Essays on Adoption and Diffusion of New Technology in Supply Chains

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**Abstract**

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Over the past decade, many network technologies across supply chains have been introduced and promoted with the premised benefits for all participants. However industry experience with an adoption process of some technology suggests that some firms have a great amount of uncertainty in estimating the benefits of its adoption. This uncertainty will lead to a slow adoption rates across population in supply chains. In my dissertation, I develop a model to analyze technology adoption in a two-level supply chain: multiple suppliers and multiple buyers. The uncertainty about the benefits is reduced as other firms adopt the technology and information from their experiences becomes available. Thus, at any given time, the estimate of benefit for a firm depends on the number of supplier firms and number of buyer firms who have already adopted the technology. I seek to capture this dependence and analyze its effect on the adoption of technology like radio frequency identification (RFID) technology both on analytical models and empirical study. This study also investigates several important aspects of technology adoption process in supply chains. The dissertation comprises three essays focusing on these aspects in a dynamic adoption process in a two-level supply chain and diffusion of technology in inter-firm networks. I investigate how the dynamic process of uncertainty resolution and environment factors affects the firm's adoption decisions, and empirically examines the diffusion of technology in supply chain networks with several hypotheses to test insights generated from the analytical model.

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## DEDICATION

To my family.

# Chapter 1 Introduction

## 1.1 Background

Over the past decade, network-based technologies have been promoted with the premised benefits in a supply chain. Such technologies cause significant changes internally in processes, work routine, and the patterns of interaction among units within an organization (Angst et al. 2010; Brynjolfsson and Hitt 2000) and among organizations as well. At the firm level, firms must consider several factors before making a decision to adopt a new technology: should they adopt a new technology now or wait and see how others do? Or should they wait for other more advanced technology? Will the benefits of the new technology outweigh the costs?

In this dissertation, we consider the case of the adoption of radio frequency identification (RFID) in supply chains. Industry experience with RFID adoption shows that some firms, especially on the supply side in the retail industry, have had a great amount of uncertainty in estimating the benefits of adoption. This uncertainty influences slow adoption rates of technology. Particularly, the retail industry is an appealing example that exhibits significant variation in the adoption rate of this technology. Some strategies in the industry, such as the buyer’s mandate through bargaining power, stimulate other firms’ adoptions, yet, suppliers have still been slow to adopt this technology (RFID Journal 2009). Table 1.1 shows the implementation status of RFID across all industry sectors (Computer Economics 2007). RFID is installed at only 10% of sites in the sample, and only 4% of these have planned additional rollout of the technology. These low levels of implementation indicate the early adopters of this technology in sites. A small portion of firms are in the pilot-testing stage and, interestingly, 26% of the respondents are researching for the potential of the technology. But the majority of companies, 60%, show no activity at all.

| Status | Percent of Respondents |
| --- | --- |
| No Activity | 60% |
| Researching | 26% |
| Piloting | 3% |
| Implementing | 2% |
| In Place: No Further Plans | 6% |
| In Place: Increasing | 4% |

Table 1.1 Implementation status of RFID across industry sectors (Source: Computer Economics 2007)

To gain coordination benefits from this technology, firms who have adopted the technology early should stimulate their trading partners to also adopt it early because such technologies cannot be used unilaterally (Hart and Saunders 1998). Potential adopters will observe those who have taken on the technology before them to reduce uncertainties. Once they have adopted the technology, they can affect the remaining potential adopters. The diffusion of innovations in the network occurs through the learning process by information and knowledge transfer by the embedded organizations (Valente 1985). Therefore potential adopters are largely influenced by prior adopters within a network, and the level of influence by prior adopters may be different according to their positions in a network as well as their own organizational factors. These reasons may lead to different adoption timing on the diffusion process of technology.

The motivation of this research is derived from the following questions: Why do firms adopt technology at different points of time across organizations in a population? How do they make a decision to adopt new technology in a supply chain network with multiple levels? What are the factors that stimulate the diffusion process of technology in a supply chain network? How do relationships between firms affect the transferability and quality of information more effectively on the adoption decision?

Based on the basic research problems above, this dissertation argues about adoption and diffusion of new technology in supply chains with three essays. In Chapter 3, we discuss the dynamic adoption model of new technology in a two-level supply chain with multiple suppliers and buyers. As mentioned earlier, the uncertainty influences the adoption rates of the technology in the industry. We see how the dynamic process of resolution of uncertainty and other environmental factors affect adoption decisions. This chapter analyzes the dynamic adoption process given the firm's probabilistic belief about the benefits gained from technology adoption. It will be proven that the optimal strategy for adoption decision should be found by the cutoff level (threshold) for each period. By utilizing the cutoff levels, potential adopters can use the information to update their beliefs with respect to the size of adopters in any period that chooses to enter a network through technology adoption. That is, the cutoff level determines the fraction of adopters in each period, and population model can be derived. We then examine various types of heterogeneity to capture the factors affecting the diffusion speed.

In Chapter 4, I collected data about RFID adoptions over a period of five years (2003-2007) and gathered information to build a network of linkages between these firms. Drawing upon the idea of an adoption threshold from the analytical models developed in Chapter 3, I combined an empirical threshold model with this data. To examine the inter-firm network effects on technology adoption, I proposed a model in which a firm's adoption decision is influenced by information and knowledge from prior adopters though network ties as well as its own attributes. The levels of influence by prior adopters are different by physical and social proximity. I tested a model by examining which network participants can become aware of information through prior adopters and how relationships between firms affect the transferability and the quality of information on decisions. Organizational factors that affect a firm's adoption decision significantly can also be found. I tested several hypotheses proposed by our analytical model proven in Chapter 3, using the adoption data of RFID technology of the consumer packaged goods (CPG) industry in the United States from 2003 to 2007.

Chapter 5 explores inter-organizational relationship factors to predict the adoption and diffusion of RFID technology in a two-level supply chain. Specifically, this chapter considers two factors available in practice between firms in a two-level supply chain; the dependence on the other (the supplier's dependence level on a buyer) and the openness for information sharing (the supplier's openness level). Based on these interactions in the network, we will see how a firm decides to adopt the technology in a two-level supply chain by the threshold model and then analyze how the technology diffuses in the network by aggregating dynamics from individual firms' decision models. I will examine the best approach that a buyer (a retailer in Chapter 5) should use with its suppliers to encourage adoption of RFID technology when the buyer can coercively or passively encourage trading partner adoption. The model will include factors associated with the perceived level of dependence on the trading partner and openness with other firms in the relationship. Furthermore, this chapter introduces four different types of suppliers facing the adoption decision under the retailer with a bargaining power. These types are classified by two factors in inter-firm relations: the degree of dependence on retailers and the degree of openness for knowledge sharing with other suppliers. Using numerical analysis, I provide some managerial insights to powerful buyers who want to identify what conditions a buyer should use positive incentives versus negative threats to persuade suppliers to adopt RFID.

### 1.1.1 A Dynamic Adoption Model of New Technology in a Two-level Supply Chain

In Chapter 3, I will first develop a model to analyze technology adoption in a supply chain. While the basic model is general in the context of technology adoption, we consider the case of RFID. Industry experience with RFID adoption shows that some firms, especially on the supply side in the retail industry, have a great amount of uncertainty in estimating the benefits of adoption. This uncertainty influences the adoption rates of the technology in the industry. However, the uncertainty may be reduced as other firms adopt and information and knowledge from their experiences becomes available. In addition, the benefit a supplier firm may experience from adopting the technology is dependent on the number of its buyers who have already adopted it, because such technologies can bring some coordination benefits with the trading partners by network effects. This chapter makes a contribution to the area of technology adoption and diffusion in supply chains with multiple levels. None of the previous research considers the effects of other adoptee firms in the other level on the availability of information signals. The impact of buyer firms' adoption decisions on the supplier firms' benefits is new in this study.

This study first focuses on an individual supplier firm's adoption decision in a finite-horizon model. The firm is risk-averse. I put elements together to specify a per-period utility function for the firm. The cost of adoption is modeled as a one-time fixed cost. At the end of each period, the firm observes an information signal that is generated based on the number of other supplier firms who have already adopted the technology in the previous period. Each of these other suppliers experiences a benefit realization drawn from the true distribution of the benefit. The firm uses this signal to develop a posterior distribution of the benefit. I model the firm's adoption decision as a dynamic program. The state space in each period includes the firm's prior belief distribution, which depends on the number of supplier firms, and the number of buyer firms that have already adopted the technology. As more firms adopt, their information reduces the uncertainty about adoption benefits. The action space includes adoption or non-adoption in this period. Using a discount factor, a finite-horizon dynamic formulation can be derived. A satisfactory model of the adoption process in a finite-horizon should be able to account for the size of adopters in any period that chooses to enter a network by technology adoption. That is, each firm can use the information to update its beliefs with respect to the expected number of additional firms who will eventually join the network. Therefore, modeling the adoption process with a dynamic model (by backward induction) is more realistic. I found that the optimal strategy is characterized by the cutoff level (threshold) in each period. That is, there exists a unique cutoff level at which the firm decides whether or not to adopt. The number of adopters can be estimated by the cutoff level.

After calculating the estimated number of adopters over periods of time, the next step is to embed the firm-level adoption model into a population model. I include various types of heterogeneity in the population to capture the factors affecting the speed of diffusion. This allows deriving an adoption curve that is specified by the accumulated fraction of firms that have adopted the technology in or before any given period. Using numerical experiments, the results show how to compare any two adoption curves so that one represents faster adoption than the other. The population model allows considering the effect of several strategies observed in practice and the numerical experiments yield many managerial implications in this area.

In summary, Chapter 3 analyzes how the dynamic process of uncertainty resolution and environment factors affect decisions, examines various types of heterogeneity to capture the factors affecting the diffusion speed, and considers the effect of several strategies observed in practice, such like cost sharing, open innovation, incentives, information sharing, pilot programs, and so on.

### 1.1.2 Diffusion of New Technology and Innovation in Inter-firm Networks

An analytical model assumes that each supplier firm in the population is connected to all the buyer firms; in reality, the specific nature of the network of linkages between supplier and buyers will influence the adoption curve. In addition, the strength of connections between supplier firms will influence the quantity and quality of information transmission between supplier firms. In Chapter 4, we collected data about RFID adoptions over a period of five years (2003 – 2007) and gathered information to build a network of linkages between these firms. Drawing upon the idea of an adoption threshold from our analytical model, we then fit an empirical threshold model to this data. We use this empirical model to test several hypotheses proposed by our analytical model proven in Chapter 3.

The diffusion of innovation in the network occurs through the learning process by information and knowledge transfer with organizations embedded in the network (Valente 1985). In other words, diffusion can occur through information transmission and knowledge sharing among firms directly or by observing and monitoring others' actions indirectly (Strang and Soule 1998). Through these interactions between firms in the networks, firms can gain access to other's information and knowledge about new technologies and innovations. From a social network perspective, total social ties created by these interactions among firms are channels for flows of information and knowledge (Tsai 1998), and these ties then serve as paths for the diffusion process of the new technology. The firms that have already adopted the technology act as boundary spanners in networks. They adopt the technology earlier than others and are willing to transfer information and share knowledge. On the contrary, potential adopters in a network have relatively lower beliefs about the value of adoption and tend to delay the adoption of the technology. Over time, they receive information and knowledge about the new technology or innovation from others and their adoption decisions are influenced by this. They also affect the other remaining potential adopters' actions after adopting the technology. In sum, the diffusion is a process of information and knowledge among actors in the networks (Valente 1985) from a social network perspective. Angst et al. (2010) studies about the dynamics of the social contagion in the context of diffusion of IT innovation. They argue that social contagion by the diffusion of innovation occurs through information and knowledge transfer, observation, and learning about it among individuals in networks. They found strong effects for social proximity on an organization's likelihood of adoption, and significant regional effects for spatial proximity. Therefore potential adopters are largely influenced by others in a network over time, and the level of influence by prior adopters varies according to their positions in a network as well as by their own organizational factors.

To examine the inter-firm network effects together with firm characteristics on the technology adoption, we first propose a threshold model in which a firm's adoption decision is influenced by information and knowledge from prior adopters though network ties as well as its own attributes such as size, profitability, risk type, operational and financial performances. The levels of influence of prior adopters are different depending on physical and social proximity with the other firms. Using our threshold model, we then empirically test a model by examining which network participants can become aware of information through prior adopters and how relationships between firms affect the transferability and the quality of information.

Through the results derived from the empirical study in Chapter 4, I found that first, social proximity plays a critical role in the adoption of technology and is the strongest predictor of adoption. Second, firms with more subsidiaries and lower types of risk adopt the technology earlier than others. Healthy financial structure is also positively related to the adoption of technology.

Chapter 4 offers the following contributions. This is one of the first studies to empirically examine the dynamics of the adoption process in the context of technology adoptions in supply chains. We examine the effects of physical proximity and social proximity among firms and the firm's own characteristics as one of time-varying attributes. From a methodological perspective, we estimate various hazard functions with time-varying covariates under the duration analysis.

### 1.1.3 Inter-organizational Relationship Factors in the Technology Diffusion

In Chapter 5, the main objective is to develop a model of inter-organizational relationships to predict the adoption and diffusion of RFID technology in a two-level supply chain. I considered two factors available in practice between organizations in a supplier-buyer relationship; the dependence on the other (the supplier's dependence level on a buyer) and the openness for information sharing (the supplier's openness level). Based on these interactions in the network, I derive a threshold model to identify how a firm decides to adopt the technology in a two-level supply chain, and then analyze how the technology diffuses in the network by aggregating dynamics from individual firms' decision models. The model will include factors associated with the perceived level of dependence on the trading partner and openness with other firms in the relationship. I explore the following research questions.

- What factors are important for predicting the adoption of inter-organizational technology such like RFID technology?
- Under what conditions a buyer should use coercive or passive approach to persuade suppliers to adopt RFID technology?

This chapter studies an individual's myopic decision about the timing of new technology adoption. As described above, a firm's adoption of a new technology depends not only on its own beliefs of the new technology's costs and benefits, but also on the adoption decisions of other firms in the supply chain. The structure of benefits includes the stand-alone and network-based benefits. Potential adopters update their beliefs about the potential of the technology through the observed outcomes by information collected from others in the network. Through these information flows, they update their perceptions of the technology, and uncertainties will be reduced over time.

I considered the inter-organizational relationships between firms in the supply chain network; the level of the supplier's dependence with a trading partner and the level of openness for information sharing. Based on these interactions, how a firm decides to adopt the technology in a two-level supply chain using the threshold model derived by the benefit-cost structure will become apparent. Many studies have argued that the dependence is considered as a factor of interaction between firms in supply chain networks. It is defined as the ability of one firm (the source) to influence the intentions and actions of another firm (the target) (Emerson 1962). It plays a critical role in the supplier-buyer relationships (Benton and Maloni 2005). That is, a firm with high level of power is less dependent on the other. Given that dependence influences inter-firm relationships, it affects a firm's technology adoption decision significantly.

Given the benefit-cost structure, we derive the threshold model for the adoption in which individual's threshold levels are determined by the myopic decision rule. A firm's threshold levels at any given time are defined from the amount of information collected from the previous adopters in a population. Therefore all potential adopters do not decide to adopt at the same time because the critical level to elicit adoption is not a unique value appropriate to all members across population at any given time period. That is, the critical level is distributed heterogeneously across a population according to a density function. We then analyze how the technology diffuses in the network by aggregating dynamics from individual firms' decision models.

During my research for Chapter 5, we can first identify the factors that lead some suppliers to adopt RFID while other suppliers are more resistant. Second, I provide an insight under what conditions a powerful buyer should use the carrot (passive) or stick (coercive) approach in dealing with their suppliers to encourage RFID adoption and usage in a two-level supply chain. Lastly, this study provides some managerial insights to buyers about supplier management policies to encourage technology adoption and use.

**1.2 Contribution**

Today, as the technological landscape is rapidly developing and evolving, understanding technology adoption decisions and diffusion of innovations remains an important practical problem in supply chains. Therefore this study makes a great contribution in the area of technology adoption and diffusion in terms of operations management. This dissertation consists of three chapters to develop the theories analytically and to empirically examine it with industry data in the area of technology adoption and diffusion. Overall, the main contribution of this dissertation work is to study the adoption model and diffusion process of new technology in supply chains considering network effects in supply chains with multiple firms. My dissertation contributes to the literature on the diffusion of new technology in operations management with several key aspects. First, this research makes a contribution to understanding how the dynamic process of uncertain resolution affects adoption decisions. Second, we will examine various types of heterogeneity to capture the factors affecting the diffusion speed. Third, the effects of several strategies observed in practice are considered using numerical experiments, and lastly, I empirically examine the dynamics of the adoption process in the context of technology adoptions in supply chains.

### 1.3 Dissertation Organization

The rest of the dissertation is organized as follows: Chapter 2 provides a review of the related literature. Chapter 3 studies the dynamic adoption model of new technology in a two-level supply chain in a view of finite periods of time. Chapter 4 empirically examines diffusion of new technology and innovation in inter-firm Networks, including hypotheses, data, models, estimation techniques, and results. Chapter 5 develops the myopic decision model to explore inter-organizational relationship factors to predict the adoption and diffusion of RFID technology in a supplier-buyer relationship, including analytical models and numerical analysis. Finally, I conclude in Chapter 6 and discuss future research directions.

# Chapter 2 Literature Review

## 2.1 Technology Adoption

This dissertation follows a stream of technology adoption literature and makes a contribution to it. There has been considerable research for the adoption and diffusion of technologies and innovations. Many prior studies have used threshold models for individuals' adoption decisions to trace the pattern of diffusion in the population, where the individual's thresholds are determined through information updating process for uncertainty of the new technology (Oren and Schwartz 1988; McCardle 1985; Chatterjee and Eliashberg 1990). Such models assumed that the firm's adoption decision is primarily associated with its own attributes. In a network perspective, however, the firm's adoption is largely influenced by others' adoption decisions within a given network (DiMaggio and Powell 1983; Angst et al. 2010). Therefore the individual firms' thresholds for adoption should be considered by other firms' decisions within a network together with their own organizational attributes. We allows for heterogeneity across the population. That is, individual firms make a decision for adopting the technology at different times due to their different prior beliefs and different amount of information they observed. Prior studies showed that the adoption decision rules are determined through information-updating process for uncertain benefits of the new technology. The Bayesian modeling approach to conceptualizing the information integration process has been employed in many models for technology adoption. Oren and Schwartz (1988) shows that consumers are Bayesian in that they update their uncertainties by combining the observed outcomes with their prior uncertainty according to the beta-Bernoulli updating. They also consider that the consumer will adopt once passing a risk-aversion threshold. McCardle (1985) considered the technology adoption decision for a firm using a dynamic modeling where, in each period, information can be purchased to update the estimate of adoption benefit. He presented that the firms updates its distribution of the firm's belief after collecting a piece of information, accounting for the new information in a Bayesian fashion. Ulu and Smith (2009) recently extended that model to consider general probability distributions for benefit and general information signals by a dynamic modeling. Chatterjee and Eliashberg (1990) presented a model to explicitly capture the effect of uncertainty on the firm's utility and to aggregate individual firms' decisions to produce a diffusion curve. They applied a Bayesian updating for the potential adopter's perception of the innovation as one unit of new information is received. They also introduce a stochastic element to the diffusion process in the paper. Eliashberg and Chatterjee (1986) has more comprehensive treatment of the stochastic models in diffusion. As another related paper, Whang (2010) considered adoption timing of RFID technology in a supply chain. None of these papers consider the effect of other adoptee firms on the availability of information signals. The impact of buyer firms' adoption decisions on the supplier firm's benefits is also new to this literature.

Most of adoption models assume that all potential adopters receive the identical quantity and quality of information from previous adopters in a population. In this case, firm's beliefs are primarily driven by the attributes of individuals. For example, firms are more or less likely to adopt the technology by their type of risk. That is, firms with low type of risk-aversion are willing to adopt early, while those with high type of risk-aversion index will wait. By the argument above, we model a dynamic adoption process on the scale of risk aversion when firm types are drawn from a commonly known distribution. At the beginning of each period, the number of adopters in both two population groups is commonly known. We show that equilibrium is characterized by a cutoff level for potential adopters on the scale of risk aversion for each period to track this adoption process. The main result is that there exists a unique set of cutoff level in each period. That is, there is only one non-adopter in the last period, and then the cutoff level in the next period is clearly determined by his adoption condition. Next, when a certain number of potential adopters exist by some period, the cutoff level that those potential adopters remain in some period also should be determined uniquely. We prove this argument by the backward induction. This means that the attractiveness of adoption in the current period is monotonic in the cutoff type of the current period, and thus the remaining firm is determined uniquely. This induction argument determined all cutoff levels the way back to when all firms remain in the first period. It enables to derive dynamics for the distribution of the thresholds to see the shape of adoption curve over time.

**2.2 Network Effects**

A firm's adoption of an innovation in network may give rise to positive externalities. The concept of network externality has been applied in the economics literature earlier. Katz and Shapiro (1985, 1986) and Farrell and Saloner (1985, 1986) consider the choice of standards and technology using the game-theoretic models. All of these studies developed decision problems through the welfare effects of aggregate behavior. As a recent literature for technology choice considering positive network effects, Kornish (2006) have studied the decision problem facing a consumer with a choice between two competing technologies each subject to positive network benefits, using a decision-theoretic model and a stochastic process that captures the dynamics of market share of two competing technologies. In this paper, we consider that adoption can generate information flows across a same population group which may spill over to the rest of the industry, and the technology have network characteristics that give rise to positive externalities between two population groups. The firm’s benefits directly depend on the number of adopters in other population group connected through the technology on supply chain network.

In addition, the number of adopters in the same population by any given time will indirectly affect the adoption decision, even though some firms are not connected directly in the network.

In recent years, many supply chain management literatures have applied the power source literature to the analysis of marketing channel relationships, finding that the different bases of power will affect inter-firm relationships in significant yet contrasting ways. The review of the marketing power literature indicates the significant effects of power upon inter-firm relationships in a supply chain. Maloni and Benton (2000) and Benton and Maloni (2005) study the power influences in the supply chain from empirical tests. They provide that the power-affected buyer–supplier relationship was found to have a significant positive effect on both performance and satisfaction from the test. Hart and Saunders (1997) have developed a theoretical framework, positing relative power and trust between trading partners as determinants of EDI adoption and usage. They propose that the greater the sales revenue from a retailer, the more dependent the supplier is on that retailer, so its power level is low.

The mechanism of how network structures affect information and knowledge transfer in inter-firm networks remains unclear because social ties among firms are combined by both cooperation and competition in a social structure. Instead, several studies pointed out the relationship between competition and knowledge transfer under limited research boundaries. On the one hand, strong competition between units inside an organization restricts the knowledge transfer between them (Szulanski 1996). On the other hand, competition motivates units to interact with each other to pursue common benefit from the synergy of knowledge sharing between them (Tsai 2002). He examined the coordination mechanisms on knowledge sharing in intraorganizational networks embedded by collaborative and competitive ties between units. He presented about the effectiveness of coordination mechanisms on knowledge sharing in intraorganizational networks that consist of both collaborative and competitive ties between organizations. He studied how a multiunit organization can coordinate its units and encourage units to enhance knowledge sharing among competitors. He found that social interaction is more positively associated with knowledge sharing among competitive organizational units than among noncompetitive units. Knoke (1982) and Fligstein (1985) found that the density of adopters is a significant influence on network adoption rates when actors are in close social proximity. Decision makers in potential firms will believe that interactions with close links will decrease uncertainties about the value of new technology and reduce the adoption risks by benchmarking and learning from others.

Several studies on the transfer of technological information and knowledge has pointed to the importance of geographical proximity and location (Almeida and Kogut 1997, Tallman et al. 2004) as a factor that could affect the efficacy of information and knowledge transfer at the network level. Porter (2001) suggests that firms with a common geographical background share certain knowledge resources that provide competitive advantage to them as a group. Sammarra and Biggiero (2008) describe the importance of geographical proximity and industrial clusters for knowledge transfer in inter-firm networks. Baum et al. (2000) argued that geographical proximity permits more interaction among firms, facilitating formal and informal knowledge transfer, and sharing of activities. The social process of learning and innovation in inter-firm cooperation works well when partners are physically close enough to allow frequent interaction and effective exchange of information (Maskell 2001). Geographically proximate firms will tend to choose each other as partners (Madhavan 2004) and be willing to share information knowledge with each other. Thus they are more likely to cooperate with each other by common factors such as regional factor, common business policy, and cultural closeness. Therefore geographic proximity is positively associated with the strength of tie between firms (Reagans and McEvily 2003) and will affect the ease of information and knowledge transfer.

As mentioned earlier, network technologies across organizations cause significant impacts to operational process, strategy on the business and the patterns of interaction within organization and/or with others. Swanson (1994) characterizes such technologies as Type III innovations that integrate IT products and services with other business technologies and have huge impacts on the business. This implies that potential adopters facing adoption decision will have uncertainty about the value of technology and managerial risk for failure.

