Reese, Michael J. (2007). *The Potential for Digital Field Assignments in Second Life*. Communication and Information Technology Section of the American Sociological Association Mini-conference. Presented in Second Life.

21. Juedes, Donald, Michael J. Reese, Ann Woodward, and Virginia M. Hall. (2006). *Visual Resources, Educational Technologies, & Teaching: A Collaborative Faculty Support Model*. Art Libraries Society of North America 34th Annual Conference. Banff, AL.
22. Reese, Michael J. and Richard Shingles. (2006). *Digital Field Assignments*. New Media Consortium Annual Conference. Cleveland, OH.
23. Shingles, Richard and Michael J. Reese. (2006). *The Interactive Map Tool*. New Media Consortium Annual Conference. Cleveland, OH.
24. Reese, Michael J. and Theron Feist. (2005). *Ensuring Success: A Process for Transforming Teaching with Technology*. Academic Technology Conference. Goucher University. Baltimore, MD.
25. Reese, Michael J., Donald Juedes, and J. Rae Brosnan. (2005). *Shared Mission, Sharing Resources: Librarians and Instructional Technologists Supporting Faculty Together*. Mid-Atlantic Regional Educause Conference. Baltimore, MD.
26. Feist, Theron, Michael J. Reese, and J. Rae Brosnan. (2004). *Digitizing the Humanities*. Mid-Atlantic Regional Educause Conference. Baltimore, MD.
27. Schulman, James and Michael J. Reese. (2004). *ARTstor: Building a Community Digital Library*. Educause National Conference. Denver, CO.
28. Reese, Michael J. (2004). *The Timeline Creator*. New Media Consortium Annual Conference. Vancouver, BC.
29. Dalrymple., Melissa and Michael J. Reese. (2004). *ARTstor: Building a Community Resource*. New Media Consortium Annual Conference. Vancouver, BC.
30. Reese, Michael J. (2003). *Enhancing Critical Thinking Skills for Humanities Students: An Art History Model*. Mid-Atlantic Regional Educause Conference. Baltimore, MD.

INVITED CONFERENCE PRESENTATIONS - Sociology

1. Reese, Michael. (2014). *Changing Course: Change Agency and Faculty's Social Position in the Diffusion of Educational Innovations*. American Sociological Association National Conference. San Francisco, CA.
2. Plank, Stephen, Michael Reese, and Christian Villenas. (2008). *How do we study diffusion of innovation in education? A Review of 20 Years of Research*. American Educational Research Association National Conference. New York, NY.

INVITED WORKSHOPS & LECTURES

American Association for the Advancement of Science Workshop on Measurement of Teaching Practices in Undergraduate STEM: Washington, DC. (Dec 17-19, 2012)

Forum on Characterizing the Impact and Diffusion of Transformative Engineering Education Innovations. Hosted by the Center for the Advancement of Scholarship on Engineering Education of the National Academy of Engineering. New Orleans, LA. (Feb 7-8, 2011)

Visual Resources, Educational Technologies, & Teaching: A Collaborative Faculty Support Model. Wesleyan University Academic Technology Roundtable. Middletown, CT. (Nov 20, 2006)

INTERVIEWS

Marrazzo, Lauren. 7 Feb 2013. "Intersession Course Tackles Local Issues." *Johns Hopkins Newsletter*. <http://www.jhunewsletter.com/2013/02/07/intersession-course-tackles-local-issues-68603/>

Zaleski, Andrew. Apr 2012. "The Wired Campus." *Urbanite Magazine*.

Heid, Susan D. 9 Jan 2007. "Course Management Systems: A Tipping Point." *Campus Technology*. <http://campustechnology.com/articles/2006/12/course-management-systems-a-tipping-point.aspx>

Schuman, Elizabeth. "Breaking Down High-Tech Barriers to Communication." *The Baltimore Sun*. 8 July 2007, Education Section p 3.

COMMITTEE SERVICE

- + Member of MSEL Usability Director Job Search (2011)
- + Sociology Department Computing Committee (2009-14)
- + Member of Head of Research Services and Collection Department Job Search (2007-8)
- + Co-chair of University ePortfolio Committee (2003-present)
- + Member of University Diversity Training Committee (2007-08)
- + Chair of Sheridan Libraries Web Steering Committee (2002-3)

HONORS

- + 2014 SAGE Teaching Innovations and Professional Development Award
- + 2014 J. Brien Key Award
Dissertation research support
- + 2011-12 George Peabody Scholar in Sociology of Education (Johns Hopkins)
Awarded to graduate student demonstrating outstanding scholarship in the field.
- + 2010 Finalist for Krieger School of Arts and Sciences Teaching Excellence Award, Graduate Student Division
- + 2007 Nominated, accepted, and attended the Johns Hopkins Leadership Development Program
- + 2003 3rd place Johns Hopkins Homewood Student Employer Award
Nominated by student worker
- + 2003 1st place Innovation Award for Higher Education (Macromedia Corporation)
For Timeline Creator Software (over 30,000 downloads to date)
- + 1999 Booz-Allen & Hamilton Award for Excellence
- + 1998 Vice President Al Gore's Hammer Award for Reinvention of the Government
- + 1995 Best Magazine All Issues: Engineering Collegiate Magazine Association
- + 1995 Best Editorials All Issues: Engineering Collegiate Magazine Association
As Editor-in-Chief of Virginia Tech's Engineers' Forum
- + 1994 Paul E. Torgerson Leadership Scholarship (Virginia Tech):
Named outstanding leader of engineering class by peers
- + 1993 Eta Kappa Nu: electrical engineering national honor society
- + 1993 Alpha Kappa Delta: sociology national honor society