**2.3 The Benefits of RFID Technology**

Many industry reports and academic papers mention about the estimates of the value of RFID. Some industry reports have showed values of RFID benefit with some numerical results. A.T. Kearney (2003) shows that retailers will reduce inventory by 5% and labor costs by 7.5%, and increase sales by 0.07%. A.T. Kearney (2004) also projects that most benefits for manufacturers will increase through better retail execution of the supply chain and replenishment processes from the retailer. That is, a good working relationship with partners is required to achieve these benefits in a supply chain. Some white papers have also demonstrated the value of RFID with some theoretical analysis. Lee and Özer (2007) have provided an excellent overview of the benefits of RFID by three categories, labor cost savings, inventory reduction, and shrinkage and out-of-stock reduction. It is actually not hard to find that RFID can reduce inventory and improve customer service level by better visibility in a supply chain. But it was not described that exactly how visibility in a supply chain could occur to inventory reduction and customer service improvement. Dutta et al. (2007) and Lee and Özer(2007) argued that most of the existing estimates of the value of RFID are at best educated guesses, often lacking any comprehensible basis. In fact, many results and estimates were either based on subjective judgment, or by a survey of practitioner, who may or may not have used RFID at all. It could be best guesses for the value. Recent researches tried to quantify the benefits of RFID adoption in a supply chain using analytical modeling. Atali, Lee, and Özer (2009) quantify the true value of inventory visibility offered by RFID. Gaukler, Seifert, and Hausman (2007) present the benefits of item-level RFID to two partners, one manufacturer and one retailer. Karaer and Lee (2007) quantify the visibility savings of RFID in the reverse channel. Heese (2007) proposed that assuming RFID can eliminate the inventory inaccuracy, a decentralized supply chain benefits more from RFID, such that RFID adoption improves supply chain coordination using the cost thresholds that RFID adoption becomes profitable.

# Chapter 3 A Dynamic Adoption Model of New Technology in a Two-level Supply Chain

This chapter proceeds as follows. In the following sections, we model the individual firm's adoption decision as a dynamic program. The individual firm's adoption model will be driven in a population model to capture a diffusion process in the population, and we then show analytical results. We then consider several important managerial implications by numerical experiments and provides some concluding comments.

## 3.1 Theoretical Background

We first focus on an individual supplier firm's adoption decision in a finite-horizon model. The firm is risk averse. We put elements together to specify a per-period utility function for the firm. The cost of adoption is modeled as a one-time fixed cost. At the end of each period, the firm observes an information signal which is generated based on the number of other supplier firms who have already adopted the technology in the previous period. Each of these other suppliers experiences a benefit realization drawn from the true distribution of the benefit. The firm uses this signal to develop a posterior distribution of the benefit.  We model the firm's adoption decision as a dynamic program. The state space in each period includes the firm's prior belief distribution, which depends on number of supplier firms that have already adopted, and number of buyer firms that have already adopted the technology. As more firms adopt, their information reduces the uncertainty about adoption benefits. The action space includes adoption or non-adoption in this period. Using a discount factor, we can specify a finite-horizon dynamic formulation.

The next step is to embed the firm-level adoption model into a population model. We include various types of heterogeneity in the population to capture the factors affecting the speed of diffusion. This allows us to derive an adoption curve that is specified by the accumulated fraction of firms that have adopted the technology in or before any given period. Using numerical experiments, we show how to compare any two adoption curves so that one can be called to represent faster adoption than the other. The population model allows us to consider the effect of several strategies observed in practice and numerical experiments yield many managerial implications in this area.

## 3.2 Models

### 3.2.1 Dynamic Adoption Process

We consider an individual firm's adoption decision on two levels in a supply chain: suppliers and buyers. There are a finite number of firms in two population groups, *N* suppliers and *M* buyers. We first focus on an individual supplier firm's adoption decision and there are *N* risk-averse firms in a supplier population. The buyers' adoption processes are exogenously given over period, which is commonly known. There are finite time periods indexed by $t = 1, 2, ..., T$. At the beginning of each period *t*, there are $n_{t-1}$ of firms who have already adopted until the beginning of period *t*. The remaining firms who have not adopted should decide whether adopt or not in period *t*, while previous adopters in any period enjoy benefit by the network size in every future period.

We first model the individual supplier's per-period benefit of adopting the technology. The firm's benefits from an adoption in time period *t* are given by

$$B_t = m_t p_t \tag{3.1}$$

where $m_t$ is the number of buyers who have already adopted until period *t*, which is determined exogenously[1]. $p_t$ is the firm's belief about the benefit in period *t*. The firm's prior belief about the per-period benefit of adopting the technology is normally distributed with unknown mean $\mu_t$ and known variance $s_t^2$.

Next, we consider the potential adopter's risk aversion by the following per-period utility function when the firm adopts in time period t (Chatterjee and Eliashberg 1990),

$$u(p_t) = 1 - e^{-am_t p_t} \tag{3.2}$$

where $a$ is the firm's type on the scale of risk aversion, $[0,1]$. This per-period utility function increases in the coefficient of risk aversion ( $a$ ), number of buyers who have already adopted ( $m$ ), and the firm's belief about adoption benefit ( $p$ ). The curve of per-period utility is non-decreasing concave function for all parameters. Per-period expected utility is written by

$$U_t = E[u_t] = 1 - e^{-am_t\mu_t + [a^2 m_t^2 (\sigma^2 + s_t^2)/2]}. \tag{3.3}$$

From equation (3.3), we can easily see that per-period expected utility increases as $\mu$ increases and/or as $s^2$ decreases. In our model, the firm's belief is updated by the information flow, which is determined by prior adopters. That is, the variance $s^2$ decreases as more potential adopters join in a network, and then $U$ increases. Some studies examined about an effect of risk aversion on the technology adoption. Tsur et al. (1990) find that risk aversion positively affects adoption. This is because risk-averse firms do not want to take the risk of not trying the innovation. If this

[1] The total per-period benefit for the firm is linear in the number of its buyers who have already adopted the technology.

is indeed the case, then risk aversion positively affects the adoption. That is, the greater the aversion to risk, the greater is the incentive to adopt.

We first derive a two-period adoption model as a finite-horizon dynamic formulation by the backward induction. The state space in each period includes the firm's prior belief distribution, which depends on number of both suppliers and buyers who have already adopted the technology. As more firms adopt, their information reduces the uncertainty about adoption benefits. The action space includes adoption or non-adoption in the period. We assume that the cost of adoption is *K* as a one-time fixed cost.

Value of adoption in the last period *T*, $VA_T$, is

$$VA_T = U_T - K + \delta V_T \tag{3.4}$$

where $U_T = 1 - e^{-am_T\mu_T + [a^2 m_T^2 (s_T^2 + \sigma^2)/2]}$. The firm's belief is updated by information from prior adopters by Bayesian updating process (DeGroot 1970). Continuing from the previous period, the firm has a belief about the unknown mean of the per-period benefit, which is normally distributed prior with a mean $\mu_{T-1}$ and a variance $s_{T-1}^2$. The firm observes $q_{T-1}$ firms that adopted in previous period *T*-1 and their benefit observations $X_1, ..., X_{q_{T-1}}$ are drawn from a normal distribution with an unknown mean and a variance. Then the firm updates its belief with a mean $\mu_T$ and a variance $s_T^2$.

$$\mu_T = \frac{\mu_{T-1} + \sum_{i=1}^{q_{T-1}} X_i (s_{T-1}^2 / \sigma^2)}{1 + q_{T-1}(s_{T-1}^2/\sigma^2)}, \; s_T^2 = \frac{s_{T-1}^2}{1 + q_{T-1}(s_{T-1}^2/\sigma^2)}.$$

If the firm adopts the technology by a fixed cost *K* in the last period *T*, he gains one-period utility (expected utility once adopting in period *T*) and fixed terminal value $V_T$ with discount rate $\delta$.[2] Therefore the optimal strategy at the beginning of the last period *T* is

$$\pi_T(s_T) = \max\left\{VA_T, 0\right\}. \tag{3.5}$$

That is, a firm's adoption condition in period *T* is simply $VA_T > 0$. If value of adoption in period *T* is larger than zero then the firm adopts in period *T*. Otherwise, the firm never adopts. By this adoption condition, we prove that there exists a threshold for the adoption decision in the last period.

***There exists a threshold $s_T^*$ such that if $s_T < s_T^*$ then the firm adopts; otherwise, the firm never adopts. (See Appendix)***

To specify the value of adoption in period *T* at the beginning of period *T*-1, the firm estimates that $\tilde{q}_{T-1}$ suppliers firms will adopt in period *T*-1, which will be revealed to the firm at beginning of period *T*. The number of buyers that will adopt in this period, $\tilde{m}_{T-1}$, can be also estimated, but still assume that it is exogenously determined. In our model, we assume that all *m* buyers have already adopted the technology before beginning of period *T*-1. Therefore predictive distribution of the sum of signal is normally distributed with a mean $\tilde{q}_{T-1}\mu_{T-1}$ and a standard deviation $\sqrt{\tilde{q}_{T-1}}\sigma$. Expected utility for adoption in period *T* as estimated at the beginning of period *T*-1, $U_{T-1,T}$, can be shown to be

$$U_{T-1,T}(\tilde{q}_{T-1}) = 1 - e^{-am\mu_{T-1} + [a^2 m^2 (\alpha(\tilde{q}_{T-1}) s_{T-1}^2 + \sigma^2)/2]} \tag{3.6}$$

---

[2] We assume that the terminal value $V_T$ might be either positive or negative value in a finite-horizon model.

where $\alpha(\tilde{q}_{T-1}) = \dfrac{1+\left(\tilde{q}_{T-1}s_{T-1}^2/\sigma^2\right)\left(1/\left(1+(\tilde{q}_{T-1}s_{T-1}^2/\sigma^2)\right)\right)}{1+\left(\tilde{q}_{T-1}s_{T-1}^2/\sigma^2\right)}$, ( $0<\alpha(\tilde{q}_{T-1})\le 1$, and $\alpha(0)=1$). The value of the firm is now a function of the variable $\tilde{q}_{T-1}$ that indicates the estimated number of suppliers who will adopt in period *T*-1. To clarify this, we define a function $\alpha(\tilde{q}_{T-1})$. As $\tilde{q}_{T-1}$ increases, $\alpha(\tilde{q}_{T-1})$ decreases and then $U_{T-1,T}$ increases (See the proof in Appendix). If the firm adopts the technology in period *T*-1, value of adoption over periods is

$$VA_{T-1} = [U_{T-1} - K] + \delta U_{T-1,T}(\tilde{q}_{T-1}) + \delta^2 V_T \,.$$

Otherwise, value of non-adoption is

$$NA_{T-1} = \delta \pi_T(s_T)\,.$$

where $\pi_T(s_T)$ is the optimal strategy in the coming period *T* as expressed in equation (3.5). Therefore, a firm will adopt in period *T*-1 if (i) $VA_{T-1}>0$ and (ii) $VA_{T-1}-NA_{T-1}>0$. Otherwise, a firm may adopt in next period or never adopt.

We then prove results about how the threshold changes as a function of the risk-aversion index of the firm. Let $v_a = VA_{T-1,T}(\tilde{q}_{T-1}) = U_{T-1,T}(\tilde{q}_{T-1}) - K + \delta V_T$ as the estimated value of adoption in period *T*. In addition, suppose that $v_b = VA_{T-1} - NA_{T-1} = U_{T-1} - (1-\delta)K$ as difference of values between adoption and non-adoption in period *T*-1, and $v_c = VA_{T-1} = [VA_{T-1} - NA_{T-1}] + \delta VA_{T-1,T}(\tilde{q}_{T-1})$ as the value of adoption in period *T*-1. Using these equations, the firm’s adoption conditions in period *T*-1 are

(1) If $v_a > 0$, the adoption condition in period *T*-1 is that $v_b > 0$ is enough. That is, adoption condition (ii) is sufficient.

(2) If $v_a \le 0$, the adoption condition in period *T*-1 is that $v_b > 0$ and $v_c > 0$. Both adoption condition (i) and (ii) should be satisfied for adopting in this period.

Let $s_a$ be a value for solving $v_a = 0$, $s_b$ be a value for solving $v_b = 0$, and $s_c$ be a value for solving $v_c = 0$. For each case below, each standard deviation can be a threshold for adopting. Let $\psi_{T-1}$ be the fixed value once adopting in period *T*-1, $\psi_{T-1} = V_T$ in a two-period model.

**Case I.** $\psi_{T-1} > K$ ($V_T > K$ in a two-period model)

This is the case that the terminal value $V_T$ is larger than the fixed cost of adoption in period *T*-1. That is, the technology is considered as an optimistic view. We can easily see that $v_a > v_b$, then $s_a(\tilde{q}_{T-1}) > s_b$. Possible values of $s_{T-1}$ for adoption at the beginning of period *T*-1 are $s_b$ below, because in which $v_a > 0$ and $v_b > 0$, and then $v_c > 0$ by adoption condition (1). If $v_b$ is negative above $s_b$, both adoption condition (1) and (2) cannot be satisfied. From Figure 3.1 (i), Potential adopters between $s_a(\tilde{q}_{T-1})$ and $s_b$ will wait and adopt in period *T*. As $\tilde{q}_{T-1}$ increases, we expect that more firms will adopt in the next period. Firms above $s_a(\tilde{q}_{T-1})$ never adopt the technology. Therefore a threshold of Case I is $s_b$. The firm below $s_b$ will adopt in period *T*-1, at which a threshold does not depend on $\tilde{q}_{T-1}$.

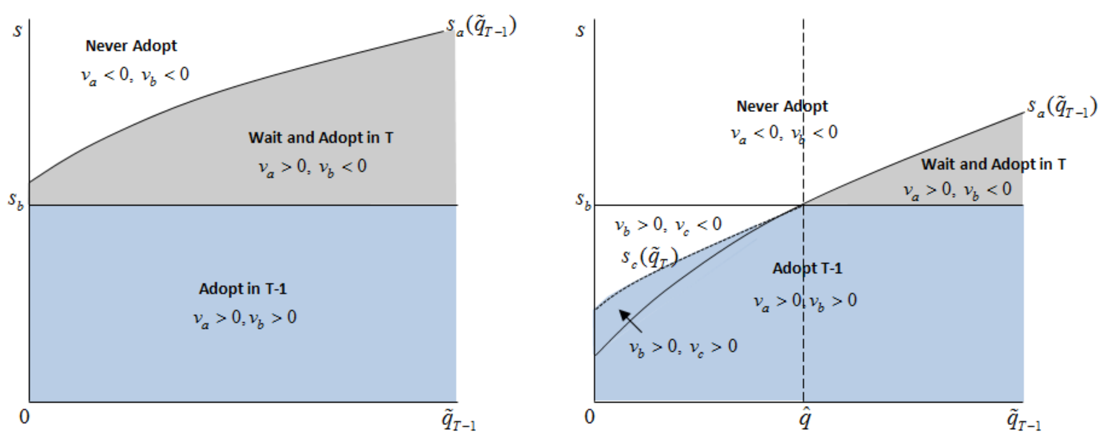
**Case II.** $\psi_{T-1} \le K$ ($V_T \le K$ in a two-period model)

This case is that the terminal value $V_T$ is less than the fixed cost of adoption. It is the case that there may be a huge investment to introduce the new technology or less optimistic view for the technology due to lots of uncertainty of the benefit.

When no one adopts in period *T*-1, $\tilde{q}_{T-1} = 0$, $v_a < v_b$ can be verified easily and then $s_a(\tilde{q}_T) < s_b$. In this case, possible values of $s_{T-1}$ for adoption are $s_a(\tilde{q}_{T-1})$ below, because in which $v_a > 0$ and $v_b > 0$ by adoption condition (1). As $\tilde{q}_{T-1}$ increases, $s_a(\tilde{q}_{T-1})$ increases and then there exists a point that $s_a(\hat{q}) = s_b$ at some critical point $\hat{q}$ as shown in Figure 3.1 (ii).

If $\tilde{q}_{T-1} < \hat{q}$, there exists a threshold $s_c(\tilde{q}_{T-1})$ which is solved for $v_c = 0$. possible values of $s_{T-1}$ for adoption are also above $s_a(\tilde{q}_{T-1})$, in which $v_a < 0$ and $v_b > 0$, and $v_c > 0$ can be satisfied for adoption in this period by adoption condition (2) ( If $v_a \le 0$, the condition for adopting in period *T*-1 is $v_b > 0$ and $v_c > 0$). So to adopt in this period, the possible values of $s_{T-1}$ should be $s_c(\tilde{q}_{T-1})$ below. That is, firms between $s_a(\tilde{q}_{T-1})$ and $s_c(\tilde{q}_{T-1})$ will adopt in period *T*-1. Firms above the threshold, $\max\{s_a(\tilde{q}_{T-1}), s_c(\tilde{q}_{T-1})\}$, never adopt because the estimated value for adopting in period *T* is negative ( $v_a < 0$ ), regardless of value of $v_b$. Thus, a firm's decision in the case of $\tilde{q}_{T-1} < \hat{q}$ is only for whether or not adopting. No firm expects waiting for the coming period to make the adoption decision if the estimated number of adopters will not come up to the critical point of $q$. From Figure 3.1 (ii), we see that there is no area for firms waiting in this period. Either $s_a(\tilde{q}_{T-1})$ or $s_c(\tilde{q}_{T-1})$ is determined by $\tilde{q}_{T-1}$. As $\tilde{q}_{T-1}$ increases until the critical point $\hat{q}$, both $s_a(\tilde{q}_{T-1})$ and $s_c(\tilde{q}_{T-1})$ increase and then more potential adopters will adopt in period *T*-1. Thus the threshold value is $\max\{s_a(\tilde{q}_{T-1}), s_c(\tilde{q}_{T-1})\}$ in the case of $\tilde{q}_{T-1} < \hat{q}$. If the firm's $s_{T-1}$ is below a threshold, he will adopt. Otherwise, he never adopts the technology because the firm is expecting more adopters, at least $\hat{q}$, for his adoption decision in next period.

If $\tilde{q}_{T-1} > \hat{q}$ then it brings this case back to case I. We do not need $s_c(\tilde{q}_{T-1})$ any more to make an adoption decision. A threshold value is $s_b$ as shown in case I, and firms below this threshold will adopt. Although the fixed cost is large, firms between $s_a(\tilde{q}_{T-1})$ and $s_b$ will wait and adopt in period $T$, because they expects that there exist critical number of adopters in period $T$-1 such that it will become large enough to compensate for the fixed cost. Thus, potential adopters expect adopting next period. Firms above $s_a(\tilde{q}_{T-1})$ never adopt the technology. Figure 3.1 (ii) shows adoption conditions for Case II. As shown in the figure, adoption area of case II is smaller than that of case I. For the reason, more potential adopters may be pessimistic due to huge investments, or may expect the low terminal value relatively due to lots of uncertainty of the benefit. As a different aspect in this case, if the terminal value is too small, a critical point $\hat{q}$ becomes larger and the tolerance level of uncertainty becomes lower. Then few firms or no one will adopt in this period. But as the expected number of adopters is larger, the estimated future benefit will be increased by network effects, and then more potential adopters are able to expect adopting next period.




(i) Case I ($V_T > K$) (ii) Case II ($V_T < K$)

Figure 3.1 Adoption Condition in Period $T$-1

***There exists a threshold $s^*_{T-1}$ for each case below such that if $s_{T-1} < s^*_{T-1}$ then the firm adopts; otherwise, the firm never adopts. $s^*_{T-1}$ is a non-decreasing in $\tilde{q}_{T-1}$ (See Appendix).***

(i) If $\psi_{T-1} > K$, $s^*_{T-1} = s_b$.

(ii) If $\psi_{T-1} \le K$,

a. $\tilde{q}_{T-1} < \hat{q}$, $s^*_{T-1} = \max\{s_a(\tilde{q}_{T-1}), s_c(\tilde{q}_{T-1})\}$, and

b. $\tilde{q}_{T-1} \ge \hat{q}$, $s^*_{T-1} = s_b$. (same as (i))

### 3.2.2 Multiple-period Model

We next extend to multiple-period model. In the multiple-period, the firm's adoption decision is a little different with the previous model. There are three possible choices at any point for adoption decision: *adopting*, *adopting in next period*, and *waiting a few more periods*, instead of *never adopting* in a two-period model.

If the firm adopts the technology in any period *t*, values of adoption is

$$VA_t = [U_t - K] + \delta U_{t,t+1}(\tilde{q}_t) + \delta^2 \psi_t ,$$

$$\text{where } \psi_t = \sum_{i=1}^{T-t-1} \delta^{i-1} U_{t+i+1}(q^*_{t+i}) + \delta^{T-t-1} V_T .$$

The value of $\psi_t$ is the sum of the discounted value of utility in the any subsequent periods and the terminal value at the last period, as the fixed value of benefits once adopting in period *t*. The values of utility in subsequent periods are determined by the set of equilibrium $q$ for each subsequent period, $\{q^*_{t+1}, q^*_{t+2}, \cdots q^*_{T-1}\}$, which are found by mapping with $s(q)$ using backward induction through dynamic modeling. Value of non-adoption is

$$NA_t = \delta \pi_{t+1}(s_{t+1}) = \delta \max\{VA_{t+1}, \delta \pi_{t+2}(s_{t+2})\} .$$

where $\pi_{t+1}(s_{t+1})$ is the optimal strategy in the coming period. The firm will adopt in period *t* if (i) $VA_t > 0$ and (ii) $VA_t - NA_t > 0$. Otherwise, a firm may adopt in next period or wait a few more periods.

We prove results about how the threshold changes as a function of the risk-aversion index of the firm. Let $v_a = VA_{t,t+1}(\tilde{q}_t) = U_{t,t+1}(\tilde{q}_t) - K + \delta\psi_t$, where $\psi_t = \delta^{T-t-1}V_T + \sum_{i=1}^{T-t-1}\delta^{i-1}U_{t+i+1}(q^*_{t+i})$ as the fixed value once adopting at period *t*. $U_2,\cdots,U_T$ are determined by the set of equilibrium $q$ for subsequent periods. $v_b = VA_t - NA_t = U_t - (1-\delta)K$ and $v_c = VA_t = [VA_t - NA_t] + \delta VA_{t,t+1}(\tilde{q}_t)$. In addition, suppose that $s_a$ is a value for solving $v_a = 0$, $s_b$ for $v_b = 0$, and $s_c$ for $v_c = 0$. For each case below, each standard deviation can be a threshold for adopting in period *t*.

Using $v_a, v_b,$ and $v_c$, the firm's adoption conditions in period *t* are

(1) If $v_a > 0$, the adoption condition in period *t* is that $v_b > 0$ is enough. That is, adoption condition (ii) is sufficient.

(2) If $v_a \le 0$, the adoption condition in period *t* is that $v_b > 0$ and $v_c > 0$. Both adoption condition (i) and (ii) should be satisfied for adopting in this period.

***There exists a threshold $s_t^*$ for each case at any period t such that if $s_t < s_t^*$ then the firm adopts; otherwise, the firm will wait more or never adopt. $s_t^*$ is a non-decreasing in $\tilde{q}_t$ (See Figure 3.2).***

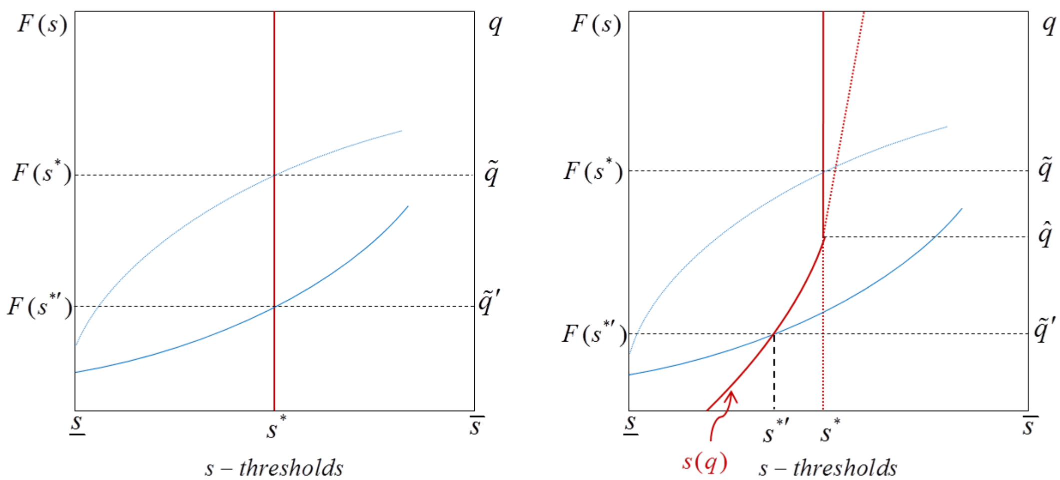
(i) If $\psi_t > K$, $s_t^* = s_b$.

(ii) If $\psi_t \le K$,

  a. if $\tilde{q}_t < \hat{q}$, $s_t^* = \max\{s_a(\tilde{q}_t), s_c(\tilde{q}_t)\}$, or

  b. if $\tilde{q}_t \ge \hat{q}$, $s_t^* = s_b$. (same as (i))

The proof of these conditions is the same as being proven in two-period model. At the beginning of period 0, we assume that an initial mean benefit is zero as $\mu = 0$ and a standard deviation is the largest one as $s = \bar{s}$ . At the starting period, firms have no any positive signal about the benefit of adoption at this decision point, and so the uncertainty level about the benefits will be too high without any prior adopters. In addition, an assumption that all buyers have already adopted is still valid over periods.




(i) Case I ( $\psi_t > K$ ) (ii) Case II ( $\psi_t \leq K$ )

Figure 3.2 Existence of Equilibrium $q$ on any CDF of $s$ – thresholds

### 3.2.3 Population Model

The next step is to embed the individual firm's adoption model into population model. To begin with, we first model the population of supplier firms as heterogeneous in risk-aversion and identical in all other respects. We also assume that each supplier is linked with all buyers.

We consider a population which is uniformly distributed along an axis of $s$ representing a standard deviation of unknown belief mean in period $T$-1, $s \sim [\underline{s}, \bar{s}]$. Analytically, firms at or below a threshold $s^*$ will adopt in the period, and firms above $s^*$ will wait and adopt later or never adopt. We define $F(s^*)$ as the fraction of adopters in the period and $f$ as the density function. The possible number of adopters in the period is at most $\tilde{q} = \lfloor F(s^*) \cdot N \rfloor$, where $N$ is a population size.

We show that the number of adopters in period $T$-1 is a fixed point of the mapping $\tilde{q}_{T-1}$ and $s^*_{T-1}$. As shown in Figure 3.2, $s(\tilde{q})$ is non-decreasing function in $\tilde{q}$. $\tilde{q}$ is a discrete variable and also increasing stepwise by $s(\tilde{q})$. $F(s)$ is continuous and non-decreasing in $s$. Using graphical observations, we see that both case I and II have a unique equilibrium of $q$ for any distribution of $s$. As the threshold gets larger (goes to right on the horizontal axis), an equilibrium point is also increasing in both cases. Thus, we prove the followings:

***There always exists equilibrium of $q$ in any period, which is a fixed point of mapping $q$ and $s^*$.***

*Case I. $(\psi_t > K)$ Threshold $s^*$ is constant over $q$. The equilibrium is the point at which the $F(s)$ crosses the threshold line. Therefore there is a unique equilibrium of $q$ for any distribution of $s$.*

*Case II. $(\psi_t \le K)$ Threshold is increasing in $q$ until the critical point of $\hat{q}$. If there exist a threshold $s^{*\prime}$ in the interval $[0, \hat{q})$, a critical point of $q$ mapped on curved threshold level $s(q)$ is less than that on the straight threshold level $s^*$, $\tilde{q}' < \tilde{q}$, as shown in Figure 3.2. For $\hat{q}$ above, the threshold is constant as case I. Therefore there is a unique equilibrium of $q$ for any distribution of $s$.*

This is very important because we are able to know $s$ based on this fixed point of $q$ over periods. That is, in each period, there exists a critical level of risk-aversion index such that all firms at or below that level will adopt the technology and all firms above that level will not adopt and chose to wait. This allows us to derive an adoption curve that is specified by the accumulated fraction of firms that have adopted the technology in or before any given period. Supposing $A_\tau, \tau \in \{T-1, T\}$ as the fraction of adopters in period $\tau$, $\{A_{T-1}, A_T\}$ represents an adoption curve in a two-period model as a cumulative distribution function. We extend the model to multi-period model. We also consider the case where there is a cost for observing information and the possibility that the information is not truthful.

In the following section, we compare any two adoption curves by numerical experiments, so that one can be called to represent faster adoption than the other.

**3.3 Numerical Analysis of the Model**

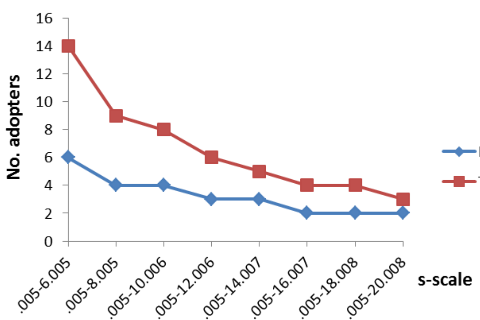
In the previous section, it is proven that there always exists equilibrium of $q$ in any period, which is a fixed point of mapping $q$ and $s^*$. In a two-period model, I show that the number of adopters in period *T*-1 is a fixed point of the mapping $\tilde{q}_{T-1}$ and $s^*_{T-1}$**.** The number of adopters in period T-1 is a fixed point of the mapping $\tilde{q}_T$ and $s^*_{T-1}(\tilde{q}_T)$. As shown above, $s^*_{T-1}(\tilde{q}_T)$ is non-decreasing function in $\tilde{q}_T$. $\tilde{q}_T$ is a discrete function and increasing stepwise by $s^*_{T-1}(\tilde{q}_T)$, i.e. $\tilde{q}_T = \lfloor s^*_{T-1}(\tilde{q}_T) \rfloor$ (See Appendix C). Recall that $s_a(\tilde{q}_{T-1})$ which is solved for $v_a = 0$, $s_b$ which is solved for $v_b = 0$, and $s_c(\tilde{q}_{T-1})$ which is solved for $v_c = 0$.

For case I ($V_T > K$), as shown in Figure 3.1 (i), firms below $s_b$ will adopt in period *T*-1, and those between $s_a(\tilde{q}_{T-1})$ and $s_b$ will wait and adopt in period *T*. As $s_a(\tilde{q}_{T-1})$ is dependent on $\tilde{q}_{T-1}$, we expect that more firms will adopt in the next period as $\tilde{q}_{T-1}$ increases. Firms above $s_a(\tilde{q}_{T-1})$ never adopt the technology. For case II ($V_T < K$), it is proven that there exists a point that $s_a(\hat{q}) = s_b$ at some critical point $\hat{q}$, at which the firm expects that there exist some number of adopters in period *T*-1 such that it will become large enough to compensate for the fixed cost (See Figure 3.1 (ii)). When $\tilde{q}_{T-1} < \hat{q}$, there exists a threshold $s_c(\tilde{q}_{T-1})$ which is solved for $v_c = 0$. Firms between $s_a(\tilde{q}_{T-1})$ and $s_c(\tilde{q}_{T-1})$ will adopt in period *T*-1. Firms above the threshold, $\max\{s_a(\tilde{q}_{T-1}), s_c(\tilde{q}_{T-1})\}$, never adopt because the estimated value for adopting in period *T* is negative ($v_a < 0$), regardless of value of $v_b$. Thus, a firm's decision in the case of $\tilde{q}_{T-1} < \hat{q}$ is only for whether or not adopting. From Figure 3.1 (ii), we can see that there is no area for firms waiting in this period. Either $s_a(\tilde{q}_{T-1})$ or $s_c(\tilde{q}_{T-1})$ is determined by $\tilde{q}_{T-1}$. As $\tilde{q}_{T-1}$ increases until the critical point $\hat{q}$, both $s_a(\tilde{q}_{T-1})$ and $s_c(\tilde{q}_{T-1})$ increase and then more potential adopters will adopt in period *T*-1. Thus the threshold value is $\max\{s_a(\tilde{q}_{T-1}), s_c(\tilde{q}_{T-1})\}$ in the case of $\tilde{q}_{T-1} < \hat{q}$. If $\tilde{q}_{T-1} > \hat{q}$ then it brings this case back to case I. We do not need $s_c(\tilde{q}_{T-1})$ any more to make an adoption decision. Firms between $s_a(\tilde{q}_{T-1})$ and $s_b$ will wait and adopt in period *T*, because they expects that there exist critical number of adopters in period *T*-1 such that it will become large enough to compensate for the fixed cost. Thus, potential adopters expect adopting next period. Firms above $s_a(\tilde{q}_{T-1})$ never adopt the technology.

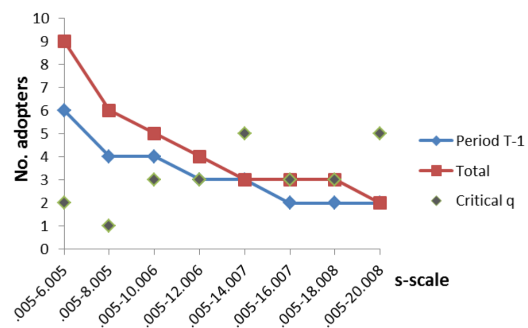
The set of experiments can focus on how the adoption curve of two-period model changes with different parameters. There are at least two important metrics inherent in adoption curve: what fraction of total population joined in both periods put together and what percentage of these were early adopters. These metrics provide coverage and speed of adoption. We can see what happens to adoption curve by the following scenarios: the effect of population characteristic, fixed costs and terminal values, risk aversion index, prior mean, and adoption patterns in the other population.

**The Effect of Population Characteristic**

We consider two cases about the spread of population on the axis of *s*-scale, $[\underline{s}, \overline{s}]$: the effect of population characteristic (a) with different range of population with same $\underline{s}$ and (b) with same range of population with different $\underline{s}$. We first examine the effect on the adoption curve with different ranges of population scale with same $\underline{s}$. All parameter are fixed as followings; $a = 0.5,\ \mu_{T-1} = 3,\ \sigma = 1,\ \delta = 0.2,\ m = 2,\ N = 25$, and $K = 1$. To consider two cases, the terminal values $V_T = 2$ for case I and $V_T = 0.8$ for case II. If firms in a population spreads within a small range of *s*-scale, it means that firms are more willing to take the risk than those in a population within large range of *s*-scale, because they are in less uncertainties. In other words, if the spread of population increases, the number of adopters decreases across periods in both case I ($V_T > K$) and case II ($V_T < K$) (See Figure 3.3.1).



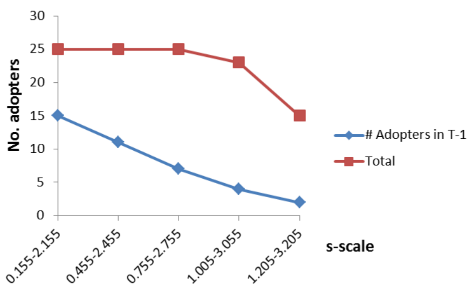

Case I ($K = 1, V_T = 2$)



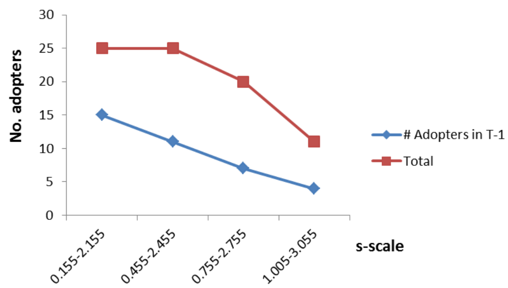

Case II ($K = 1, V_T = 0.8$)

Figure 3.3.1 Effect of Population Characteristic (a) ($a = 0.5,\ \mu_{T-1} = 3,\ \sigma = 1,\ \delta = 0.2,\ m = 2,\ N = 25$)

Second, we test the effect on the adoption curve with a same range of population with different $\underline{s}$. That is, each population group has a different value of $\underline{s}$ and $\overline{s}$, but they all have a same mean of *s*. If a population has a smaller $\underline{s}$ then it has a larger $\overline{s}$. On the contrary, if a population has a larger $\underline{s}$ then the range of scale is smaller because it should have a smaller $\bar{s}$ to have a same mean of *s* in this experiment. From the result in Figure 3.3.2, all firms with low level of uncertainty will finally adopt in a two-period model. But as the mean of uncertainty get larger, total number of adopters decreases as well, in both case I and case II.




Case I ( $K=1, V_T=2$ )




Case II ( $K=1, V_T=0.8$ )

Figure 3.3.2 Effect of Population Characteristic (b) ( $a=0.5,\ \mu_{T-1}=3,\ \sigma=1,\ \delta=0.2,\ m=2,\ N=25$ )

**The Effect of Fixed Costs and Terminal Values**

Second, we test the effects of fixed adoption costs ( $K$ ) and terminal values ( $V_T$ ) in the finite horizon model. From the results of numerical analysis in both Case I and Case II, as adoption costs increase with fixed terminal values, the number of adopters decreases across periods and the number of firms waiting in period *T*-1 also decreases in both two cases. As terminal values gets larger with fixed costs, the number of adopters in period *T*-1 does not change across periods. However the number of firms waiting in period *T*-1 increases in both two cases, then total number of adopters in population increases (See Figure 3.4.1 and Figure 3.4.2).

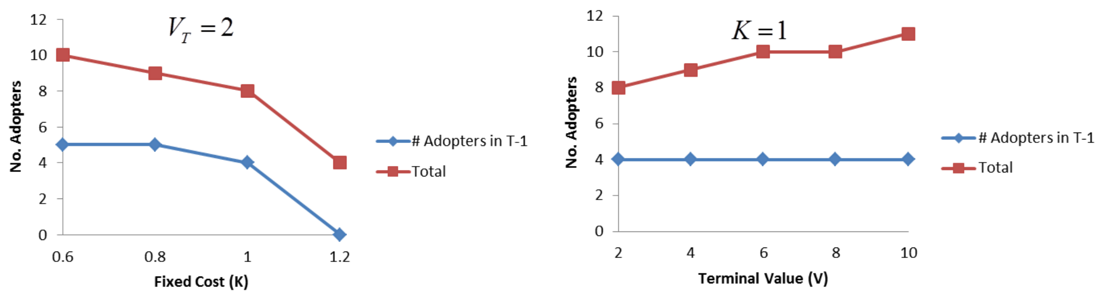



Figure 3.4.1 Effect of Fixed Costs and Terminal Values in Case I ($V_T > K$)
($a = 0.5,\ \mu_{T-1} = 3,\ \sigma = 1,\ \delta = 0.2,\ m = 2,\ N = 25$)

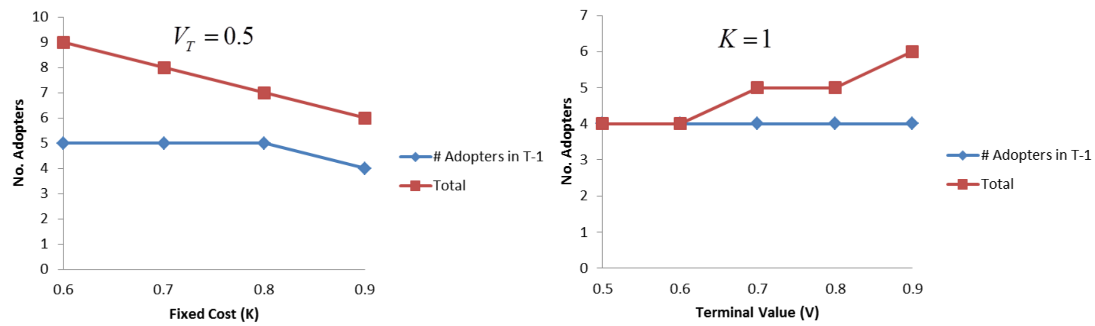



Figure 3.4.2 Effect of Fixed Costs and Terminal Values in Case II ($V_T < K$)
($a = 0.5,\ \mu_{T-1} = 3,\ \sigma = 1,\ \delta = 0.2,\ m = 2,\ N = 25$)

**The Effect of Risk Aversion Index**

Third, we see how different types of risk aversion ($a$) affect the adoption rates of the technology significantly. Firms with lower degree of risk aversion are more optimistic to adopt the technology, while those with higher degree of risk aversion are more pessimistic then they are less willing to adopt or wait. As shown in Figure 3.5, as a risk aversion index increases, the number of firms who waits in this period and will be adopting in next period decreases. Therefore total number of adopters in a population decreases.

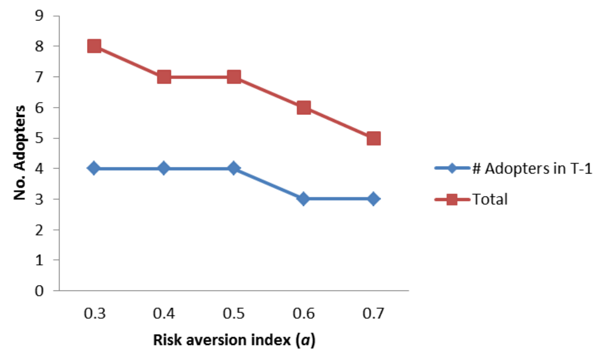



Figure 3.5 Effect of Change of Risk Aversion Index ( $a$ )
( $\mu_{T-1} = 3,\ \sigma = 1,\ K = 1,\ V_T = 2,\ \delta = 0.2,\ m = 2,\ N = 25$ )

## The Effect of Prior Mean

Fourth, we look at the effects of prior mean ( $\mu$ ) about the benefits of adoption. As the mean of prior about the benefits increases, both number of adopters and firms waiting in period $T$-1 increases, and therefore total number of firms waiting also increases as shown in Figure 3.6.

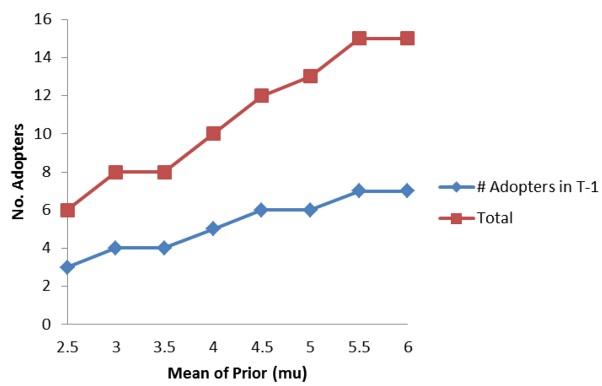
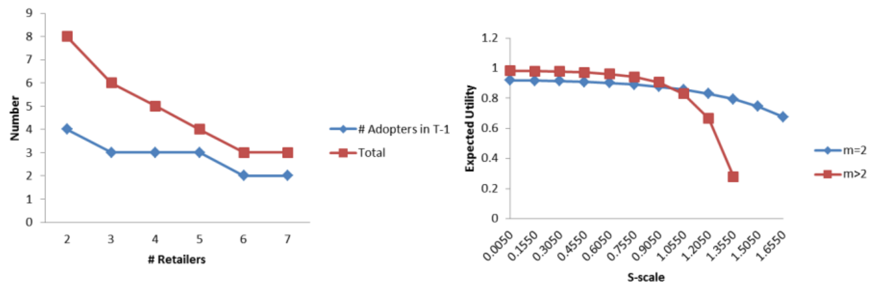



Figure 3.6 Effect of Prior Mean ( $\mu$ ) about the Benefits of Technology Adoption
( $a = 0.5,\ \sigma = 1,\ K = 1,\ V_T = 2,\ \delta = 0.2,\ m = 2,\ N = 25$ )

## The Effect of Adoption Patterns in the Other Population

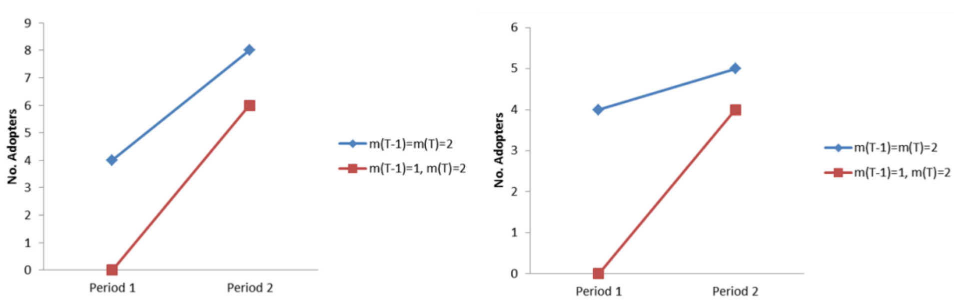
Lastly, I consider the effect of adoption patterns in the other population group – effects of buyers' behavior in the two-level supply chain. This experiment is to test the effects of buyer firms in a two-level supply chain. We consider two scenarios; the effects of number of prior adopters in a buyer population and the adoption speed in a buyer population. First, as the number of adopters in a buyer population increases, both number of adopters and firms waiting in period $T$-1 decreases. This is counter-intuitive. Because we may expect that buyer firms that have adopted stimulate suppliers to adopt the technology, the effects of the number of adopters in a buyer firms intuitively should be positive in the rate of adoption in a supplier population. From changes of supplier's expected utility on the right side in Figure 3.7.1, we see that the supplier's expected utility decreases in values on the axis of the *s*-scale for both two tests; one is the case that there are only two adopters in a buyer population, and the other is the case of at least three adopters in a buyer population. The higher degree of uncertainty the firm has, the less expected utility is. That is, firms with the high level of uncertainty are not affected by the number of buyers who have already adopted in the past. Rather, it is negative to firms with the high level of uncertainty. Intuitively, the buyer's adoption level should be positive to suppliers with low level of uncertainty. Due to less uncertainty about the benefits from the technology adoption, they can identify the coordination benefits of the technology and easily make a decision for adopting it. For suppliers with high level of uncertainty, however, the buyer's adoption level is negative. They are still doubtful about the benefits of technology adoption. As the number of adopter in a buyer population increases, supplier's expected utility values decrease because they might feel pressured for technology adoption significantly due to high level of uncertainty.




Effect on Supplier's Adoption    Changes of Utility Values on Uncertainty Level

Figure 3.7.1 Effect of the Number of Adopters in a Buyer Population
($a = 0.5,\ \mu_{T-1} = 3,\ \sigma = 1,\ K = 1,\ V_T = 2,\ \delta = 0.2,\ N = 25$)

We next examine about what happens if buyers themselves adopt slowly, say some of total buyers adopt at the beginning of period and the rest adopt in period $T$ and suppliers know it. We numerically test this effect with two test groups. One is a group that all buyers have already adopted before of processing the model. The other is a group that some buyers adopt in the next period, which is exogenously determined by our assumption. From the results in Figure 3.7.2, more suppliers adopt in the next period in both test groups in the case that all buyers have adopted at the starting point. We can also see that there is a same number of adopters in the first period for both case I ($V_T > K$) and case II ($V_T < K$), but more suppliers adopt in the next period in both test groups.




Case I ($K = 1, V_T = 2$)    Case II ($K = 1, V_T = 0.8$)

Figure 3.7.2 Effect of the Diffusion Speed in a Buyer Population
($a = 0.5,\ \mu_{T-1} = 3,\ \sigma = 1,\ K = 1,\ V_T = 2,\ \delta = 0.2,\ N = 25$)

### 3.4 Managerial Implications

The population model discussed in the previous section allows us to consider the effect of several strategies observed in practice. We can discuss conditions under which such an action is useful for the firm. First, RFID adoption is characterized in practice by some large retailers (buyers) adopting the technology and then mandating supplier firms to adopt it. For example, in recent years, mandates from major players such as several large retailers and government agencies have required their suppliers to label shipments with RFID tags. In this case, the choice for suppliers has been to make the investment to adopt, or to stop being a supplier to partner. That is, the market power of the mandating entities is such that suppliers overwhelmingly complied with the mandates. But such mandates may stimulate the speedy diffusion of the technology in a supply chain. We can capture this in our model by various combinations of number of buyer and supplier firms that have adopted at time zero or at an early time. We provide insights into what particular combinations and timing of mandated adoption will be more effective in achieving a faster adoption curve.

Second, many firms invest in RFID pilot programs to get a better estimation of the benefit. Small portion of firms are actually in the pilot-testing stage and, interestingly, many firms are researching for the potential of the technology and considering testing the pilot program to reduce uncertainty of the benefits about the technology adoption (Computer Economics 2007). We can simply analyze the effect of pilot testing on the adoption curve by introducing another possible action for the firm; a reduction in the standard deviation of the prior can be obtained at a fixed cost.

At present, adopting RFID technology is costly. The cost of RFID includes the fixed costs and the variable costs. Typically, one-time investment for building IT infrastructure as the fixed costs tend not to vary significantly, while variable costs like tag costs might be very significant for suppliers who should pay for placing RFID tags on products (Gaukler and Seifert (2007)). Actually, installation costs and tag costs have come down over time, and then it will encourage more non-adopted firms no doubt. But they are still high compared to previous technology like barcoding. In practice, suppliers want to negotiate for sharing costs with their trading partners for a return on investment (ROI). Some researchers have already studied about the optimal policies for RFID investment. Gaukler et al. (2006) show that in the absence of mandating entities, there exists a unique optimal way of sharing the cost of tags between a manufacturer and a retailer. Sharing the tag cost is the optimal in the sense that the total supply chain profits are maximized. Whang (2010) proposed that the equal-cost-split arrangement always induces the upstream (suppliers) to adopt RFID earlier than under no cost sharing and the cost split will be able to speed up the retailer's adoption under some conditions. For example, the retailer can share some portion of tag costs with the supplier. In our model, the effects of cost-sharing or decreasing costs on the adoption curve can be examined by changing cost parameter.

**3.5 Further Study**

Our analytical model assumes that each supplier firm in the population is connected to all the buyer firms; in reality the specific nature of the network of linkages between supplier and buyers will influence the adoption curve. In addition, the strength of connections between supplier firms will influence the quantity and quality of information transmission between supplier firms. We collected data about RFID adoptions over a period of five years (2003-2007) and gathered information to build a network of linkages between these firms. Drawing upon the idea of an adoption threshold from our analytical model, we then fit an empirical threshold model to this data. We use this empirical model to test several hypotheses proposed by our analytical model.

# Chapter 4 Diffusion of New Technology and Innovation in Inter-firm Networks: An Empirical Analysis of Information and Knowledge Transfer

## 4.1 Background

Network-based technologies across organizations are significantly changing the way business functions internally and with other organizations (Hart and Saunders 1998) in a network. Such technologies cause changes internally in processes, work routine, and the patterns of interaction among units within organization (Angst et al. 2010; Brynjolfsson and Hitt 2000). Firms who have adopted earlier should persuadably or coercively stimulate others into adopting it in order to gain coordination benefits by network externalities because such technologies cannot be used unilaterally (Hart and Saunders 1998). Therefore potential adopters are largely influenced by prior adopters in a network over time, and the level of influence by prior adopters may be different by relationship among organizations in network and their own organizational factors. Therefore this leads different adoption timing on the diffusion process of technology.

In this cahpter, we consider RFID technology as the object for a diffusion process of network technology in supply chains. Because increasing adoption rates of this technology may be an important issue in some industry. Particularly, some powerful retailers in retail industry have required their suppliers to label shipments with RFID tags by mandates. Many of suppliers may adopt earlier by this mandate, regardless of their own beliefs about benefits, and thus this may lead a speedy adoption rate and diffusion process in the industry. But yet, they have been slow to adopt this technology (RFID Journal 2009). Some industry articles have introduced several reasons of the slow diffusion such that lots of firms have concerns about implementation costs, lack of a standard and uncertain return on investment (ROI) (IDC report, Sep. 2008, Computer Economics 2007). The motivation of our study starts from the following questions; why do firms adopt the technology at different points of time across a population? What are the factors that stimulate the diffusion process of the network-based technologies in a supply chain network?

There has been considerable research for the adoption and diffusion of technologies and innovation in existing research. In the microeconomic view, many prior studies have used threshold models for individuals' adoption decisions to trace the pattern of diffusion in the population, where the individual's decision is determined through information updating process for uncertainty of the new technology (Oren and Schwartz 1988; McCardle 1985; Chatterjee and Eliashberg 1990). Such models assumed that the quality of information coming from others is equivalent across all firms, and thus individuals' adoption timings are different only by their different thresholds for adoption values. In a social system, however, the quality of Information and knowledge from others is largely affected by the structure of a whole network and on the potential adopter's different position in the network (DiMaggio and Powell 1983; Angst et al. 2010). That is, different levels of influence can cause certain potential adopters to find out more or less information than others and to experience a different pressure about the adoption. This heterogeneity, combined with organizational attributes, causes firms to optimally choose to adopt a technology at different times. Consequently, these differences lead the extent of diffusion of the technology in a network.

The diffusion of innovation in the network occurs through learning process by information and knowledge transfer with organizations embedded in the network (Valente 1985). In other words, diffusion can occur through information transmission and knowledge sharing among firms directly or by observing and monitoring others' actions indirectly (Strang and Soule 1998). By these interactions among firms in networks, the firm can gain access to other firms' information and knowledge about new technologies and innovations. In a social network perspective, total social ties creating by these interactions among firms are channels for flows of information and knowledge among firms (Tsai 1998), and then such ties play a role as paths for diffusion process of the new technology. Firms, who have already adopted, act as boundary spanners in networks. They adopt the technology earlier than others and are willing to transfer information and share knowledge with others. On the contrary, potential adopters in a network have relatively lower beliefs about the value of adoption and then tend to delay an adoption of the technology. Over time, they receive information and knowledge about the new technology or innovation from others and their adoption decisions are influenced by others who have already adopted. They also affect the other remaining potential adopters' actions after adopting the technology. Recently, Angst et al. (2010) have studied about the dynamics of the social contagion in the context of diffusion of IT innovation. They argue that social contagion by the diffusion of innovation occurs through information and knowledge transfer, observation, and learning about it among individuals in networks. They found strong effects for social proximity on an organization's likelihood of adoption, and significant regional effects for spatial proximity. Therefore potential adopters are largely influenced by others in a network over time, and the level of influence by prior adopters may be different by their positions in a network as well as by their own organizational factors.

To examine the inter-firm network effects together with firm characteristics on the technology adoption, we first propose a threshold model whereby a firm's adoption decision is influenced by information and knowledge from prior adopters though network ties as well as its own attributes such as size, profitability, risk type, operational performances, and so on. The levels of influence by prior adopters are different by physical and social proximity with them. Using our threshold model, we then empirically test a model by examining which network participants can become aware of information well by prior adopters and how relationships between firms affect the transferability and the quality of information more effectively on the adoption decision.

Our work contributes to the empirical literature on the diffusion of new technology in operations management (OM) area with several key aspects. First, this is one of the first studies to examine the dynamics of the adoption process in the context of technology adoptions in supply chains. Using a panel data set for adoption from 2003 to 2007, we examine the adoption process in the context of RFID adoptions in the retailer industry with time-varying covariates. Second, we examine the effect of physical proximity and social proximity among firms as one of time-varying attributes as well as the firm's own characteristics, while most of prior research about the diffusion process of new technology has mainly focused on the firm's own characteristics as factors that affect the adoption and diffusion. Specifically, to examine the social proximity between firms, we provide the combined level of cooperation and competition between firms over time, which determines transferability and quality of information through ties on a network. Third, from a methodological perspective, we estimate various hazard functions with time-varying covariates. The estimation of such hazard functions falls under the duration analysis. The benefit of using this method is that we can find the institutional factors through a parametric (PH models) and non-parametric (Cox PH models) specification for the relationship between hazard rates and several factors for adoption. Then, to confirm the results from the hazard models, we use the Accelerated Failure Time (AFT) models to examine the relationship between survival times and several factors. Further, the tobit model, which is based on cross-sectional data from the last period for the explanatory variables, is used as a supplement to the results of the duration model above.

This chapter proceeds as follows. In Section 2, we introduce the related theory background and develop hypotheses. In Section 3, we proposed the theoretical framework of a threshold model whereby a firm's adoption decision is influenced by information and knowledge from prior adopters though network ties as well as its own attributes. We discuss the statistical models and the data used to test these models in Section 4, and in Section 5 we present our results. Section 6 provides some concluding comments.

## 4.2 Theoretical Framework and Hypotheses Development

### 4.2.1 The Mechanism of Information and Knowledge Transfer in Networks

The mechanism of how network structures affect information and knowledge transfer in inter-firm networks remains unclear because social ties among firms are combined by both cooperation and competition in a social structure. Instead, several studies pointed out the relationship between competition and knowledge transfer under limited research boundaries. On the one hand, strong competition between units inside an organization restricts the knowledge transfer between them (Szulanski 1996). On the other hand, competition motivates units to interact with each other to pursue common benefit from the synergy of knowledge sharing between them (Tsai 2002). He examined the coordination mechanisms on knowledge sharing in intraorganizational networks embedded by collaborative and competitive ties between units. He presented about the effectiveness of coordination mechanisms on knowledge sharing in intraorganizational networks that consist of both collaborative and competitive ties between organizations. He studied how a multiunit organization can coordinate its units and encourage units to enhance knowledge sharing among competitors. He found that social interaction is more positively associated with knowledge sharing among competitive organizational units than among noncompetitive units. Knoke (1982) and Fligstein (1985) found that the density of adopters is a significant influence on network adoption rates when actors are in close social proximity. Decision makers in potential firms will believe that interactions with close links will decrease uncertainties about the value of new technology and reduce the adoption risks by benchmarking and learning from others.

HYPOTHESIS 1 (H1). *Social proximity positively affects the transferability and quality of information and knowledge though more interactions between firms in networks.*

To measure a social proximity between firms, we consider a level combining with the geographical proximity, industry closeness, and network commonality between firms. It determines the level of transferability and quality of information and knowledge between firms.

Several studies on the transfer of technological information and knowledge has pointed to the importance of geographical proximity and location (Almeida and Kogut 1997, Tallman et al. 2004) as a factor that could affect the efficacy of information and knowledge transfer at the network level. Porter (2001) suggests that firms with a common geographical background share certain knowledge resources that provide competitive advantage to them as a group. Sammarra and Biggiero (2008) describe the importance of geographical proximity and industrial clusters for knowledge transfer in inter-firm networks. Baum et al. (2000) argued that geographical proximity permits more interaction among firms, facilitating formal and informal knowledge transfer, and sharing of activities. The social process of learning and innovation in inter-firm cooperation works well when partners are physically close enough to allow frequent interaction and effective exchange of information (Maskell 2001). Geographically proximate firms will tend to choose each other as partners (Madhavan 2004) and be willing to share information knowledge with each other. Thus they are more likely to cooperate with each other by common factors such as regional factor, common business policy, and cultural closeness. Therefore geographic proximity is positively associated with the strength of tie between firms (Reagans and McEvily 2003) and will affect the ease of information and knowledge transfer.

HYPOTHESIS 2A (H2A). *Geographic proximity positively affects the transferability and quality of information and knowledge though more interactions between firms in networks.*

HYPOTHESIS 2B (H2B). *Geographically proximate firms are more positively associated with likelihood of adoption than geographically remote firms.*

An industry cluster is a group of proximate firms in the same or related industry (Harrison et al. 1996, Storper and Harrison 1991). Porter (1990) pointed out that firms in the cluster have more ability to access to information about the innovation. They are more likely to share information and knowledge with each other and search and monitor with each other to acquire information and knowledge of innovations (Burt 1987, Harrison et al. 1996). Firms in the industry cluster also have more chance to observe others (Burt 1987, Rogers 1995).

As mentioned earlier, network technologies across organizations cause significant impacts to operational process, strategy on the business and the patterns of interaction within organization and/or with others. Swanson (1994) characterizes such technologies as Type III innovations that integrate IT products and services with other business technologies and have huge impacts on the business. This implies that potential adopters facing adoption decision will have uncertainty about the value of technology and managerial risk for failure. Therefore firms in a same industry cluster and a same network group will more closely monitor and evaluate each other’s actions well because of a resource similarity and common background of industry and market. Then firms generate the collective information and knowledge with high quality from the other. In this case, thus, they may tend to mimic other's actions and adopt the innovation intentionally or inadvertently (March 1994). Even though they are strongly competitive each other due to same or similar industry type, social interaction may be more positively associated with information transmission among competitive firms than among noncompetitive firms. Thus, the industry closeness is a positive factor to establish social ties for information and knowledge transfer about the new innovation.

HYPOTHESIS 3A (H3A). *Industry closeness between firms positively affects the transferability and quality of information and knowledge though more interactions between firms in networks.*

HYPOTHESIS 3B (H3B). *Firms in a same industry group are more accessible to higher quality information than those in a different industry group.*

### 4.2.2 Threshold Models in the Technology Adoption

An individual's threshold is the proportion of a group needed to engage in a behavior before the individual is willing to do so (Valente 1995). Existing threshold models generally assume that potential adopters have varying predispositions against adopting the new technology by firm's inherent attributes, and then they will be ready to adopt only if the critical point exceeds this threshold (Oren and Schwartz 1988, Chatterjee and Eliashberg 1990, McCardle 1985, Ulu 2009). Therefore individuals with low thresholds engage in collective behavior before many others do, whereas those with high thresholds do so only after most of the group has engaged in the collective behavior. That is, when the same information reaches organizations, the firm updates its belief after collecting information about the value of technology from previous adopters in a Bayesian fashion. Then, firms with lower thresholds adopt it earlier before those with higher thresholds.

Several studies of diffusion theory introduce some structural concepts on the network (Abrahamson and Fombrun 1994, Burt 1987, Friedkin 1984). A network is the structure of patterns of individuals through any kind of relationships that exist among them in a social system (Burt and Minor 1983). One of them is that the more similar the pattern of linkages binding actors to a network that is the more structurally equivalent the network position of these actors the more intensely they will compete, and the more likely each is to adopt an innovation adopted by its competitor, even if they are not willing to communicate with each other directly (structural equivalence, Burt 1987) under strong competition. This argument is the key of our approach to define the social proximity between firms later. Prior threshold models generally assume that all potential adopters receive the same amount of information about the technology by previous adopters and thus, in terms of information, each potential adopter has the same weight to adopt the technology. In this case, firm's beliefs are primarily driven by its own attributes. All individuals have the relationships between the other and these relationships may be strong or weak, depending on how close the relationship is between the individuals. Therefore the effects of network structure can bring them the different levels of influence and cause them to experience a different pressure.

In earlier, Burt (1973, 1980) presented about information transition in social networks with two key indicators, *cohesion* and *structural equivalence*. Social cohesion has a positive effect on knowledge transfer (Reagans and McEvily 2003). Cohesive contacts that strongly connected to each other are likely to have similar information and so provide redundant information. Cohesion affects the motivations of an individual to transfer knowledge to others and such a willingness to transfer represents cooperative behavior among them. Structural equivalent individuals have the same position in the network, and thus they have identical relations with all others in the network and lead to same sources of information. Thus, structural equivalence model leads the concept of competition between individuals (Burt 1995). Reagans and McEvily (2003) also studied about how network structure influences the knowledge transfer process. They propose that social cohesion affect the motivation of individuals to spend effort in knowledge sharing with others in a network. It can be used to describe how the existing network structure affects the extent of use of the technology.

Based on the arguments above, structural relationship in social networks like ties between organizations largely affects the diffusion process driven by information and knowledge transfer. Different network positions make certain potential adopter to receive more or less information than others, and then firms will adopt the technology at different points of time. Consequently, these differences lead the extent of diffusion of the technology in a network.

The individual firms' thresholds for adoption decision are determined by their own attributes. We consider several organizational attributes to measure the firm's threshold. Angst et al. (2010) examined that size has a positive influence on infectiousness, and there is a significantly related with each other. Miller and Tucker (2009) found that size as a control variable positively influences the EMR adoption in the U.S. Health system. Larger firm size is positively related to the likelihood of adoption for potential adopters. Large size leads to more project-involved employees and more slack to permit failures (March 1981). Dewar and Dutton (1986) also presented that large size firms are more likely to permit more risk-taking, a necessary condition for adoption of radical innovation. It implies that large size firms have lower threshold for adoption than those of small size, assuming that other conditions are same. We use both the number of employees (SIZE) and sales (SALE) as a measure of firm size in this chapter.

HYPOTHESIS 4 (H4). *Firm sizes and sales are positively associated with likelihood of adoption.*

The structure of the firm may also affect the adoption decision of enterprise-wide technology like RFID. A firm with more subsidiaries may be less receptive to the technology. Each subsidiary may make a decision on its own perception and some of them may be less interested in adopting the technology. Conversely, a firm with fewer subsidiaries will be more receptive to the technology. Such a firm will be more inclined to centralize its adoption decision and thus is more likely to adopt earlier than others. For those reasons, we include the number of subsidiaries (BRANCH) in our model as a variable.

HYPOTHESIS 5 (H5). *A firm with the less number of subsidiaries is more positively associated with likelihood of adoption earlier than that with the more number of subsidiaries.*

The profitability of a firm may affect its adoption decision. That is, more profitable firms are more willing to invest in the new technologies or innovations, while less profitable firms are less able to invest. As measures of profitability, we include return on total assets (ROA), liquidity ratio (LIQDT), and solvency ratio (SOLVC) in our model. Return on total assets (ROA) indicates the rate of return earned by management through operations and is determined by total assets. This measure is usually used by investment analysts to assess firm's performance. Liquidity ratio (LIQDT) provides a measure of the firm's ability to meet its short-term financial obligations. Generally, the higher the firm's liquidity ratios are, the larger the margin of safety that the firm possesses to cover short-term debts. Thus a firm with higher liquidity ratio may be more inclined to adopt the new technology. Solvency ratio (SOLVC) provides a measure of the firm's ability to meet its long-term financial obligations. Generally, the lower a firm's solvency ratios are, the greater the probability that the company will default on its debt obligations. Thus, a firm with higher solvency ratio may be more interested in adopting the new technology with a view of long-term.

HYPOTHESIS 6 (H6). *The firm's profitability such as return on tatal assets, liquidity ratio, and solvency ratio is positively associated with the potential adopter's likelihood of adoption.*

We use research and development (R&D) intensity (RISK) as a measure of firm's risk type. It is the ratio of a firm's R&D expenses compared to the firm's sales. R&D intensity reflects the extent to which a firm chooses to develop new processes or products (Miller and Bromiley 1990). It activities often involve a high degree of uncertainty (Robinson 2008), and firm's investments face both technological and market uncertainty (Kamien and Schwartz 1971, Loury 1979). They argued that technological uncertainty results from decision makers' inability to perfectly foresee the connection between R&D expenditures and the actual introduction of a new product or process. Baird (1986) used R&D intensity as a measure of innovation risk, finding that it varied significantly across several risk groups in the industry. Miller and Friesen (1982) equated subjective measures of risk taking and innovation. Their subjective measures of risk taking and innovation correlated very significantly. From our data, firms with high R&D intensity are more likely to tend toward risk taking, and then their levels of risk aversion are low. On the contrary, firms with low R&D intensity have high level of risk aversion. In our test, we include R&D expenditures (RND) and R&D intensity (RISK) as a measure of the firm's risk type in our model.

HYPOTHESIS 7 (H7). *The high type of risk is negatively associated with likelihood of adoption. That is, the firm with low level of risk aversion is more likely to adopt the technology, while the firm with high level of risk aversion is less likely to adopt.*

In supply chains, the ratio of inventory turnover (STOCK) may largely influence the adoption of inventory tracking technology like RFID. The ratio is computed by dividing the cost of goods sold by the average inventory levels held. It measures the speed with which business can sell its average stock level. The higher the ratio is, the shorter the time stock is held awaiting sale. We will see how this ratio affects the timing of RFID adoption.

We include the distance between the firm and its trading partner (GEOPRX) as a measure of physical proximity. We use the geographical distance between the firm and its trading partner as the influence level by powerful partner. For the physical proximity, we measured the distance between firms using zip codes of the firm's headquarter, which is measured by the Euclidian distance between two firms. As mentioned earlier, potential adopter's decision can be by external pressures such as its partner's mandate, which have required their trading partners to adopt the technology. For example, some powerful retailers actually have turned to mandates for speeding up adoption rates in their supply chain networks. In this chapter, we do not measure a partner's mandate directly as a variable due to the restriction of data. Instead, the influence level of a partner is measured by the geographical distance between a supplier and a trading partner (retailer) as the physical proximity. Firms being near its trading partner are more influenced by a partner's policy than those being far away. We will examine how the geographical distance with a trading partner influences its adoption decision.

HYPOTHESIS 8 (H8). *The geographical distance as physical proximity is associated with likelihood of adoption. That is, the firm being more closer with its trading partner is more likely to adopt earlier than others being far away.*

Using these measures above, individual firm's thresholds for adoption at time period t are determined by their own attributes as $\theta\left(\mathrm{X}(t)\right)$, where $\mathrm{X}(t)$ is a set of firm characteristics describing above, considering time-varying covariates.

### 4.2.3 Heterogeneity in the Network Effects

In a social network perspective, social ties are channels for information flows among nodes (Tsai 1998). A firm gains access to other firms' information and knowledge about new technologies and innovations by interactions through social ties in networks. As mentioned earlier, physical or social proximity plays a role in the transmission of information and influence. It is argued that structural relationships such as social ties among organizations affect the rate and extent of influence transmittal (Ahuja 2000). But constructing social network for information and knowledge transfer in the inter-firm relationship is not easy, due to the combined relationship of cooperation and competition between firms. So it is needed to model the strength of social ties using the combined level of factors such as geographic proximity, industry closeness, and network commonality. In this chapter, we define the strength of tie as the quality of information and knowledge between firms.

The strength of ties is computed by each period, and all firms have different values for the strengths of tie. Let $S_{ij}$ denote the strength of tie between firm *i* and firm *j*. $S_{ij}$ is simply defined as a function of the geographic proximity and industry closeness between two firms, $S_{ij} = f\left(GP_{ij}, IC_{ij}\right)$. $GP_{ij}$ is the geographic (physical) proximity between firms and $IC_{ij}$ is the degree of industry closeness between two firms. We assume that these two attributes are independent with each other. $GP_{ij}$ is the actual geographic distances (in miles) between firm *i* and *j*. To control for distributional skewness, if any, we transform geographic distance using a log transformation. Geographical proximity positively influences only the transferability and quality of information and knowledge independently, regardless of industry closeness. Rather, we propose that industry closeness between firms is correlated with the network groups they are located in. Table 4.1 shows the relationship between industry closeness and degree of competition. Industry closeness between firms is determined by the combination between industry relatedness $(IR_{ij})$ and commonality of network group $(NG_{ij})$ they are belonging in. As categorized in the table, the competition is positively associated with the quality of information and knowledge. For example, if they are in the same network group and in the same industry, they are strongly competitive with each other. Due to the properties of network-based technology across organizations, as discussed earlier, they can gain the high quality information and knowledge through direct transfer from the other and/or observing and monitoring the other indirectly. In sum, a close industry cluster between firms and a same network group are positively associated with the quality of information and knowledge.

We define cases of the relationship between industry relatedness and commonality of network group. First, if two firms indexed by *i* (adopter) and *j* (non-adopter) are in a same network group and in a same industry cluster (case I), they are strongly competitive with each other. But firm *i* may transfer information and knowledge to firm *j* directly by strategic alliance between them, or firm *j* can gain high quality information and knowledge through observing and monitoring firm *i* indirectly.

| Industry Relatedness \ Network Commonality | Same | Different |
|---|---|---|
| Different | **Weakly competitive** Information and knowledge with low quality are transferred. | **No competitive** Information and knowledge with lowest quality are transferred. |
| Same | **Strongly competitive** Information and knowledge with high quality are transferred. | **Potentially competitive** Information and knowledge with high quality can be transferred, but it will be limited. |

Table 4.1 The Level of Competition and the Quality of Information

Second, if they are in a same network group and in quite different industry clusters (case II), they are not competitive with each other. Rather, they may be strongly cooperative by alliance for the technology adoption. In this case, firm *i* can willingly transfer information and knowledge to firm *j*. But the quality of information and knowledge will be lower than case I due to different industry backgrounds. Third, if they are in different network groups and in a same industry cluster (case III), they are not competitive with each other directly. But these firms can be potentially competitive in the future because either one might join the network group the other are belonging. Firm *i*'s information and knowledge can be transmitted to firm *j* through direct transfer and/or indirect observations, but it will be limited by different network environments each other. Therefore the quality will be higher than case II but lower than case I. In last, if they are in different network groups and in quite different industry clusters (case IV), they are neither competitive nor cooperative with each other. Even if they strategically form an alliance with each other, information and knowledge transfer is limited due to different network environments and different industry backgrounds. Thus information and knowledge with very low quality will be transferred from the other. Based on four extreme cases above, the quality of information and knowledge for each case can be ranked as Case I > Case III > Case II > Case IV.

We redefine the strength of tie as $S_{ij} = f\left(GP_{ij}, IR_{ij}, NG_{ij}\right)$. To capture the effects of industry relatedness, we use the firm's 4-digit SIC codes as a relatedness measure (Miller 2006, Robins 2003) from our data. $IR_{ij}$ is assigned a four if they are in the same 4-digit SIC codes, as a three if they are in the same 3-digit but the different 4-digit SIC codes, as a two if they are in the same 2-digit but the different 3-digit SIC codes, and as a one if they are in the different 2-digit SIC codes. Finally, we define the strength of tie from firm *i* to *j* as a function below,

$$S_{ij} = \frac{IC_{ij}}{\ln(GP_{ij})} = \frac{IR_{ij} \cdot NG_{ij}}{\ln(GP_{ij})}. \tag{4.1}$$

In this chapter, we assume that all firms are in a same network group, i.e. $NG_{ij} = 1$ for all *i* and *j*.

## 4.3 Models

### 4.3.1 Adoption Condition

In our model, the potential firm's adoption decision is determined by the quality of information and knowledge through social ties connected with adopters who have already adopted together with own threshold. The potential firms face adoption decision at each period, and each firm makes a decision by the updated strengths of all ties linked with firm *j*.

Let $w_{jt}$ denote the strength of all ties linked to firm *j* by period *t*. We assume that each firm has a zero strength of tie at the starting point of process, $w_{j0} = 0$, for all *i* and *j* ($i \neq j$). Over time, total strength of ties coming to firm *j* will be updated by all ties coming from prior adopters by previous period and additional ties coming from new adopters in previous period. We also assume that the firm continuously receives and observes prior adopters' information in each period until the firm adopts. Thus, total strength of ties coming to firm *j* in period *t* is defined as

$$w_{jt} = w_{j,t-1} + \sum_{i \in n_t} S_{ij} \text{, for all } j,$$

where $n_t$ is the set of new adopters at time period *t*. $w_{j,t-1}$ is the strength of ties by period *t*-1, and $\sum_{i \in n_t} S_{ij}$ is the strength of ties produced by new adopters at time period *t*, $n_t$.

Firm *j*'s adoption condition at time period *t* is simply

$$\Pi_{jt} = w_{jt} - \theta_{jt} > 0. \qquad (4.2)$$

That is, the firm adopts when total strength of ties exceeds the firm's threshold. If total strength of ties does not exceed the firm's threshold, the firm will wait and make a decision to adopt it next period again.

### 4.3.2 Statistical Models

We have assumed so far that there is no variation in the valuation of a technology network among firms. In practice, however, this is unlikely to be the case. To take account of such differences among firms, define $\varepsilon_j \equiv \bar{\Pi}_j - \Pi_j$, where $\bar{\Pi}_j$ denotes the mean values of similar firms. Thus as $\varepsilon_j$ is larger, the firm *j*'s likelihood of adoption is lower relatively. Firm *j*'s adoption condition at time period *t* is changed into $\Pi_{jt} = w_{jt} - \theta_{jt} - \varepsilon_j$. Thus the condition of adoption becomes

$$\varepsilon_j < w_{jt} - \theta_{jt}. \qquad (4.3)$$

From the equation (4.3) above, firms with relatively low $\varepsilon$ adopt the technology earlier. The rate of adoption may change over time, depending on how $\varepsilon_j$ is distributed. We define

$$\varepsilon^*(n(t), \mathrm{X}(t), t) \equiv w_j(t; n(t)) - \theta_j(t; \mathrm{X}(t)) . \tag{4.4}$$

$\varepsilon^*(n(t), \mathrm{X}(t), t)$ is the function of the firm with new adopters $n(t)$ and the time-varying covariates $\mathrm{X}(t)$ at time period *t*.

This chapter applies a duration (survival) model to explain patterns of adoption and diffusion of new network-based technology. To examine the determinants of the likelihood and timing of RFID technology adoption, we estimate a survival model using data. The survival model allows us to determine simultaneously the factors that influence both the probability and rate of adoption. This approach views the adoption as the hazard and therefore includes only observations during which these models are not being used by the firm. Survival analysis attempts to answer the following questions; what is the fraction of a population which will wait past a certain time, of those that wait, at what rate will firms adopt or not, and how do particular circumstances or characteristics increase or decrease the adoption rate (hazard rate)?

We assume that $G(\cdot)$ is the cumulative distribution function (cdf) for $\varepsilon_j$ as

$$G(t) = \Pr(T \leq t) ,\ t \geq 0 .$$

That is, $G(t)$ is the probability that the random variable *T* is less than some value *t*. This probability presents the proportion of the population that has adopted before time period *t*. Let $g(t)$ denote the density function by $g(t) = dG(t)/dt$ . Using the probability above, we can specify a survivor function as $S(t) = 1 - G(t) = \Pr(T > t)$ , and this is the proportion of the population that has not yet adopted at time period *t*. Therefore, the hazard rate, the proportion of adopters in some interval $[t, t+1)$ of those who have not yet adopted at the beginning of the period, is $\Pr(t \le T \le t+1 \mid T \ge t)$. In terms of the density and cdf, the hazard function is given by

$$\Pr(t \le T \le t+1 \mid T \ge t) = \frac{\Pr(t \le T \le t+1)}{\Pr(T \ge t)} = \frac{G(t+1) - G(t)}{1 - G(t)} \tag{4.5}$$

When the hazard function is not constant over time, the process exhibits duration dependence (Wooldridge 2001). There exists positive duration dependence at time *t* if the rate $d\lambda(t)/dt > 0$ for all $t > 0$, and then the probability of exiting the initial state increases the longer one is in the initial state. If the derivative is negative, there is negative duration dependence.

Next, we want to model the effects of time-varying covariates on the hazard function. From (5),

$$\lambda(t; n(t), \mathrm{X}(t)) = \frac{g\left[t \mid n(t), \mathrm{X}(t)\right]}{1 - G\left[t \mid n(t), \mathrm{X}(t)\right]},$$

where $g(t \mid \cdot)$ is the density function given $w_j(t-1)$, $n(t)$ and time-varying explanatory variables $\mathrm{X}(t)$. Then the probability that a firm adopts in period *t* (the hazard rate at period *t*) is

$$\frac{G\left[\varepsilon^*(n(t+1), \mathrm{X}(t+1), t+1)\right] - G\left[\varepsilon^*(n(t), \mathrm{X}(t), t)\right]}{1 - G\left[\varepsilon^*(n(t), \mathrm{X}(t), t)\right]} \tag{4.6}$$

where $G[\cdot]$ is the cumulative distribution function for $\varepsilon_j$. The behavior of the hazard rate over time depends both on $G[\cdot]$ and on the rate at which $\varepsilon^*(\cdot)$ increases over time. If $\varepsilon_j$ is normally distributed, then in the early periods when the normal density is an increasing function, the hazard rate tends to increase over time. That is, even if the change in $\varepsilon^*(\cdot)$ is constant over time, firms with less values of $\varepsilon_j$ find it worthwhile to adopt. Since the density of such $\varepsilon_j$ is higher, the hazard rate increases. This tendency is reinforced if $\varepsilon^*(\cdot)$ increases at an increasing rate. The data we collected are based on the early period of RFID adoption, and thus the positive duration dependence can be found in the hazard rate. Such a finding would also be consistent with the standard diffusion curve. Given functions above, we present the hazard function as

$$\lambda(t) = g(t) / \left(1 - G(t)\right) = g(t) / S(t).$$

Furthermore, using that the derivative of $S(t)$ is $-g(t)$, we can this equation above as $\lambda(t) = -d \ln S(t) / dt$.

### 4.3.3 The Hazard Function incorporating Learning Processes

With time-varying covariates, we can express a proportional hazard as

$$\lambda\left[t; n(t), \mathrm{X}(t)\right] = \lambda_0(t)\kappa\left[\mathrm{X}(t)\right]\Theta\left[t; n(t)\right], \tag{4.7}$$

where $\kappa(\cdot)$ is a nonnegative function and $\lambda_0(t) > 0$ is the baseline hazard, which is common to all units in the population. Generally, $\kappa(\cdot)$ is parameterized as $\kappa(\mathrm{X}) = \exp\{\mathrm{X}'\beta\}$, where $\beta$ is a vector of parameters to be estimated[3], and $\mathrm{X}$ describes a set of characteristics of a firm. Function $\Theta$ incorporates the learning effects by information transmission. There are many different parameterizations of the function $\Theta$ in the literature. Karshenas and Stoneman (1993) argue that the behavior of $\Theta$ remains invariant under a wide range of specification; however, the simplest

[3] It should be careful to interpret the estimates of $\beta$: If $\beta > 0$, it implies the positive effect of survival time (adoption lag), or the negative effect of diffusion rate, whereas, If $\beta < 0$, it represents the positive effect of more rapid adoption by the firms.

and most used form is based on the logistic function. In our model, only $n(t)$ is considered in the behavior of the function $\Theta$, and so it may not be required to show the behavior of this function parametrically[4]. Instead, proving $d\Theta / dt > 0$ is needed to proceed by assuming a nonparametric model that the hazard rate should be increasing. Thus, equation (4.7) can be written as

$$\lambda\left[t; \mathrm{X}(t)\right] = \lambda_0(t)\kappa\left[\mathrm{X}(t)\right]\Theta(t).$$

This is a general model that incorporates the learning process as well as explanatory variables. However, it is not possible to separately identify the baseline hazard from the learning process in this equation. From Karshenas and Stoneman (1993), we suggest that the learning process is absorbed into the baseline hazard, and in the empirical work the time dependence of the baseline hazard is tested. In addition, for notational reasons, $n(t)$ is incorporated in $\mathrm{X}(t)$ as a part of observed covariates for measuring the tie strengths to explain the network effect. Finally, the estimated form of a model is simply rewritten by

$$\lambda\left[t; \mathrm{X}(t)\right] = \lambda_0(t)\kappa\left[\mathrm{X}(t)\right]. \tag{4.8}$$

Individual hazard functions differ based on a function $\kappa[\cdot]$ of observed covariates. This heterogeneity causes firms to optimally choose to adopt a technology at different times. We first focus on estimates from a model with time-varying covariates, assuming that the time until adoption conditional on its characteristics has a Weibull distribution. The Weibull distribution is selected because it is consistent with the overall-increasing rate of adoption observed during the

[4] Karshenas and Stoneman (1992) showed different parameterizations of the function $\Theta$ in the literature. In addition, they provided that the hazard rate increases with the elapsed duration from the epidemic hazard function (the probability for a firm that has not adopted by time $t$ to "get informed" about the technology and adopt in the small interval), using the simple logistic curve for the spread of the epidemic (See also Karshenas and Stoneman (1993)).

sample period. Because our data are for the early period of RFID adoption, we would not be surprised to find positive duration dependence in the hazard rate. Let $x_j$ be the vector of observed characteristics for firm *j* and $\beta$ be the coefficients. Then the probability that firm *j* adopts before time period *t* is given by

$$F(x_j'\beta, t, \alpha) = 1 - \exp\left(-\psi(x_j'\beta)t^{\alpha}\right), \tag{4.9}$$

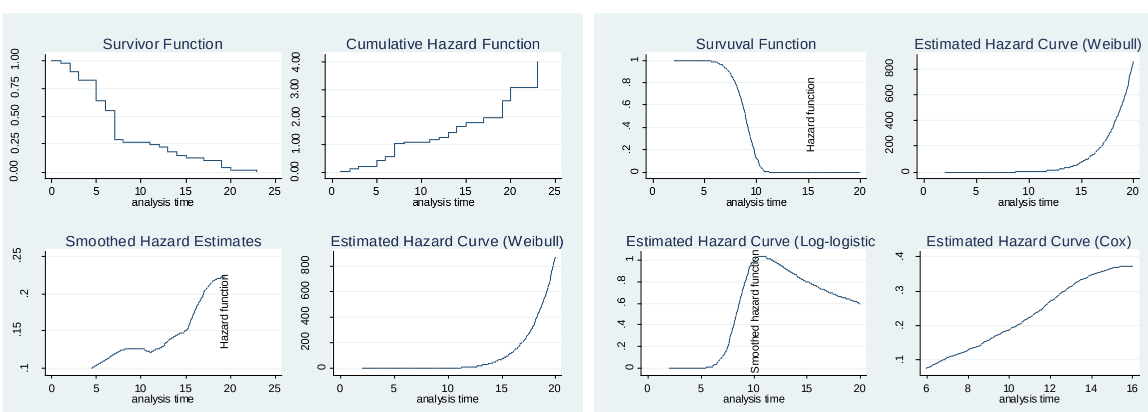
where $\alpha$ is nonnegative parameter. The density is $f(\cdot)$, and then the hazard rate is $\psi(x_j'\beta)\alpha t^{\alpha-1}$ (See Appendix). To make it simple, we assume that $\psi(x_j'\beta)$ can be written by $\exp(x_j'\beta)$. From (4.9), we obtain a proportional hazard model with the baseline hazard $\lambda_0(t) = \alpha t^{\alpha-1}$. The log of the hazard rate is $\ln\alpha + x_j'\beta + (\alpha - 1)\ln t$. The Weibull distribution allows the hazard rate for a given firm to change monotonically over time. That is, if $\alpha > 1$, the hazard rate is monotonically increasing which, as discussed above, indicates the existence of learning process (See Figure 4.1 (i)). If $\alpha < 1$, the hazard is monotonically decreasing. If $\alpha = 1$, the hazard is constant over time.

The Weibull distribution, however, requires that duration dependence should be monotonic either increasing or decreasing. A standard empirical regularity in diffusion studies is an initially increasing then declining hazard rate. Since we collect data on only the beginning stages of the diffusion process for RFID technology, it seems likely that a functional form that allows a monotonically increasing rate will be adequate.

To test the results for sensitivity imposed by the Weibull, we estimate a duration model in which the underlying distribution of adoption timing is assumed to be log-logistic. The log-logistic distribution allows a nonmonotonic hazard rate and allows relative hazard rates to change over time. It approximates a model in which the log of adoption dates is normally distributed. For the log-logistic distribution, the probability that firm *j* has an adoption earlier than *t* (the hazard rate) is given by $\alpha\psi(x_j'\beta)t^{\alpha-1}/\left[1+\psi(x_j'\beta)t^{\alpha}\right]$ (See Appendix). If $\alpha > 1$, the hazard function initially increases until $t' = \left[1/\alpha\psi(x_j'\beta)\right]^{\alpha-1}$ and then decreases to zero over time (See Figure 4.1 (ii)). Otherwise, $\alpha \leq 1$, the hazard function has negative duration dependence. For both distributions, the conditional likelihood for firm *j* can be written by

$$f(x_j'\beta,t,\alpha)^{d_j}\left[1-F(x_j'\beta,t,\alpha)\right]^{1-d_j}, \qquad (4.10)$$

where $d_j$ is an indicator variable equal to one if firm *j* adopts and zero otherwise. The first term is the contribution to the likelihood of a firm observed to adopt at time *t*; the second term is the contribution of a firm failing to adopt prior to time *t*, after which it is no longer observed (censored). By Greene (1997), censoring is a pervasive and usually unavoidable problem in the duration analysis.




(i) Survival Function with Weibull Distribution (ii) Comparison with various distributions

Figure 4.1 Survivor / Hazard Function and Estimated Hazard Curve from Data

## 4.4 Technology and Data

### 4.4.1 Technology

Over the past decade, radio frequency identification (RFID) has been promoted as a technology with the premised benefits in a supply chain. Some industry reports have showed values of RFID benefit with some numerical results. A.T. Kearney (2003) shows that retailers will reduce inventory by 5% and labor costs by 7.5%, and increase sales by 0.07%. A.T. Kearney (2004) also projects that most benefits for manufacturers will increase through better retail execution of the supply chain and replenishment processes from the retailer. That is, a good working relationship with partners is required to achieve these benefits in a supply chain. Some academic papers have also demonstrated the value of RFID with some theoretical analysis. Lee and Özer (2007) have provided an excellent overview of its benefits by three categories, labor cost savings, inventory reduction, and shrinkage and out-of-stock reduction. It is actually not hard to find that RFID can reduce inventory and improve customer service level by better visibility in a supply chain. Atali et al. (2009) quantify the true value of inventory visibility offered by RFID. Gaukler et al. (2007) present the benefits of item-level tag to two partners, one manufacturer and one retailer. Heese (2007) proposed that RFID can eliminate the inventory inaccuracy, and a decentralized supply chain benefits more such that adoption improves supply chain coordination using the cost thresholds that RFID adoption becomes profitable.

But most of studies have considered about the benefits in the individual firm level. In terms of supply chain network, such network technologies cause significant changes internally in processes and the patterns of interaction among units (Angst et al. 2010; Brynjolfsson and Hitt 2000) within firms in networks. Thus Firms who have adopted earlier should persuadably or coercively stimulate their partners into adopting it in order to gain coordination benefits by network externalities because such technologies cannot be used unilaterally (Hart and Saunders 1998). Some powerful organizations have turned to mandates for speeding up adoption rates in their networks. For example, mandates from major players such as several large retailers have required their suppliers to label shipments with RFID tags in recent years. The supplier's choice has been to make the investment, or to stop being a supplier. In this case, many of them may adopt earlier than others by mandate, regardless of their own thresholds, and thus this may lead a speedy adoption rate and diffusion process in the industry. But yet, they have been slow to adopt this technology (RFID Journal 2009). Because many firms have concerns about implementation costs, lack of a standard and uncertain return on investment (ROI) (IDC report, Sep. 2008, Computer Economics 2007). Therefore increasing adoption rates may be an important policy issue in some industry. Particularly, the retail industry is an appealing example of a population that exhibits significant variation in the adoption rate of RFID technology. In this chapter, we consider the adoption and diffusion process in only supplier population, because we assume that there is no effect of adopters in retailer population directly, and in which adoption process determines exogenously.

### 4.4.2 Data

The data was restricted to consumer packaged goods companies with 100 or more employees in the United States. We obtained the firm list on 2-digit US SIC codes selected between 20 and 39 because they correspond to CPG industry (See Table 4.2). We collected the data of firm characteristics throughout the 2003 – 2007 sample period from this database; (1) fixed characteristics such as industry type, number of subsidiaries, and location; and (2) time-varying characteristics such as number of employees, sales, R&D expenses, and financial and operational ratios. All variables have been explained earlier. The Bureau Van Dijk database provides business and financial information of each company, and original documents are made up of company annual reports. Table 4.3 provides the descriptive statistics for our sample, as of 2007. The RFID adoption data come from manual search of all firms since such adoption data is a part of private information of each firm. We have the date (the month and year) of RFID adoption of some firms. This information was obtained from industry journals and articles like RFID Journal and InformationWeek.

We observed that half of firms in the data have never experienced the adoption of RFID technology during the period in which the data are collected (right censored). This implies that the firm will experience the event after the period we observe. In addition, there is no left censoring in this study, i.e. the first instance of adoption is captured. To measure the strength of ties of each firm, we have already shown the detail information in section 4.2.3 about how to compute and update the strength of ties. The strength of ties of each firm is computed every period, and it is accumulated over period. As assumed earlier, a firm continuously receives and observes prior adopters' information in each period until it adopts. A firm faces adoption decision at next period again, and then she will make a decision to adopt by its updated strengths of all ties linked with it.

To examine the determinants of the likelihood and timing of the technology adoption, we estimate various hazard models and the tobit model using sample data. Duration modeling views the adoption as the hazard and therefore includes only observations during which these models are not being used by the firm. The data we use are five years of observations on firms, some of which adopt. Firms failing to adopt in the sample period are censored observations: we know only that they had not yet adopted. The dependent variable in this model is the natural logarithm

| 2-digit SIC Codes | Industry Description | Final (Initial) Sample Size |
|---|---|---|
| 20 | Food and kindred products | 30 (99) |
| 21 | Tobacco products | 3 (8) |
| 23 | Apparel and other finished products made from fabrics | 7 (40) |
| 25 | Furniture and fixtures | 1 (29) |
| 26 | Paper and allied products | 2 (28) |
| 28 | Chemicals and allied products | 36 (110) |
| 30 | Rubber and miscellaneous plastics products | 2 (30) |
| 31 | Leather and leather products | 6 (11) |
| 32 | Stone, clay, glass and concrete products | 1 (5) |
| 34 | Fabricated metal products, except machinery and transportation equipment | 2 (13) |
| 35 | Industrial and commercial machinery and computer equipment | 2 (5) |
| 36 | Electronic and other electrical equipment and components, except computer equipment | 7 (40) |
| 38 | Measuring, analyzing and controlling instruments; photographic, medical and optical goods; watches and clocks | 2 (26) |
| 39 | Miscellaneous manufacturing industries | 6 (23) |
| | Total | 107 |

Table 4.2 Two-digit SIC codes of CPG Companies used in the analysis

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| *TIME1* | 77 | 1.979968 | 0.649428 | 0 | 3.135494 |
| *ADOPT* | 107 | 0.467290 | 0.501277 | 0 | 1 |
| *BRANCH* | 134 | 3.406758 | 1.488302 | 0 | 6.350886 |
| *SIZE* | 134 | 9.054289 | 1.608272 | 5.513429 | 12.12811 |
| *SALE* | 134 | 14.92463 | 1.411896 | 12.3 | 18.1 |
| *RND* | 53 | 12.39057 | 2.056348 | 5.51 | 15.9 |
| *RISK* | 53 | 0.814453 | 0.087375 | 0.44 | 0.97 |
| *STOCK* | 134 | 9.277164 | 4.739680 | 2.07 | 28.65 |
| *LIQDT* | 134 | 1.561791 | 1.116491 | 0 | 7.01 |
| *SOLVC* | 133 | 43.07962 | 24.6299 | -34.14 | 88.05 |
| *ROA* | 134 | 9.387612 | 9.476354 | -26.66 | 44.02 |
| *GEOPRX* | 134 | 6.726012 | 0.556197 | 2.657252 | 7.345834 |
| *TIES* | 133 | 9.483537 | 6.045172 | -1.691452 | 18.10083 |
| *FIRM* | 134 | 52.87313 | 30.15435 | 1 | 107 |

Table 4.3 Sample descriptive statistics for sample CPG companies (data as of 2007)

of the number of periods until adoption occurs. The tobit model, which relies on cross-sectional data from the last period for the explanatory variables, provides a supplement to the results of the hazard model. The dependent variable in the tobit model is the number of periods that the firm had been using the technology. Therefore, the estimated coefficients in the tobit model tell us what variables influence the timing of adoption.

### 4.5 Test and Results

We first test several hypotheses with only the firm's attributes. Table 4.4 shows the estimation results for the parametric hazard function under a Weibull distribution for the hazard rate. These results are based on only the firm's own attributes, except tie strengths as a factor of social proximity. The Weibull imposes a structure on the adoption process that may affect the coefficient estimates.

In Table 4.4, the estimates in the first and second column are clearly robust across these functional forms. The similarity of the Weibull and Cox estimates argues that imposing the additional structure for the Weibull has not substantively affected the estimates. From the results, we found that the R&D intensity (RISK) and the liquidity ratios (LIQDT) are statistically related to early adoption of the technology. As firms invest R&D activities more aggressively, they tend to adopt the new technology sooner. Liquidity ratios indicate a firm's ability to pay off its short-terms debts obligations. The higher the value of this ratio, the larger the margin of safety, and thus it implies that the firm with higher liquidity ratios is willing to invest the new technology more easily than others. The model indicates that both variables are negatively related to the probability of not adopting the technology through the sample period. The firm sizes (number of employees) (SIZES) and sales (SALE) are also positively related with an early adoption (H4).

That is, firms with large size of sales tended to adopt the technology sooner. The number of subsidiaries (BRANCH) shows a positive coefficient (i.e. a negative effect on adoption decision) (H5). This implies that firms with more subsidiaries tended to delay an adoption, because some subsidiaries may have own business and responsibility for adoption decision. Each subsidiary may make a decision on its own perception and then there may have difficulty for centralizing with many subsidiaries. Conversely, a firm with fewer subsidiaries will be more receptive to the technology. Such a firm will be more inclined to centralize its adoption decision and thus is more likely to adopt earlier than others.

Table 4.4 presents the empirical evidence for a network effect, the physical and social proximity among firms, on adoption rates with parametric hazard function under a Weibull and Cox model for the hazard rate. From the results, the social proximity (TIES) is strongly related to early adoption of the technology (H1). As noted earlier, such network technology across organizations causes significant impacts to operational process, strategy on the business and the patterns of interaction within organization. Therefore firms tend to mimic others' actions and adopt the innovation intentionally or inadvertently (March 1994). That is, even though they are purely competitive each other, transfer of information and knowledge may occur regardless of geographical distance. As results show, the geographic proximity (GEOPRX) is not significantly related with adoption.

We estimated the models so far used a parametric (PH model) and non-parametric (Cox PH model) specification for the relationship between hazard rates and firm characteristics, considering social proximity between firms. Table 4.4 shows that the estimates in the first and second column are close each other, and so the results are robust across these functional forms.

The first column presents the estimates of a parametric hazard model, and it shows that some explainable variables are significant for hazard rates, whereas a non-parametric hazard model does not show significant results for hazard rates.

| | **Weibull** | **Cox-PH** |
|---|---|---|
| *BRANCH* | 0.447 | 0.377 |
| | (1.17) | (1.01) |
| *SIZE* | -1.183 | -1.043 |
| | (-1.28) | (-1.04) |
| *SALE* | -0.570 | 0.0737 |
| | (-0.62) | (0.02) |
| *RND* | 1.372 | 0.624 |
| | (1.53) | (0.14) |
| *RISK* | -23.76 | -9.397 |
| | (-1.51) | (-0.13) |
| *STOCK* | 0.0224 | 0.00921 |
| | (0.18) | (0.07) |
| *LIQDT* | -0.978* | -0.589 |
| | (-2.08) | (-1.03) |
| *SOLVC* | 0.00938 | -0.00213 |
| | (0.62) | (-0.11) |
| *ROA* | 0.0397 | 0.0270 |
| | (0.83) | (0.50) |
| *GEOPRX* | 2.150 | 1.269 |
| | (1.58) | (1.02) |

t statistics in parentheses
+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Table 4.4 Comparison of Estimates of the Length of Time to Adoption of RFID (Weibull Model and No Restriction on the Shape of the Baseline Hazard)

Next, confirming the results from the hazard models above, we estimate the AFT (Accelerated Failure Time) models to examine the relationship between survival times and firm characteristics. These results show that the estimates in the third and fourth column are also close each other, and so the results are robust across these functional forms. The third column in Table 4.5 presents the AFT representation of Weibull estimation results for the relationship between survival times and firm characteristics, with considering the physical and social proximity. The fourth column in Table 4.5 shows the Log-logistic estimation results. The negative values of the AFT coefficients represent the negative association with the survival times, which can be interpreted as the positive relationship with the hazard rates. These results are also consistent with the PH models and Cox PH models above. As shown on both results, the Log-logistic estimates are similar to those derived from the Weibull model. Apparently, the time invariance of relative probabilities imposed by the Weibull has not adversely affected the coefficient estimates. The estimate for the Log-logistic implies that a hazard rate increases initially. Although this functional form implies that the hazard will decrease as *t* gets large, the hazard is increasing at mean values throughout sample periods. This suggests that a monotonic Weibull hazard is an adequate characterization of the time path of adoption over sample periods.

| | **WEIBULL (PH)** | **COX-PH** | **WEIBULL (AFP)** | **LOG-LOGISTIC (AFP)** |
|---|---|---|---|---|
| *BRANCH* | 0.633+ | 0.210 | -0.0652+ | -0.0764* |
| | (1.68) | (0.52) | (-1.77) | (-2.04) |
| *SIZE* | -2.611* | -1.169 | 0.269** | 0.316** |
| | (-2.57) | (-0.96) | (2.80) | (3.02) |
| *SALE* | 0.188 | 0.904 | -0.0194 | -0.0954 |
| | (0.21) | (0.20) | (-0.21) | (-0.98) |
| *RND* | 2.292** | 0.455 | -0.236** | -0.210** |
| | (2.62) | (0.10) | (-3.10) | (-2.71) |
| *RISK* | -46.14** | -13.79 | 4.755*** | 4.418** |
| | (-2.84) | (-0.18) | (3.56) | (3.17) |
| *STOCK* | -0.205 | -0.173 | 0.0212+ | 0.0226+ |
| | (-1.55) | (-1.06) | (1.72) | (1.74) |
| *LIQDT* | -1.454* | -0.705 | 0.150** | 0.129* |
| | (-2.50) | (-1.03) | (2.86) | (2.54) |
| *SOLVC* | -0.00547 | -0.00283 | 0.000564 | -0.0000581 |
| | (-0.32) | (-0.13) | (0.32) | (-0.03) |
| *ROA* | 0.0690 | 0.0472 | -0.00711 | -0.00490 |
| | (1.39) | (0.80) | (-1.46) | (-0.96) |
| *GEOPRX* | 2.493+ | 1.650 | -0.257* | -0.163 |
| | (1.85) | (1.20) | (-2.10) | (-1.56) |
| *TIES* | -1.107*** | -1.226* | 0.114*** | 0.122*** |
| | (-4.23) | (-2.36) | (11.52) | (12.33) |

t statistics in parentheses
+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Table 4.5 Comparison of Estimates of the Length of Time to Adoption of RFID with the Physical and Social Proximity

In summarize, Table 4.5 shows that all estimates are presented along with the results from duration models that allows the underlying hazard to have a Weibull, a log-logistic distribution and a nonparametric (Cox PH) likelihood with no restriction on the shape of the hazard. The results are robust across these functional forms. The estimate of $\gamma$ for the log-logistic represents that a hazard rate increases initially. This implies that the monotonic Weibull hazard function is appropriate on the diffusion process over the sample period.

The tobit model, which is based on cross-sectional data from 2007 as the last period in our sample for the explanatory variables, provides a supplement to the results of the duration model. The dependent variable is the number of periods that the firm had been using RFID technology as of 2007. The estimated coefficients in the tobit model tell us what variables influence an early adoption. Table 4.6 shows the results using this model. Surprisingly, we found that social proximity has a negative relationship for early adoption very significantly. This implies that many potential adopters' adoption decisions were largely influenced by information coming through ties linked with prior adopters over time. In other words, they are willing to wait and adopt the technology after receiving information from others in order to reduce the risk that can be occurred by adopting the technology. Sales and R&D intensity are positively related to the early adoption very significantly as hazard models indicates.

Further, firm size and the number of subsidiaries do not directly appear to be significantly related to the early adoption. Although these two variables are not directly related with an early adoption, it will be influenced indirectly through the parameter that corrects for possible bias.

| | WEIBULL (PH) | WEIBULL (AFP) | TOBIT |
|---|---|---|---|
| *BRANCH* | 0.633+ | -0.0652+ | 0.0847 |
| | (1.68) | (-1.77) | (0.69) |
| *SIZE* | -2.611* | 0.269** | 0.142 |
| | (-2.57) | (2.80) | (0.56) |
| *SALE* | 0.188 | -0.0194 | 1.216*** |
| | (0.21) | (-0.21) | (5.38) |
| *RND* | 2.292** | -0.236** | -1.752*** |
| | (2.62) | (-3.10) | (-6.51) |
| *RISK* | -46.14** | 4.755*** | 25.71*** |
| | (-2.84) | (3.56) | (5.94) |
| *STOCK* | -0.205 | 0.0212+ | -0.407 |
| | (-1.55) | (1.72) | (-0.16) |
| *LIQDT* | -1.454* | 0.150** | -7.583 |
| | (-2.50) | (2.86) | (-0.63) |
| *SOLVC* | -0.00547 | 0.000564 | 0.130 |
| | (-0.32) | (0.32) | (0.27) |
| *ROA* | 0.0690 | -0.00711 | 1.279 |
| | (1.39) | (-1.46) | (0.95) |
| *GEOPRX* | 2.493+ | -0.257* | 0.299 |
| | (1.85) | (-2.10) | (1.00) |
| *TIES* | -1.107*** | 0.114*** | -1.354*** |
| | (-4.23) | (11.52) | (-31.77) |

t statistics in parentheses
+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Table 4.6 Comparison of Estimates of the Hazard Models and Tobit Model

## 4.6 Discussions and Further Research

In this chapter, we first propose the theoretical framework of statistical model and test a diffusion model of technology adoption in supply chain networks. Specifically, we examine the characteristics of the early adopters of RFID technology using statistical models. We find that firms with more subsidiaries and lower type of risk adopt RFID earlier than others. The healthy financial structure is also positively related with the adoption of technology. The main finding is that the social proximity plays a critical role in the adoption of technology. That is, a firm can gain access to other firms' information and knowledge about new technologies by interactions through social ties in networks. It is argued that structural relationships such as social ties among firms affect the rate and extent of adoption and diffusion. Although firm size did not directly influence diffusion in the way we expected, it appears to have done so indirectly, through the parameter that corrects for possible bias. Geographic proximity is not directly related with the adoption by itself, but social proximity includes its concept indirectly.

There have several limitations of the research that are available for extension from this study. In our empirical study, first, we use the data set from CPG industry to collect firm's time-varying attributes during the sample period. But many firms that we are interested in are not available to collect data during sample periods due to missing data or not-opened publicly. However, we found that the test results are consistent, providing that the findings are robust. The second is an issue for firm's governance. We only observed the data of headquarter of each firm because it was hard to search and collect the adoption data of each subsidiaries. Most of firms have publicly announced about adoption of RFID technology at parent firm level, so we assume that adoption decision is only from a main headquarter, not any subsidiary firm. However, because some subsidiaries may have own business and responsibility for adoption decision, we would suggest that investigating firm's governance and differentiating adoption decision by each subsidiaries would be taken into consideration in the further study. Third, differentiation between pilot project and full adoption would be required. As mentioned earlier, RFID technology is still on the beginning stage of diffusion process in the industry. Some firms have adopted it as a pilot project to test on sites, while some firms have fully adopted it willingly or by mandates. We could not observe exactly whether firms who have partly adopted as a pilot is still using it or not over time periods. Although this problem has not been considered in our study, there are significant challenges associated with a duration (survival) model that would take into account some factors influencing continuity of technology. Lastly, although we considered the social proximity between firms as measuring strength of ties using several factors, our theoretical stance naturally precluded other potential factors and we could not truly measure a dyadic relationship between firms. Network structure consists of dyadic relationships between suppliers in a network of suppliers, such as how a firm works with other supplier and how tightly or loosely coordinated its relationships are. There may have many potential factors to affect such a dyadic relationship between firms as well as the level of competition and cooperation we used. In spite of this reason, however, our results show that social proximity between firms is significantly related with information transfer and knowledge sharing, and then this leads the likelihood of adoption for each firm.

We finally introduce several interesting problems related to the technology adoption that we do not address here. One set of problems is, what are the mechanisms of network structure that affect the diffusion of new technology? That is, how existing social network structures and potential adopters' positions in a network influence the diffusion of innovation by determining which network participants can become aware of information about the technology and adopt it. Furthermore, one can do experimental studies about the following research problems; does the strength of a core network affect the potential adopter's diffusion of technology in a periphery network? And if so, what are the factors of network structure that stimulate the diffusion process? One can study how it generalizes to diffusion across different types of potential adopters, in different types of network structures, and with different types of diffusion processes (both diffusion by cohesion and by structural equivalence). Different types of core network structures can be provided and then one can examine how the pattern of diffusion changes by each type of core network structures. Different network structures and different positions make certain potential adopter to receive more or less information than others, and then potential adopters have different points of timing to adopt. These differences lead the extent of diffusion process in a network.

# Chapter 5 Inter-organizational Relationship Factors in the Technology Diffusion

## 5.1 Theoretical Background

This chapter explores inter-organizational relationship factors to predict the adoption and diffusion of RFID technology in a two-level supply chain. Specifically, this chapter considers two factors available in practice between firms in a two-level supply chain; the dependence on the other (the supplier's dependence level on a buyer) and the openness for information sharing (the supplier's openness level). Based on these interactions in the network, we will see how a firm decides to adopt the technology in a two-level supply chain by the threshold model and then analyze how the technology diffuses in the network by aggregating dynamics from individual firms' decision models. I will examine the best approach that a buyer (retailer) should use with its suppliers to encourage adoption of RFID technology when the buyer can coercively or passively encourage trading partner adoption. The model will include factors associated with the perceived level of dependence on the trading partner and openness with other firms in the relationship. Furthermore, this chapter introduces four different types of suppliers facing the adoption decision under the retailer with a bargaining power. These types are classified by two factors in inter-firm relations: the degree of dependence on retailers and the degree of openness for knowledge sharing with other suppliers. Using numerical analysis, I provide some managerial insights to powerful retailers who want to identify what conditions a buyer should use positive incentives versus negative threats to persuade suppliers to adopt RFID.

We first model the supplier's benefit-cost structure of each firm. The structure of benefits includes the stand-alone and network-based benefits. We consider the supplier's beliefs about the benefits from adoption as a part of the stand-alone benefits. Potential adopters update their beliefs about the potential of the technology by the observed outcomes through information collected from others in network. By these information flows, they update their perceptions of the technology, and then the uncertainties about new technology might be reduced over time. As mentioned by Mansfield (1968) earlier, one of the implications of the epidemic model is that as more of competitors adopt, the remaining potential adopters are able to get a more informed view of the new technology. Firms can gather information about the potential of the technology by observing changes of the performance of the adopters who have already adopted, even though the extent of the inter-firm information sharing may depend upon the competitive structure in the industry (Tsai 2002, Reagans and McEvily 2003). In fact, lots of information about the technology can be from the external sources, the technology suppliers, consulting services, trading partners and so on. But in this chapter, we consider only the costless information by observing the previous adopters who have already adopted in a population. Firm's benefits from the technology adoption depend *directly* on the network size, which is defined by the number of trading partners in the network. The cumulative number of previous adopters in a same population by any given time will *indirectly* affect the decision whether or not adopt it by network effects, that is, the total amount of information about the benefits from the adoption is determined from the integral under the adoption curve of a same population.

In the firm's benefit structure, we consider the inter-firm power as a factor of interaction between firms in supply chain networks. The power is defined as the ability of one firm (the source) to influence the intentions and actions of another firm (the target) (Emerson 1962). It plays a critical role in the supplier-buyer relationships (Benton and Maloni 2005), and it also can be defined as the dependence on the other. That is, suppliers with high level of power are less dependent on the buyers. Given that power may influence the inter-firm relationships, it may affect the technology adoption in a two-level supply chain network significantly. Therefore, we define the network size as a combination of two components; the number of partners who have already adopted and the level of dependence in the inter-firm relationship.

Based on the benefit-cost structure, we derive the threshold model for the adoption in which individual's threshold levels are determined by the myopic decision rule from an updating process of the beliefs about the benefits by any given time. Individual thresholds explain the micro-level process through which aggregated individual decisions make up the critical mass in a system. Firm's threshold levels at any given time are defined from the amount of information collected from the previous adopters in a population. Therefore all potential adopters do not decide to adopt at a same time because the critical level to elicit adoption is not a unique value appropriate to all members across population at any time period. That is, the critical value is distributed heterogeneously across a population according to some density function. We then model the aggregating dynamics for the distribution of the individuals' threshold levels in a population to see how the technology adoption in the network diffuses over time and to know when the critical point of time is on the diffusion process of network technologies.

Our contribution is that we study the adoption model and diffusion process of new technology considering network effects in a two-level supply chain consisting of heterogeneous individual firms for the benefits of adoption. We also consider the adoption model with all possible relationships among them on the network; the level of dependence with partners in the other group and the level of openness within the same group. Based on these interactions in the network, we study how a firm decides to adopt the technology in a two-level supply chain using the threshold model derived by the benefit-cost structure. We then analyze how the technology diffuses in the network by aggregating dynamics from individual firms' decision models. In addition, we examine which factors influence the adoption rate of new technology in the network and suggest some policies contributing to increase the diffusion speed of the technology in a two-level supply chain. Furthermore, we consider four different types of manufacturers facing the adoption under the powerful retailer. These types are classified by the degree of dependence on retailers and the degree of openness for knowledge sharing with other suppliers. Using the numerical results based on our model, we provide the insights for powerful retailers who want to improve the adoption rates of their trading partners (suppliers) with different types.

## 5.2 Models

We consider a two-level supply chain network with two population groups, $N$ retailers and $M$ manufacturers. We assume that retailer's adoption processes are commonly known, and we consider only manufacturer's problem in this chapter. We assume that all firms in a population are identical in size. Firms in each population may have different benefits and costs from an adoption based on their network sizes. Individual firm's network size is defined by the number of trading partners in the other population group. That is, one retailer (manufacturers) may have more or less manufacturers (retailers) than other retailers (manufacturers) at any given time.

### 5.2.1 The Supplier's Benefits and Costs

As we have already defined it earlier, the benefits from an adoption come from two sources: internal benefits and coordination benefits from trading partners. Each firm's benefits are determined by the prior beliefs about the benefits from an adoption and her own network size. It is usually considered that larger network size yields greater returns by network externalities (Emerson (1962)). In our model, the firm's network size is defined by the combination of the firm's power level and the number of linked users on the other side. Only network size at the date of adoption is considered and the size may change over time in such a way that the whole benefit distribution not only shifts but also changes shape of distribution.

The manufacturer $j$ 's network size is $Q_j(t) = w_j n_{jt}$ where $w_j$ is the manufacturer $j$ 's fraction of his power level, which is defined as the ability of one firm to affect the intentions and actions of firms on the other side. $n_{jt}$ is the number of retailers who have adopted by time $t$ and linked with manufacturer $j$ , $j = 1,...,M$ . We assume that manufacturer $j$ 's fraction for power is known but differ across firms by $(0,1]$ and can be explained by the dependence on the manufacturer group. $m_{it}$ and $n_{jt}$ are commonly known to all firms at the beginning of each period. The manufacturer's benefits depend upon their network size and belief about benefits from an adoption. The manufacturer $j$ 's benefit function is given by below.

$$B_j(t) = \prod_M (t, Q_j(t), \mu_{jt}) = Q_j(t)\mu_{jt}, \quad j = 1,...,M . \tag{5.1}$$

$\mu_{jt}$ represents the manufacturer $j$ 's beliefs about unknown benefits at time period $t$ . Manufacturer $j$ 's belief will be updated by information flow over time. We assume that the manufacturer's benefits from adoption are normally distributed with unknown mean $\mu(> 0)$ and variance $\sigma^2$ , which is independent and identically distributed among manufacturers and time periods.

We provide the simple cost structure, which consists of two components: fixed costs and variable costs. The fixed costs are incurred once at the time of installation on both retailers and manufacturers. There is no variable cost for retailers and only manufacturer charges variable costs for tags continuously. We define that the cost variables as $c_f$ is the fixed costs of the manufacturer, and $c_v$ is the variable costs of the manufacturer. We assume that there is no any discount rate, so the adoption costs are same at every period across all manufacturers. In general, discounting factor might significantly affect the benefit-cost structure, but it would distract from our main analysis because we focus on aggregate dynamics based on the individual firms' myopic adoption decision of the new technology at any given time[5]. The manufacturer's costs are defined as

$$C_j(t) = c_f + n_{jt} c_v , \tag{5.2}$$

where $n_{jt}$ is the number of retailers who have connected with a manufacturer $j$ and already adopted by time $t$. The adoption costs, $c_f$, are also same at every time period across all manufacturers, whereas they all may have different variable costs for tags by different size of network $n_{jt}$, which is the number of their partners (retailers).[6] For simplicity, we assume that firms adopt it once and they do not switch back to the old system within the time frame of the analysis. Firms are not allowed to make change their decisions. This is a reasonable assumption for many technology markets under consideration, particularly when the goods, in general, are durable and switching costs are relatively high.

### 5.2.2 The Decision Rule

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[5] If we focus on the long-term decision about the technology adoption, we need to construct the decision model considering net present value, the discount rate and return on investment. But, in this chapter, we ignore the discount rate because we study the individuals' myopic decision models at any given time and also focus on the impacts of the perception updated from information and the network size on firms' decisions.

[6] In general, the number of items or pallets should be considered for the tag costs, but only the number of linked retailers is considered because we have already assumed that all retailers are identical in size. If this assumption is relaxed, the problem will get more complicated because all firms have different produced items at different times.

In this section, we suggest the adoption decision rule for the manufacturer, based on the benefit and cost structure provided from previous sections. At any given time $t$, a manufacturer will have seen prior outcomes from other firms in the same population. In a continuous time phase, the total prior outcomes by time $t$ are measured by the cumulative amount of information generated by all prior adopters. Let $p(t)$ be the proportion of adopters at time $t$, and set that $p(0)=0$. We can simply define the cumulative amount of information generated by all prior adopters by time $t$ which is given by the integral under the adoption curve, namely,

$$q(t)=\int_0^t p(s)ds. \tag{5.3}$$

To make a decision rule, suppose that each manufacturer has a prior belief about the benefits with unknown mean $\mu$ and unknown precision $\rho\,(=1/\sigma^2)$. For each value of $\rho$, the conditional distribution of $\mu$ is normally distributed with mean $\mu_{j0}$ and precision $\rho\tau_j$ (DeGroot (1970)). Low values of $\mu_{j0}$ mean pessimism about the benefits from the adoption and low values of $\rho\tau_j$ reflect flexibility in beliefs. At starting point of the process, if manufacturer $j$'s benefits are initially larger than the costs, he will want to adopt. Otherwise, he will not adopt and update the beliefs about the benefits by information flow. In other words, manufacturer $j$ updates the perception of the technology and the uncertainties about it are reduced over time.

We consider the manufacturer's decision rule. Assuming that the manufacturer is equally likely to see any outcome from retailers who have already adopted it, manufacturer's information flow can be modeled by followings. Let $\tilde{M}_{jt}$ be the number of manufacturer $j$'s observations by time $t$, and the expected number of manufacturer $j$'s observations by time $t$ is

$$E[\tilde{M}_{jt}] = \alpha_j q(t), \tag{5.4}$$

where the parameter $\alpha_j$ represents the degree of openness which is the willingness to share information in a same population (among manufacturers). $q(t) = \int_0^t p(s)ds$ is the integral under the adoption curve, which means the cumulative information collected from all previous manufacturers who have already adopted by time $t$. That is, all manufacturers may have different weights of $\alpha_j$ and will have different amount of information by their different degree of openness for information and knowledge sharing.

Let $I_{jt}$ be the realization of $\tilde{M}_{jt}$ and $\bar{m}_{jt}$ be the mean of the benefits among $I_{jt}$ observations at time $t$. We assume that $\bar{m}_{jt}$ is normally distributed with mean $\mu$ and variance $\sigma^2 / I_{jt}$. We use the normal-normal updating process. Manufacturer $j$ 's posterior estimate of the mean benefits, $\mu_{jt}$, can be defined as the weighted average of the prior and the observed mean (DeGroot (1970)), namely,

$$\mu_{jt} = \frac{I_{jt}\bar{m}_{jt} + \tau_j \mu_{j0}}{I_{jt} + \tau_j}. \tag{5.5}$$

Manufacturer $j$ 's benefits from an adoption at period $t$ is,

$$\prod_M (t, Q_j(t), \mu_{jt}) = w_j n_{jt} \cdot \frac{I_{jt}\bar{m}_{jt} + \tau_j \mu_{j0}}{I_{jt} + \tau_j}.$$

If manufacturer $j$ is myopic, then he will adopt when the benefits are at least equal to the fixed adoption costs $c_f$, which is, $w_j n_{jt}\left(I_{jt}\bar{m}_{jt}+\tau_j\mu_{j0}\right)\geq\left(c_f+n_{jt}c_v\right)\left(I_{jt}+\tau_j\right)$. Again,

$$\left(w_j n_{jt}\bar{m}_{jt}-c_f-n_{jt}c_v\right)I_{jt}\geq\left(c_f+n_{jt}c_v-w_j n_{jt}\mu_{j0}\right)\tau_j\,. \tag{5.6}$$

Suppose that $\bar{m}_{jt}$ follows the standard normal distribution with mean 0 and standard deviation 1, so we can rewrite it as

$$\bar{m}_{jt}=\mu+\frac{\sigma}{\sqrt{I_{jt}}}z_{jt}\,. \tag{5.7}$$

For manufacturer $j$ 's decision, we consider the population of retailers who have already adopted by time $t$. We have already defined $I_{jt}=\alpha_j q(t)$, thus rearranging this inequality,

$$q(t)\geq\frac{\left(\left(c_f+n_{jt}c_v\right)-w_j n_{jt}\mu_{j0}\right)\tau_j}{\alpha_j\left(w_j n_{jt}\mu-\left(c_f+n_{jt}c_v\right)\right)}-\frac{w_j n_{jt}\sigma\sqrt{q(t)}}{\sqrt{\alpha_j}\left(w_j n_{jt}\mu-\left(c_f+n_{jt}c_v\right)\right)}z_{jt} \tag{5.8}$$

We define manufacturer $j$ 's threshold level of the amount of information at time $t$, $r_{jt}$, to be the first term of the right-hand side of this inequality as,

$$r_{jt}=\frac{\left((c_f+n_{jt}c_v)-w_j n_{jt}\mu_{j0}\right)\tau_j}{\alpha_j\left(w_j n_{jt}\mu-(c_f+n_{jt}c_v)\right)}. \tag{5.9}$$

From (5.9), manufacturer $j$ adopts as $q(t)$ passes the marginal information level $r_{jt}$. We observe that firms with high threshold values are pessimistic about the technology: low initial belief for the technology or small number of previous adopters (large values of

$(c_f + n_{jt}c_v) - w_j n_{jt}\mu_{j0}$), high level of uncertainty (large $\tau_j$), low marginal profits (low values of $w_j n_{jt}\mu - (c_f + n_{jt}c_v)$), and relatively uninformed knowledge from previous adopters (low $\alpha_j$).

### 5.2.3 Aggregating Dynamics

We consider the adoption process in which firms adopt when they see positive outcomes from the information among previous adopters. We first model it in discrete time and a large population, but the population size is finite ($N$ retailers and $M$ manufacturers). In the previous section, we have developed the myopic decision rule from the updating process of individual's belief about the benefits by normal-normal updating. We could define the individual firm's marginal information levels for adopting the technology, which is called by the threshold levels.

Let $\phi(q)$ be the probability that the firm is ready to adopt the technology, given that the cumulated information collected by the prior adopters is $q$. In other words, this is the probability that a firm's information thresholds have been exceeded by the total amount of information from the previous adopters. It can be written as $\phi(q) = \Pr(r \le q)$.

We look at the manufacturer's dynamics. We suppose that manufacturer $j$'s number of observations, $I_{jt}$, is Poisson distributed with mean $\alpha_j q$ from equation (5.10) and $\bar{m}_{jt}$ is normally distributed with mean $\mu$ and variance $\sigma^2 / d$, given any observation $I_{jt} = d$ ($>0$). The probability that manufacturer $j$ ($=1,\ldots,M$)'s threshold level exceeds the amount of information by time $t$ is

$$\phi_j(q(t)) = \sum_{d=1}^{\infty} \Pr\left(I_{jt} = d \,\middle|\, \alpha_j q\right) \cdot \Phi\left( \frac{\left(w_j n_{jt}\mu - \left(c_f + n_{jt}c_v\right)\right)\sqrt{d}}{\sigma} - \frac{\left(\left(c_f + n_{jt}c_v\right) - w_j n_{jt}\mu_{j0}\right)\tau_j}{\sigma\sqrt{d}} \right) \tag{5.10}$$

where $\Phi$ is the standard normal cumulative distribution function. We next derive the aggregate dynamics of this process. The dynamics can be determined by the distribution of the threshold levels in the population.

Let $F(q)$ be the cumulative distribution function of the information threshold levels in a population.

$$F(q(t)) = \sum_j \phi_j(q(t)),\ t > 0,\ \textit{for all}\ \ j \in \{1,...,M\}, \tag{5.11}$$

where $\phi(q(t))$ is defined as (10). $F(q)$ is a monotone non-decreasing function and $\lim_{q\to\infty} F(q)$ may be less than 1 since the firm with the infinite threshold value should be allowed. Let $p(t)$ is the proportion of adopters at time period $t$ and we assume that $p(0) = 0$, i.e. the process starts in period zero when no one has adopted yet. In the initial period, however, some firms may adopt the technology, and we call that these firms are innovators or early adopters. They are in the fraction $F(0)$ of the population, and we assume that $F(0) > 0$ and $F$ has a continuous density $f$. The reason is that the process is initially driven by the innovators who represent a positive fraction $F(0)$ of the population by assumption.

From equation (5.11), we can model the dynamics for the distribution of the firms' threshold values. The proportion of the population whose thresholds have been exceeded is $F(q)$. Recall

$q(t)=\int_0^t p(s)ds$, which is the cumulative amount of information collected from prior adopters in a same population by time $t$. $p(t)$ is the proportion of adopters in each population at time $t$, and $F(q(t))-p(t)$ is the proportion of potential adopters at time $t$, that is, the proportion of remaining firms whose thresholds have been exceeded but have not adopted yet at time $t$. Let $\lambda$ be the instantaneous rate at which these remaining firms adopt. We assume that $\lambda$ is constant to make it simple[7]. Then we model the adoption process by the differential equation in the discrete time setting as

$$p(t+1)-p(t)=\lambda\left[F(q(t))-p(t)\right].$$

In the continuous time setting, this can be rewrite as, simply,

$$\dot{p}(t)=\lambda\left[F(q(t))-p(t)\right],\ t>0,\ \lambda>0. \tag{5.12}$$

It shows that firms use the accumulated information from all prior adopters in a same population group. This equation is always positive, which means that the rate of adoption increases for all time.

### 5.2.4 The Shape of Diffusion Curve

In this section, we examine the pattern of diffusion based on the aggregate dynamics. As Chatterjee and Eliashberg (1990) addressed about it, the shape of the curve can be determined by convexity or concavity properties and by the number and location of inflection points. It is a well-known fact that, in general, when the number of users of a new technology or product is accumulated over time, the curve is typically an S-shaped. That is, adoption proceeds slowly at

7 The instantaneous rate can be relaxed as random variables in some limit.

first, and accelerates as it spreads throughout the potential adopting population, and then slows down as the relevant population becomes saturated. To see the shape of diffusion curve over time in our model, we first differentiate equation (5.12) with respect to $t$ again, and then we obtain the second order (acceleration) equation below.

$$\ddot{p}(t) = \lambda\left[ p(t) f\left(q(t)\right) - \dot{p}(t)\right]. \tag{5.13}$$

We first examine the shape of the curve of the initial period. When $t$ is 0, the first term in brackets of equation (5.13) is zero and the second term is not zero because $p(0) = 0$ and $\dot{p}(0) = \lambda F(0) > 0$ since $F(0) > 0$. Thus, the equation is less than 0. When $t$ goes to 0, that is, in the initial period, we can state it as

$$\lim_{t\to 0} \ddot{p}(t) = \lambda p(0) f(p(0)) - \lambda^2\left[F(0) - p(0)\right] = -\lambda^2 F(0). \tag{5.14}$$

The above will be less than zero since $F(0) > 0$ and $p(t)$ is close to 0 as $t \to 0$. We see that the adoption curve has weak growth in the early phases and there is a weak acceleration in the initial period until arriving at some point that the process begins to accelerate. Intuitively, the reason is that there are only few early adopters in the initial period, so the amount of information collected from them is not enough. Moreover, early adopters are not willing to share the information about the technology until the outcomes from adoption will be validated later.

We next consider about the inflection point of the adoption curve. Let $Y_1$ and $Y_2$ denote the fraction of the early adopters and potential adopters in each population. Then $G(t) = Y_1 + Y_2 F(q(t))$ is the penetration curve for proportion of the population in which firms are ready to adopt by time $t$. The first term is the proportion of firms who will adopt the technology immediately after launch, $F(0)$. For example, top suppliers of Wal-Mart are included in here because they adopted RFID technology by mandate by Wal-Mart. They had no any information from prior adopters and have adopted it by a major trading partner's mandate. The second term represents the proportion of the population in which thresholds have been exceeded by the cumulative information by period $t$, that is, firms are ready to adopt it. In here, we consider only the second term for the shape of an adoption curve because the adoption curve depends upon the change of $F$ over time. As addressed earlier, the number and locations of inflection points are determinants for the shape of the adoption curve. The inflection point actually occurs when a curve increases or decreases most rapidly. The first-order inflection point occurs when the rate of adoption is fastest and the second derivative equals to zero. The second-order inflection point occurs when the rate of the rate of adoption is fastest and the third derivative equals zero (Valente 1995). $G(t)$ can be differentiated as

$$\dot{G}(t) = Y_2 p(t) f(q(t)), \quad t > 0. \tag{5.15}$$

**Proposition 5.1** The rate of adoption is fastest at time $\hat{t}$ such that $\ddot{G}(\hat{t}) = 0$ is satisfied, that is,

$$\dot{p}(\hat{t}) = -p^2(\hat{t}) \frac{f'(q(\hat{t}))}{f(q(\hat{t}))}.$$

It is hard to find the second-order inflection points in our diffusion model. Therefore we derive a reasonable approximation of this model to examine the shape of a diffusion curve, using two different patterns of information flows. Following Chatterjee and Eliashberg (1990), we examine two patterns of information flows over time – monotone decreasing rate and monotone increasing rate of information[8].

***Monotonically decreasing information rate.*** If the information rate is monotonically decreasing, $\dot{p}_{\kappa}(t)$ is less than zero. Differentiating equation (5.15) with respect to $t$ again, then

$$\ddot{G}(t) = Y_2 \dot{p}(t) f(q(t)) + Y_2 p^2(t) f'(q(t)), \quad t > 0. \tag{5.16}$$

At any time $t > \hat{t}$, equation (5.16) is less than 0 since $\dot{p}(t) < 0$ and $f'(q(t)) < 0$. Therefore, the diffusion curve must be concave for $\hat{t} < t < \infty$.

Let $t_1$ denote any possible point of time that the rate of information flow changes rapidly after a slow diffusion in the initial period. For $t_1 < t \le \hat{t}$, if we have the following condition

$$\dot{p}(t) < -p^2(t) \frac{f'(q(t))}{f(q(t))},$$

then the penetration curve will be concave in this range. Thus, there is no inflection point in the whole process because the initial period ($0 < t \le t_1$), the second period ($t_1 < t \le \hat{t}$), and the third period ($\hat{t} < t < \infty$) are concave for all $t > 0$.

***Monotonically increasing information rate.*** If the information rate is monotonically increasing, $\dot{p}(t)$ is larger than zero. From equation (5.16), at any time $t \le \hat{t}$, $\ddot{G}(t) > 0$ since $\dot{p}(t) > 0$ and $f'(q(t)) > 0$. Therefore, the adoption curve should be convex for $t \le \hat{t}$. After a slow diffusion in the initial period, the speed of adoption of technology will rapidly increase by the increasing rate

[8] To illustrate the shape of the diffusion curve, Chatterjee and Eliashberg (1990) consider three patterns of information flows over time-constant, monotonically decreasing, and monotonically increasing. In our work, however, the constant rate is ignored.

of information. In this case, there exists a second-order inflection point satisfying the condition, $\ddot{G}(t) = 0$, in the range $t \le \hat{t}$ . For $\hat{t} < t < \infty$, it is not easy to find the inflection points. Instead, we can intuitively think of the case that $f(q(t)) \to 0$ as $q(t) \to \infty$. In other words, the rate of information flow will decrease and then go to zero as $t$ goes to infinity. We can check this from

$$\lim_{t \to \infty} \ddot{G}(t) = \dot{p}(t) f(q(t)) + p^2(t) f'(q(t)) < 0,$$

because of $f(q(t)) \to 0$ and $f'(q(t)) < 0$ as $t \to \infty$. The adoption curve should be concave in this range. In this case, there should exist one first-order inflection point and at least two second-order inflection points since the initial part of the diffusion curve is concave, the second part is convex, and the third is concave. This draws the traditional S-curve in the diffusion model.

In the initial phases, the diffusion of the technology is initially driven by very few adopters who are convinced that this technology is good enough (pure inertia) or who are persuaded by mandates from powerful leaders. Once this situation is overcome by increase of the cumulative information from all previous adopters at some time point, there is rapid acceleration by the information collected from prior adopters, combined with the increasing number of firms who are persuaded by the new information. Therefore, in order to increase the adoption rates in a supply chain rapidly, more firms should adopt in the initial periods.  In other words, as more firms adopt initially, the total amount of information to the potential adopters in the population increases, and then the number of firms persuaded by the information increases as the process moves up the distribution. In next section, we will consider about how to push up the time that the process begins to accelerate and which factors are able to make to speed up the diffusion process in the initial periods.

## 5.3 The Factors affecting the Diffusion Speed

### 5.3.1 The Mean Benefits

We consider the factors affecting the diffusion speed of the new technology in a two supply chain using our threshold model. We introduce three factors in this section – mean benefits, cost sharing, and information provision. We show that individual threshold levels will decrease by these factors. This implies that reductions in threshold levels have an aggregate effect by accelerating the rate of adoption, thus resulting in an earlier critical mass. First, the mean benefits from the adoption are considered as a key factor to shift the individual firms' threshold values from the analysis in the previous section.

**Proposition 5.2** *The adoption occurs more rapidly in firms with higher mean benefits from adoption than in those with lower mean benefits. (See the proof in Appendix.)*

If we assume that $q$ is the same threshold level for all two populations, the distributions satisfy $F_H(q) \geq F_L(q)$ for all $q$, that is, $F_L$ first-order stochastically dominates $F_H$. Under these conditions, adoption occurs more rapidly in firms with higher mean benefits than in those with lower mean benefits. In other words, $p_H(t) \geq p_L(t)$ is satisfied for all time $t$. This result can be also used in the case of firms with different mean benefits each other if we relax the assumption that all firms in same population group are identical in the mean benefits from same size and capacity.

### 5.3.2 Cost Sharing

A big hurdle of RFID adoption is the cost issue. As mentioned earlier, the cost of RFID includes the cost of IT infrastructure as fixed costs for both groups and tags as variable costs for manufacturers. Typically, fixed costs for hardware and infrastructure tend not to vary significantly with the amount of product that passes through the supply chain while tag costs as variable costs might be very significant for manufacturers who should pay for placing RFID tags on products (Gaukler and Seifert (2007)). Actually, fixed costs and tag costs have come down over time, and then it will encourage more non-adopted firms no doubt. But they are still high compared to previous technology like barcoding. In practice, the manufacturers may want to negotiate for sharing the variable cost with the retailer for a return on investment (ROI). Under these cost issues, some researchers have already studied about the optimal policies for RFID investment. Gaukler et al. (2006) show that in the absence of mandating entities, there exists a unique optimal way of sharing the cost of RFID tags between a manufacturer and a retailer. Sharing the RFID tag cost is optimal in the sense that the total supply chain profits are maximized. Whang (2010) found that the *equal-cost-split arrangement* always induces the upstream (suppliers) to adopt RFID earlier than under no cost sharing and the cost split will be able to speed up the retailer's adoption under some conditions.

We have already assumed that retailers have only the fixed adoption costs and manufacturers have the variable costs for tags as well as the fixed adoption costs. There has no discount rate for both cost components. In this section, we suppose that all retailers equally share the tag costs with manufacturers who have already adopted. The costs of manufacturer $j$ who are facing the decision are defined as

$$C_j(t) = c_f + \frac{n_{jt}}{2} c_v .$$

where $n_{jt}$ is the number of retailers who have connected with manufacturer $j$ and already adopted by time $t$, and $c_v$ is the variable cost per one retailer. That is, all retailers linked with manufacturer $j$ takes the equal-cost-split for tags. Manufacturer $j$ 's threshold value of the amount of information at time $t$ will be

$$r_{jt,cs} = \frac{\left((c_f + n_{jt}c_v / 2) - w_j n_{jt}\mu_{j0}\right)\tau_j}{\alpha_j\left(w_{Mj}n_{jt}\mu_M - (c_f + n_{jt}c_v / 2)\right)} \ .$$

From Equation above, the manufacturer's threshold values will decrease significantly. In a total supply chain's perspective, one can expect more speedy diffusion in total network due to significant decreases of manufacturers' threshold values for the adoption. This result corresponds with Gaukler et al. (2006) such that in the absence of mandating entities, there exists a unique optimal way of sharing the cost of RFID tags between a manufacturer and a retailer. They also found that sharing the RFID tag cost is optimal in the sense that the total supply chain profits are maximized.

### 5.3.3 Information Provision

We consider that firm's threshold values will decrease and the speed of diffusion process will increase as information increases. We have already defined that $I_{jt}$ are the amount of information from previous adopters in a manufacturer population as $I_{jt} = \alpha_j q(t)$. In this section, we analyze the case that the additional information is provided by trading partners who have adopted in the other population. We define that $\hat{I}_{jt}$ are new amount of information for manufacturers which are expressed as $\hat{I}_{jt} = \alpha_j q(t) + G(n_{jt})$ where $G(\cdot)$ is non-decreasing function with $G'(\cdot) > 0$. New manufacturer $j$ 's threshold values of the amount of information at time $t$ are

$$r_{jt,bi} = \frac{\left((c_f + n_{jt}c_v) - w_j n_{jt}\mu_{j0}\right)\tau_j}{\alpha_j\left(w_j n_{jt}\mu - (c_f + n_{jt}c_v)\right)} - \frac{G(n_{jt})}{\alpha_j} .$$

We see that the manufacturer's threshold levels decrease by additional information, $G(n_{jt})/\alpha_j$ for manufacturer $j$ . That is, each potential adopter has more information about the technology, and then has lower resistance level required adopting it than before. This will lead to an increase of adoption rates. Therefore, the manufacturer's threshold values decrease over all possible number of trading partners once considering a case that additional information coming from partners increase linearly by the number of trading partners in the other population. Therefore we expect that the diffusion process with enhanced information will be faster than before. This implies, for the manufacturer group, that manufacturers need to collect more confidential information about RFID implementation from previous adopters in same population group. In addition, retailers who wish to speed up their partners' adoption rates should also need share more trustable information with manufacturers.

## 5.4 Managerial Implications

### 5.4.1 Different Types of Manufacturers under the Powerful Retailer

As mentioned earlier, mandates from major players require their suppliers to label shipments with tags, but most of them are still less willing to consider about the adoption due to the uncertainties about the benefits from an adoption, even though the technology becomes more mature.

In the retail supply chain, RFID can enable retailers to achieve the best level of performance by improved efficiency, cost savings, and so on. In terms of total supply chain, it brings the enhanced supply chain collaboration, which can improve supply chain performances like customer satisfaction, demand fulfillment, and stock level by visibility and partnership among all participants. For these reasons, powerful retailers stimulate their suppliers as trading partners and put more pressure on them to link up. But, many small- or mid-sized suppliers still hesitate to adopt RFID, and even some large suppliers have not adopted yet. To spur suppliers to adopt the technology, therefore, a retailer needs to stimulate suppliers with appropriate approaches under different conditions they have.

We look at four different types of the manufacturer in this section (See Figure 5.1). All types are classified by two inter-organizational factors, $w_j$ and $\alpha_j$, $j = 1,...,M$ . As defined earlier, $w_j$ represents the power of manufacturer $j$ over the retailer. The level of power can be explained by the dependence. Following Emerson's (1962) definition of dependence, manufacturer's dependence is based on the percent of sales revenue from a particular retailer and the ability of the retailer to reselect another supplier. That is, the greater the sales revenue from a retailer, the more dependent the supplier is on that retailer (Hart and Saunders 1997), so its dependence is low. But in our model, we already assumed that all manufacturers' sizes are identical. So we define the manufacturer's degree of power in this section as the measure of dependence on the retailer, that is, manufacturer $j$ with a high $w_j$ has less dependence on retailers and more ability to reselect other retailer. $\alpha_j$ represents the degree of openness of manufacturer $j$ for the information (or know-how) coming from other adopted manufacturers. Manufacturer $j$ with a high $\alpha_j$ is more likely to receive the information from other manufacturers who have already adopted. Such firm is willing to listen to new ideas and share the know-how about an adoption.

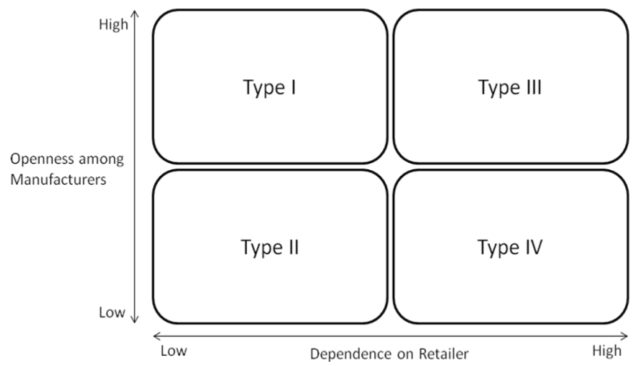


Figure 5.1 Four different types of manufacturers

However, manufacturers under extremely competitive industry are less willing to share the information with their competitors, because they want to keep their superior position in the linked network, while manufacturers under more localized and less competitive industry structure are frequently share the information among them. So we define, in this section, that the parameter $\alpha_j$ is the degree of openness, which means the willingness to share the information with other manufacturers.

Figure 5.2 shows the change of the threshold of each type over the network sizes. As shown in this figure, the curves of type I and II are short while those of type III and IV are long. It implies that the degree of dependence ($w$) on the retailer determines the length of curve. That is, if the firm has a low dependence level on retailer, they have more resistance level on the pressure from retailers and it causes delay the adoption. On the other dimension, we see that the threshold values of type I and III are small while those of type II and IV are so large. It means that the degree of openness ($\alpha$) for information sharing decides their threshold values to enable them to adopt the technology. It points out that manufacturers with high openness level are more willing to share their information and know-how with others, so they can acquire more information about the technology. This will enable them to reduce their threshold levels, which is the marginal level needed to adopt the technology.

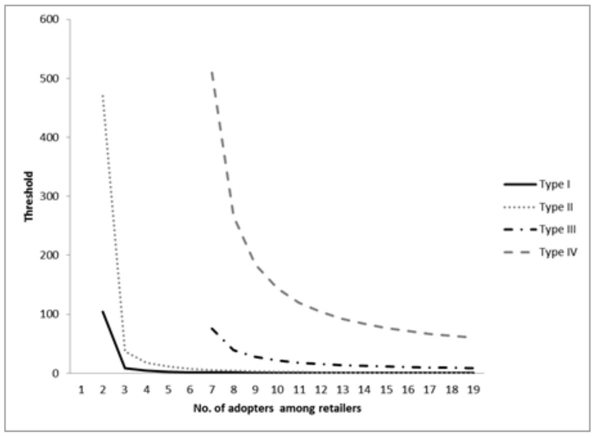


Figure 5.2 The change of threshold of four types of manufacturers by the number of retailers

**Type I Manufacturers ( high $w$ and high $\alpha$ )**

These manufacturers are relatively less dependent on retailers and have higher openness for information sharing among other manufacturers. Supplier pool might be relatively small due to less dependence and they may be under weak competition due to high openness level. These firms are willing to share the information with other manufacturers and are less affected by the retailer's persuasion. So many small and mid-sized firms in this type may cooperate defensively when the powerful retailer push to adopt. On the other hand, they will adopt the technology at some time that they have the total amount of information they want, because they have relatively low resistance level under the conditions they have.

From Figure 5.3, we see that cost sharing is a little bit better than providing additional information, but there is no significant difference between each approach. In this case, retailers do not need to push to manufacturers of this type with more pressures to adopt because they may act more defensively to the retailer.  Rather than, the retailer needs to push with persuasive approaches to reduce their resistance levels.

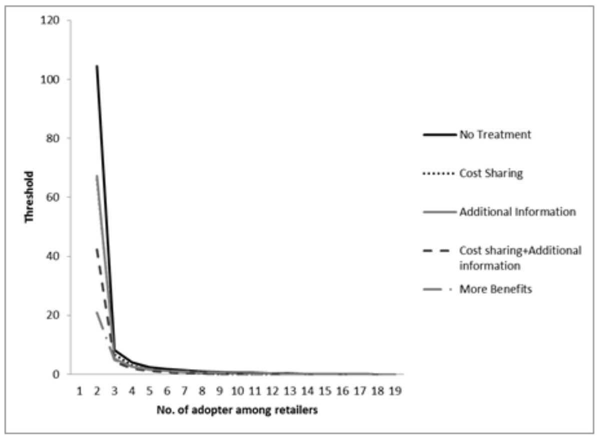


Figure 5.3 The change of threshold of Type I manufacturer

**Type II Manufacturers ( high $w$ and low $\alpha$ )**

These manufacturers are relatively less dependent on retailers and have less openness among other manufacturers. Supplier pool might be small, but they might pursue the product differentiation or provide relatively expensive products to the retailer. Examples of these firms may belong in the electronics, pharmaceutical, and high fashion industries. These manufacturers may experience significant out-of-stocks and shrinkage due to their product types. There is almost no information or know-how sharing among other manufacturers by strong competition. In this case, it is hard for retailers to reselect other suppliers, even if some firms do not adopt RFID, because the opportunity costs for reselection are high, or alternative manufacturers may not be able to available. They do not tend to cooperate defensively and their resistance levels for required information are very high. In other word, they will adopt RFID only to the degree that is absolutely necessary. For such type of manufacturers, the persuasive policy is more effective, rather than force these firms to adopt RFID at the risk of losing them. For example, the retailer can share some portion of tag costs or provide more and better information about the adoption. In addition, promising more benefits or incentives after an adoption will be better strategy to hold major partners.

The numerical results show that the approach combined with cost sharing and additional information or promising more benefits from an adoption will be better strategy for this manufacturer type in the initial period. We see that promising more benefits from an adoption (higher $\mu$) reduce the type II manufacturer's resistance level significantly, rather than cost sharing and additional information approaches. Intuitively, these firms will actually gain more benefits from an adoption than other types of manufacturers, because they may experience significant losses under no RFID. Supposing that type II manufacturer's promising mean benefits is $\hat{\mu}$ where $\hat{\mu} > \mu$, then adoption occurs more rapidly in the case of promising more benefits than in that of other approaches as proven in section 4.

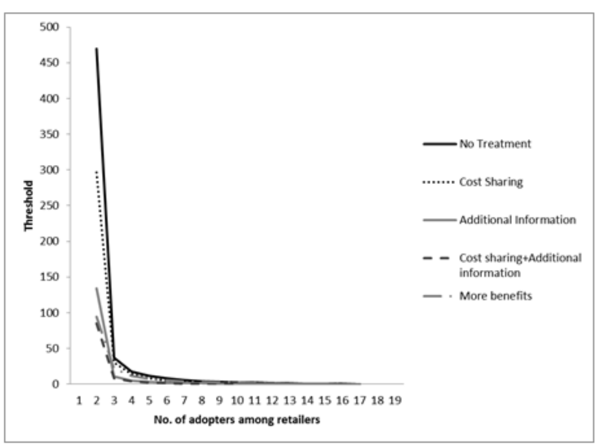


Figure 5.4 The change of threshold of Type II manufacturer

**Type III Manufacturers ( low $w$ and high $\alpha$ )**

These manufacturers are relatively more dependent on retailers than others and have more openness among manufacturers. Supply pool may be large and these firms are in weak competitive industry due to high openness. For example, the manufactured food suppliers are in this type. That is, there are many other firms producing same or similar products in the industry, but they are willing to share the information or know-how about the technology adoption friendly. Like the type I manufacturers, many small and mid-sized firms in this type may cooperate defensively when the powerful retailer pushes to adopt it, but it will be weaker than type I manufacturers because they are more dependent on the retailer. As seeing the figure 5.5, this type has very low resistance level for information needed to adopt RFID. Therefore the retailer can stimulate their adoptions with other ways. For example, persuasive power like cost sharing may be useful for this manufacturer type, but powerful retailers do not want to share tag costs because supplier pool is large and she can select other suppliers instead of non-adopters. Following Hart and Saunders (1997), coercive power is often used to influence adoption by powerful buyer when the supplier pool is large and reselection costs are low. They also say that more powerful firms may be forced to adopt a coercive strategy when partners fail to realize long-term benefits using a persuasive approach.

From our numerical results, as a persuasive approach, cost sharing is better than the additional information approach for this manufacturer type. But as mentioned above, if powerful retailers do not want to share the costs or manufacturers still fail to adopt it after taking some persuasive approaches, the retailer need to put more pressure on them. For example, non-RFID suppliers are able to be reevaluated or dropped from the retailer by the powerful retailer as the strongest approach.

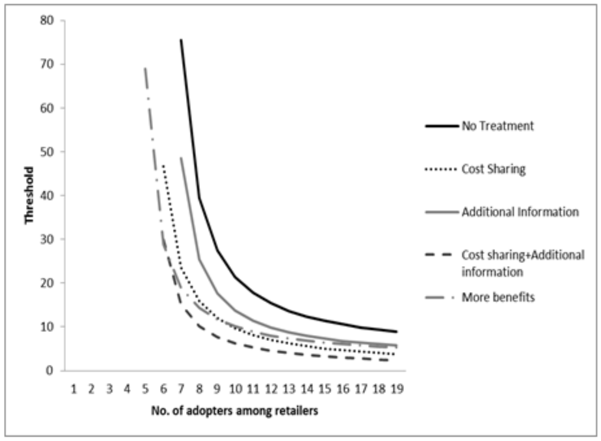


Figure 5.5 The change of threshold of Type III manufacturer

**Type IV Manufacturers ( low $w$ and low $\alpha$ )**

This type of manufacturers is relatively more dependent on retailers and has less openness degree among other manufacturers. These firms might be in the large-sized supply pool and strong competitive industry, and so they are less willing to share the information about RFID adoption to keep their own profits in the network. Therefore this manufacturer type has no enough information about the adoption, and so they have too high resistance level for information than those of other types. Unlike type I and type III manufacturer, firms do not cooperate defensively when the powerful retailer pushes to adopt RFID due to high dependence levels over the retailer. Like Type III manufacturers, the coercive approach is also more required than persuasive approach for this type. Because the reselection costs might be not high due to large-sized supply pool, the powerful retailer can stimulate remaining non-adopters' adoptions forcefully.

As seeing the numerical results, providing additional information has more significant effect than sharing tag costs for type IV manufacturers. That is, the threshold levels are reduced significantly when manufacturers takes better information. In addition, when the retailer takes both approaches or promises more benefits for them, the results are more significant. But, if manufacturers still fail to adopt it after taking a persuasive approach or the retailer will not be willing to share costs, the retailer need to put more pressure on them using the coercive approach such like strengthening the partnership with manufacturers who have already adopted, reevaluating, or dropping from the partnership.

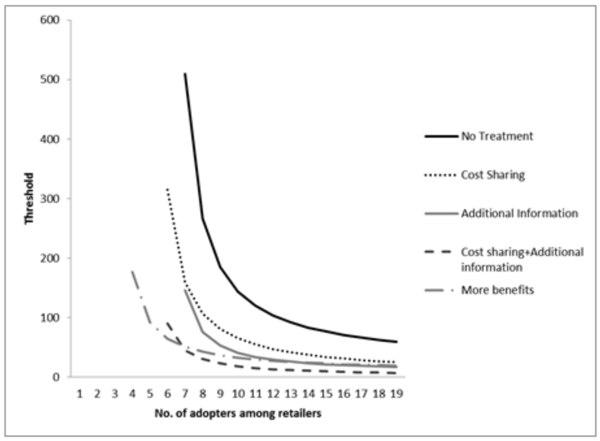


Figure 5.6 The change of threshold of Type IV manufacturer

### 5.5 Discussions

This chapter has presented a new technology adoption and diffusion in a two-level supply chain. All firms in the same population are identical in size, but they are heterogeneous in benefits from the technology adoption, which are determined from their own network size and the beliefs updated from prior adopters in a same group. Based on this benefit-cost structure, we have studied the individual firm’s threshold model to make a decision to adopt the technology or delay. Then we model the aggregating dynamics for the distribution of the threshold values to see how the technology adoption in the network diffuses over time. From the shape of adoption curve, we are able to know the critical point of time that the diffusion process begins to accelerate. In our model, as more firms adopt in the initial period, the total amount of information to the potential adopters in the population increases, and then the number of firms persuaded by the information increases as the process moves up the distribution. We found that cost sharing and better information approaches are useful to increase adoption rates at the initial period in the centralized supply chain. For the cost sharing, even though retailers actually share tag costs with their suppliers, the retailer's threshold value will not be changed significantly while the manufacturer's threshold value will decrease from our numerical results. Therefore, one can expect more speedy diffusion in the centralized supply chain's perspective by cost sharing. The manufacturer's threshold values decrease by providing better information. From the numerical results, we have found that the manufacturer's threshold values decrease more than the retailer's. This implies that manufacturers need to share more trustable information about the RFID implementation in their own population group. In addition, the retailer as trading partners with these manufacturers should be also able to stimulate manufacturers for sharing trustable information or know-how to enable them to speed up their adoptions. But in the decentralized supply chain, it might be different from various industry types and it is actually difficult to consider many cases; firm size, competition, relationship among partners, contract types and so on. One can develop more rigorous model about which factors can speed up the diffusion process in the initial period. Despite of these limits, we have provided some important implications to the powerful retailers who wish to improve supply chain collaboration with their trading partners through RFID. We have also considered four different types of manufacturers under powerful retailers by the degree of dependence on the retailer and the degree of openness for information sharing with other manufacturers. We suggest some policies for each type of manufacturer to the retailer who wish to increase her partners' adoption rates in the network. By our assumptions that all firms are identical in size, the dependence can be considered by the size of supplier pool over retailers and the openness can be regarded as the strength of competence in a same industry group. The retailers should use persuasive and coercive approaches to their partners to adopt the technology appropriately. In general, for manufacturers with less dependence on retailers, the persuasive approach is more effective rather than force these firms to adopt RFID at the risk of losing them, while the coercive approach is better for manufacturers with high dependence on retailers. The limit in this part is that we have only considered about the case of the powerful retailer and not developed the model precisely for this case. But one can develop specific models under different scenarios as future researches: (1) the retailer is dominant; (2) the manufacturer is dominant; and (3) the supply chain system is under centralized control. One can study a game theoretic approach to find an equilibrium strategy for the adoption decision under each scenario.

We have modeled a simple benefit-cost structure for the adoption. But more explicit structure to explain benefits and costs from adoption will be required, and then one can develop the technology adoption model precisely. In addition, we have considered only costless information from previous adopters in a same population group. But, many firms receive the information from various sources as well as from adopters in same group, and they sometimes pay huge costs for such information. In this case, our model will be changed significantly if we consider the weighted value of information instead of the amount of information. For these issues, one can develop the model based on some economic theories. For example, one can develop the model combined with principal-agent theory or game theoretic approach to modeling competition between two different channels.

# Chapter 6 Conclusions and Future Directions

I develop a model to analyze technology adoption in a two-level supply chain in chapter 3. The objective of this work is to analyze an individual firm's adoption decision in a dynamic adoption process given the firm's probabilistic belief about the technology's benefits and costs. This study optimizes an individual firm's adoption decision of a new technology in a dynamic model that captures the effect of other firms' adoptions on the firm's probabilistic belief about the technology's benefits and costs. A model of the adoption process accounts for the size of adopters that chooses to enter a network by technology adoption. That is, each firm can observe at each moment in time how many firms have already adopted the network technology. In addition, each firm can also use the information to update its beliefs with respect to the expected number of additional firms who will eventually join the network.

This chapter shows a firms' decision model, our analytical results, and the extension to a population model. The impact of buyer firms' adoption decisions on the supplier firm's benefits is also new to this literature. At the end of each period, the firm observes an information signal which is generated based on the number of other supplier firms who adopted the technology in the previous period. Each of these other suppliers experiences a benefit realization drawn from the true distribution of the benefit. The firm uses this signal to develop a posterior distribution of the benefit which is also normally distributed.

We modeled the firm's adoption decision as a dynamic program. The state space in each period includes the firm's prior belief distribution (which depends on number of supplier firms that have already adopted) and number of buyer firms that have already adopted the technology.

As more firms adopt, their information reduces the standard deviation of the firm's prior distribution of benefit and that, in turn, increases the firm's per-period utility. The action space includes adoption or no-adoption in this period. Using a discount factor, we can specify a finite horizon dynamic formulation. Our analytical results show that the firm will adopt if a function of number of supplier and buyer adoptee firms is more than a threshold value. That is, a firm's adoption decision is made based on a state-dependent threshold. We then prove results about how this threshold changes as a function of the risk-aversion index of the firm. I also show the effect of the mean and standard deviation of the prior at time zero on the threshold.

The next is to embed the firm-level adoption model into a population model. The population model allows us to consider the effect of several strategies observed in practice. First, RFID adoption is characterized in practice by some large retailers (buyers) adopting the technology and then mandating supplier firms to adopt it. The model captures this argument by various combinations of number of buyer and seller firms. This study provides insights into what particular combinations and timing of mandated adoption will be more effective in achieving a faster adoption curve. Second, many firms invest in RFID pilot programs to get a better estimation of the benefit. I model this by introducing another possible action for the firm. I discuss conditions under which such an action is useful for the firm, and extend the model in several directions. I consider the case where there is a cost for observing information and the possibility that the information is not truthful. The numerical experiments also yield other managerial implications as discussed earlier.

Analytical models assume that each supplier firm in the population is connected to all the buyer firms; in reality the specific nature of the network of linkages between supplier and buyers will influence the adoption curve. In addition, the strength of connections between supplier firms will influence the quantity and quality of information transmission between supplier firms. In chapter 4, to test insights generated from the analytical model and examine the effects of inter

firm network structures on the technology adoption, I first proposed a threshold model whereby a firm's adoption decision is influenced by information and knowledge from prior adopters though network ties as well as its own attributes. The levels of influence by prior adopters are different by *social proximity* with them. Next, I empirically tested a model using the adoption data of RFID technology of U.S. consumer packaged goods (CPG) industry between 2003 and 2007. I examined which network participants can become aware of information by prior adopters well and how relationships between firms affect the transferability and the quality of information on firms' adoption decisions.

The main finding is that the social proximity plays a critical role in the adoption of technology. We also found that firms with fewer subsidiaries (more centralized) and lower type of risk adopt the technology earlier than others. The healthy financial structure is also positively related with the adoption of technology. That is, a firm can gain access to other firms' information and knowledge about new technologies by interactions through social ties in networks. It is argued that structural relationships such as social ties among firms affect the rate and extent of adoption and diffusion. Although firm size did not directly influence diffusion in the way we expected, it appears to have done so indirectly, through the parameter that corrects for possible bias. Geographic proximity is not directly related with the adoption by itself, but social proximity includes its concept indirectly. Hence, the results indicate that a potential adopter's decision is largely influenced by the proximity with prior adopters in a network over time, while a firm's likelihood of adoption at the initial period is mainly determined by its own attributes.

This study contributes to the empirical literature on the diffusion of new technology in operations management (OM) with several key aspects. First, this is one of the first studies to examine the dynamics of the adoption process in the context of technology adoptions in supply chains. Second, we examine the effect of social proximity between firms as well as the firm's own attributes, while prior research about the diffusion process of new technology has mainly focused on the firm's attributes as factors that affect the adoption and diffusion. Specifically, to examine the social proximity between firms, we provide the combined level of cooperation and competition between firms over time, which determines transferability and quality of information through ties on a network. Lastly, from a methodological perspective, we estimate various hazard functions with time-varying covariates.

There have several limitations of the research that are available for extension from this study. In our empirical study, first, we use the data set from CPG industry to collect firm's time-varying attributes during the sample period. But many firms that we are interested in are not available to collect data during sample periods due to missing data or not-opened publicly. However, we found that the test results are consistent, providing that the findings are robust. The second is an issue for firm's governance. We only observed the data of headquarter of each firm because it was hard to search and collect the adoption data of each subsidiaries. Most of firms have publicly announced about adoption of RFID technology at parent firm level, so we assume that adoption decision is only from a main headquarter, not any subsidiary firm. However, because some subsidiaries may have own business and responsibility for adoption decision, we would suggest that investigating firm's governance and differentiating adoption decision by each subsidiaries would be taken into consideration in the further study. Third, differentiation between pilot project and full adoption would be required. As mentioned earlier, RFID technology is still on the beginning stage of diffusion process in the industry. Some firms have adopted it as a pilot project to test on sites, while some firms have fully adopted it willingly or by mandates. We could not observe exactly whether firms who have partly adopted as a pilot is still using it or not over time periods. Although this problem has not been considered in our study, there are significant challenges associated with a duration (survival) model that would take into account some factors influencing continuity of technology. Lastly, although we considered the social proximity between firms as measuring strength of ties using several factors, our theoretical stance naturally precluded other potential factors and we could not truly measure a dyadic relationship between firms. Network structure consists of dyadic relationships between suppliers in a network of suppliers, such as how a firm works with other supplier and how tightly or loosely coordinated its relationships are. There may have many potential factors to affect such a dyadic relationship between firms as well as the level of competition and cooperation we used. In spite of this reason, however, our results show that social proximity between firms is significantly related with information transfer and knowledge sharing, and then this leads the likelihood of adoption for each firm.

Chapter 5 has presented a new technology adoption and diffusion in supply chains. All firms in the population are identical in size, but they are heterogeneous in benefits from the technology adoption, which are determined from their own network size and the beliefs updated from prior adopters in a same group. This benefit-cost structure determines the individual firm's threshold model to make a decision to adopt the technology or delay. Then I modeled the aggregating dynamics for the distribution of the threshold values to see how the technology adoption in the network diffuses over time. From the shape of adoption curve, the critical point of time that the diffusion process begins to accelerate can be found. In this model, as more firms adopt in the initial period, the total amount of information to the potential adopters in the population increases, and then the number of firms persuaded by the information increases as the process moves up the distribution. We found that cost sharing and better information approaches are useful to increase adoption rates at the initial period in the centralized supply chain. For the cost sharing, even though retailers actually share tag costs with their suppliers, the retailer's threshold value will not be changed significantly while the manufacturer's threshold value will decrease from our numerical results. Therefore, one can expect more speedy diffusion in the centralized supply chain's perspective by cost sharing. The manufacturer's threshold values decrease by providing better information. From the numerical results, we have found that the manufacturer's threshold values decrease more than the retailer's. This implies that manufacturers need to share more trustable information about the RFID implementation in their own population group. In addition, the retailer as trading partners with these manufacturers should be also able to stimulate manufacturers for sharing trustable information or know-how to enable them to speed up their adoptions. But in the decentralized supply chain, it might be different from various industry types and it is actually difficult to consider many cases; firm size, competition, relationship among partners, contract types and so on. One can develop more rigorous model about which factors can speed up the diffusion process in the initial period. Despite of these limits, we have provided some important implications to the powerful retailers who wish to improve supply chain collaboration with their trading partners through RFID.

I also considered four different types of manufacturers under powerful retailers by the degree of dependence on the retailer and the degree of openness for information sharing with other manufacturers. Some policies have been suggested for each type of manufacturer to the retailer who wish to increase her partners' adoption rates in the network. By an assumption that all firms are identical in size, the dependence can be considered by the size of supplier pool over retailers and the openness can be regarded as the strength of competence in a same industry group. The retailers should use persuasive and coercive approaches to their partners to adopt the technology appropriately. In general, for manufacturers with less dependence on retailers, the persuasive approach is more effective rather than force these firms to adopt RFID at the risk of losing them, while the coercive approach is better for manufacturers with high dependence on retailers.

The limit of this chapter is that this chapter considered only about the case of the powerful retailer and not developed the model precisely for this case. But one can develop specific models under different scenarios as future researches: (1) the retailer is dominant; (2) the manufacturer is dominant; and (3) the supply chain system is under centralized control. One can study a game theoretic approach to find an equilibrium strategy for the adoption decision under each scenario. Second, this chapter modeled a simple benefit-cost structure for the adoption. But more explicit structure to explain benefits and costs from adoption will be required, and then one can develop the technology adoption model precisely. Lastly, I have considered only costless information from previous adopters in a same population group. But, many firms receive the information from various sources as well as from adopters in same group, and they sometimes pay huge costs for such information. In this case, the model will be changed significantly if one consider the weighted value of information instead of the amount of information. For these issues, one can develop the model based on some economic theories.

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# Appendices

## Appendix A: Proof of the expression of $U_{T-1,T}$

$$U_{T-1,T} = U' = 1 - e^{-am\mu' + \frac{a^2m^2(\sigma^2 + s'^2)}{2}}$$

where $\mu' = \dfrac{\mu + \sum_{i=1}^{q} X_i (s^2/\sigma^2)}{1 + q(s^2/\sigma^2)}$ and $s'^2 = \dfrac{s^2}{1 + q(s^2/\sigma^2)}$.

Given a belief q, the distribution of $\mu'$ is determined by the distribution of sum of $X$ which is distributed normally with mean $q\mu$ and $q\sigma^2$. Therefore $\mu'$ is normally distributed with mean $\dfrac{\mu + q\mu(s^2/\sigma^2)}{1 + q(s^2/\sigma^2)}$ and variance $\left(\dfrac{s^2/\sigma^2}{1 + q(s^2/\sigma^2)}\right)^2 q\sigma^2$.

Now we take expression of $U'$ to get $EU'$.

$$EU' = \int_{-\infty}^{\infty} \left[ 1 - e^{-am\mu + \frac{a^2m^2(\sigma^2 + s^2)}{2}} \right] N(x;\mu,s)dx \ .$$

We know that $\int_{-\infty}^{\infty} e^{cx} n(x; mean, SD)dx = e^{c\,mean + \frac{c^2SD^2}{2}}$. Using this,

$$EU' = 1 - e^{-am\mu + \frac{a^2m^2\left(\frac{s^2/\sigma^2}{1+q(s^2/\sigma^2)}\right)^2 q\sigma^2}{2} + \frac{a^2m^2(\sigma^2 + s'^2)}{2}} = 1 - e^{-am\mu + \frac{a^2m^2\left(\frac{qs'^4}{\sigma^2} + \sigma^2 + s'^2\right)}{2}}$$

$$\frac{qs'^4}{\sigma^2} + s'^2 = \left(\frac{qs'^2}{\sigma^2} + 1\right)\frac{s^2}{1 + q(s^2/\sigma^2)} = \frac{1 + \frac{q}{\sigma^2}\left(\frac{s^2}{1 + q(s^2/\sigma^2)}\right)}{1 + q(s^2/\sigma^2)} s^2 = \frac{1 + \left(q'/(1+q')\right)}{1 + q'} s^2 = \alpha(q)s^2$$

where $q' = q(s^2/\sigma^2)$. Thus,

$$EU' = 1 - e^{-am\mu + \frac{a^2m^2\left(\sigma^2 + \alpha(q)s^2\right)}{2}}.$$

As $q_T$ increases, $q'$ increases, and thus $\alpha(q)$ decreases. Therefore $U_T$ increases. Notice that $\alpha(0) = \dfrac{1+\left(q'/\left(1+q'\right)\right)}{1+q'} = 1$ when $q = 0$. You are back to same estimate as in the prior period.

**Appendix B: Defining $\psi_t$,**

Let $\psi_t$ be the fixed value of benefits once adopting in period *t*.

$$\psi_{T-1} = V_T$$
$$\psi_{T-2} = U_T(q_{T-1}^*) + \delta\psi_{T-1} = U_T(q_{T-1}^*) + \delta V_T$$
$$\psi_{T-3} = U_{T-1}(q_{T-2}^*) + \delta\psi_{T-2} = U_{T-1}(q_{T-2}^*) + \delta U_T(q_{T-1}^*) + \delta^2 V_T$$
$$\ldots$$
$$\begin{aligned}\psi_t = U_{t+2}(q_{t+1}^*) + \delta\psi_{t+1} &= U_{t+2}(q_{t+1}^*) + \delta U_{t+3}(q_{t+2}^*) + \cdots + \delta^{T-t-2}U_T(q_{T-1}^*) + \delta^{T-t-1}V_T \\ &= \delta^{T-t-1}V_T + \sum_{i=2}^{T-t}\delta^{i-2}U_{t+i}(q_{t-1+i}^*) \\ &= \delta^{T-t-1}V_T + \sum_{i=1}^{T-t-1}\delta^{i-1}U_{t+i+1}(q_{t+i}^*)\end{aligned}$$
$$\ldots$$
$$\begin{aligned}\psi_0 = U_2(q_1^*) + \delta\psi_1 &= U_2(q_1^*) + \delta U_3(q_2^*) + \cdots + \delta^{T-2}U_T(q_{T-1}^*) + \delta^{T-1}V_T \\ &= \delta^{T-1}V_T + \sum_{i=2}^{T}\delta^{i-2}U_i(q_{i-1}^*)\end{aligned}$$

**Appendix C: Deriving s – thresholds in a two-period model**

If the firm adopts now, the value is

$$VA_{T-1} = U_{T-1,T-1} - K + \delta U_{T-1,T}(\tilde{q}_T, \tilde{m}_T) + \delta^2 V_T. \text{ --- (1)}$$

If the firm does not adopt now, the value is

$$NA_{T-1} = \max\left[\delta\left(U_{T-1,T}(\tilde{q}_T) - K + \delta V_T\right), 0\right] = \max\left[\delta VA_{T-1,T}(\tilde{q}_T), 0\right]. \text{ --- (2)}$$

For adopting now (*T-1*), $VA_{T-1}$ (value of adoption in period T-1) should be positive and $D_{T-1} = VA_{T-1} - NA_{T-1}$ should also be positive (value of adoption should be larger than that of non-adoption). Therefore, if $VA_{T-1} > 0$ and $D_{T-1} > 0$, then the firm adopts now (*T-1*). Otherwise, the firm does not adopt now (may *adopt in next period* or *never adopt*).

RHS of (1) can be rewritten by

$$\begin{aligned}
&U_{T-1,T-1} - K + \delta U_{T-1,T}(\tilde{q}_T, \tilde{m}_T) + \delta^2 V_T \\
&= U_{T-1,T-1} - (1-\delta)K - \delta K + \delta\left\{U_{T-1,T}(\tilde{q}_T, \tilde{m}_T) - K + \delta V_T + K\right\}. \\
&= \left[VA_{T-1} - NA_{T-1}\right] + \delta VA_{T-1,T}(\tilde{q}_T)
\end{aligned}$$

Therefore, the value of adoption in period *T-1* is

$VA_{T-1} = D_{T-1} + \delta VA_{T-1,T}(\tilde{q}_T)$. --- (3)

The first term in (3), $D_{T-1} = VA_{T-1} - NA_{T-1}$, is the difference of value between adoption and non-adoption in period *T-1*. If $NA_{T-1}$ is zero then condition (1) is sufficient. Otherwise, it should be required to examine all conditions. The second term is the estimated value of adoption in period *T* at the beginning of period *T-1*, which is discounted by $\delta$.

There exists a threshold for adoption at the beginning of period *T-1*, $s_{T-1}^{Threshold}$, such that $VA_{T-1} > 0$ and $D_{T-1} = VA_{T-1} - NA_{T-1} > 0$.

**Proof.**

Let $s_{a,T-1}(\tilde{q}_T)$ be for **(a)** $VA_{T-1,T}(\tilde{q}_T) = U_{T-1,T}(\tilde{q}_T) - K + \delta V_T = 0$.
Let $s_{b,T-1}$ be for **(b)** $D_{T-1} = 0$ ($VA_{T-1} - NA_{T-1} = U_{T-1,T-1} - (1-\delta)K = 0$). (There is no *q* in (b).)
Let $s_{c,T-1}(\tilde{q}_T)$ be for **(c)** $VA_{T-1} = D_{T-1} + \delta VA_{T-1,T}(\tilde{q}_T) = 0$.

**Adoption condition in period *T-1*:**
**V**alue of adoption in period *T-1* should be positive (**(c) > 0)**, and value of adoption has to be larger than that of non-adoption (**(b) > 0)**.

**Case I:** $s_{b,T-1} < s_{a,T-1}(\tilde{q}_T)$

Possible values of $s_{T-1}$ for adoption at the beginning of period T-1 are $s_{b,T-1}$ below, because in which $VA_{T-1,T}(\tilde{q}_T) > 0$ and $D_{T-1} > 0$, and then $VA_{T-1} > 0$ for sure [**(c) > 0 and (b) > 0]**. $D_{T-1}$ is always negative above $s_{b,T-1}$ (**(b) < 0)**, and thus the adoption conditions cannot be satisfied. Therefore a threshold value of case 1 is $s_{T-1}^{Threshold} = s_{b,T-1}$, adopt below the threshold. In this case, a threshold value does not depend upon $\tilde{q}_T$, because only a marginal value of adoption in period *T*-1 is required to adopt.

**Case II:** $s_{b,T-1} > s_{a,T-1}(\tilde{q}_T)$

a. Possible values of $s_{T-1}$ for adoption at the beginning of period T-1 may be $s_{a,T-1}(\tilde{q}_T)$ below, because in which $VA_{T-1,T}(\tilde{q}_T) > 0$ and $D_{T-1} > 0$, and then $VA_{T-1} > 0$ for sure [**(c) > 0 and (b) > 0]**. (same as case I)
   Therefore $s_{T-1}^{Threshold} = s_{a,T-1}(\tilde{q}_T)$, adopt below the threshold.

b. Possible values of $s_{T-1}$ for adoption at the beginning of period T-1 may also be above $s_{a,T-1}(\tilde{q}_T)$, in which $VA_{T-1,T}(\tilde{q}_T) < 0$ and $D_{T-1} > 0$, and so $VA_{T-1} = D_{T-1} + \delta VA_{T-1,T}(\tilde{q}_T) > 0$ for adoption in period T-1 [**(c) > 0 and (b) > 0]**. So Possible values of $s_{T-1}$ for adoption should be $s_{c,T-1}(\tilde{q}_T)$ below.
   Therefore $s_{T-1}^{Threshold} = s_{c,T-1}(\tilde{q}_T)$, adopt below the threshold.

Therefore a threshold value of case II is $s_{T-1}^{Threshold} = \max\left\{s_{a,T-1}(\tilde{q}_T), s_{c,T-1}(\tilde{q}_T)\right\}$, adopt below the threshold. In this case, a threshold value depends upon $\tilde{q}_T$, because $VA_{T-1,T}(\tilde{q}_T)$ (the estimated value of adoption in period T) for both $s_{a,T-1}(\tilde{q}_T)$ and $s_{c,T-1}(\tilde{q}_T)$ should be considered to adopt. There exists a threshold such that adopt below the threshold. Also notice that as $\tilde{q}_T$ increases then for a given $s_{T-1}$, $U_{T-1,T}(\tilde{q}_T, \tilde{m}_T)$ increases. Therefore, at any of these breakpoint $s_{a,T-1}(\tilde{q}_T)$ and $s_{c,T-1}(\tilde{q}_T)$, if we increase $\tilde{q}_T$, the function will become larger than 0 and therefore breakpoint *s* can be increased to bring the function back to 0. Therefore the threshold is nondecreasing in $\tilde{q}_T$.

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Breakpoints, $s_{a,T-1}(\tilde{q}_T)$ and $s_{c,T-1}(\tilde{q}_T)$, are nondecreasing in $\tilde{q}_T$.

For $s_{a,T-1}(\tilde{q}_T)$, $VA_{T-1,T}(\tilde{q}_T) = U_{T-1,T}(\tilde{q}_T) - K + \delta V_T = 0$.

$$1 - e^{-a\tilde{m}_T\mu_{T-1} + \frac{a^2\tilde{m}_T^2(\alpha(\tilde{q}_T)s_{T-1}^2+\sigma^2)}{2}} - K + \delta V_T = 0.$$

$$s_{T-1}^2 = \frac{2}{am\alpha(\tilde{q}_T)}\left[\mu_{T-1} + \frac{\ln(1-K+\delta V_T)}{am} - \frac{am\sigma^2}{2}\right] \equiv s_{a,T-1}^2(\tilde{q}_T),$$

where $\alpha(\tilde{q}_T) = \dfrac{1+\left(\tilde{q}_T s_{T-1}^2/\sigma^2\right)\left(1/\left(1+(\tilde{q}_T s_{T-1}^2/\sigma^2)\right)\right)}{1+\left(\tilde{q}_T s_{T-1}^2/\sigma^2\right)}$. ( $0 < \alpha(\tilde{q}_T) \le 1$)

As $\tilde{q}_T$ increases, $\alpha(\tilde{q}_T)$ decreases and then $s_{a,T-1}(\tilde{q}_T)$ increases.

We already proved that $\alpha(\tilde{q}_T)$ decreases and then $U_{T-1,T}$ increases as $\tilde{q}_T$ increases. Therefore the second term in (3), $VA_{T-1,T}(\tilde{q}_T)$, is increasing in $\tilde{q}_T$ and thus equation (3), $VA_{T-1} = D_{T-1} + \delta VA_{T-1,T}(\tilde{q}_T)$, is nondecreasing in $\tilde{q}_T$. $s_{c,T-1}(\tilde{q}_T)$ is also nondecreasing in $\tilde{q}_T$.

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**The closed form of threshold in period *T-1***

$$s_{a,T-1}^2(\tilde{q}_T) \equiv \frac{2}{am\alpha(\tilde{q}_T)}\left[\mu_{T-1} + \frac{\ln(1-K+\delta V_T)}{am} - \frac{am\sigma^2}{2}\right]. \text{ (by } VA_{T-1,T}(\tilde{q}_T) = 0\text{)}$$

$$s_{b,T-1}^2 \equiv \frac{2}{am}\left[\mu_{T-1} + \frac{\ln(1-(1-\delta)K)}{am} - \frac{am\sigma^2}{2}\right]. \text{ (by } U_{T-1,T-1} - (1-\delta)K = 0\text{)}$$

In case II,

At $s_{a,T-1}(\tilde{q}_T)$, $VA_{T-1} = U_{T-1,T-1} - (1-\delta)K > 0$, because $VA_{T-1,T}(\tilde{q}_T) = 0$.

Let $s'_{T-1}(\tilde{q}_T) = s_{a,T-1}(\tilde{q}_T) - \Delta$ ( $\Delta > 0$).

At $s_{a,T-1}(\tilde{q}_T) - \Delta$ ( $\Delta > 0$), $VA_{T-1} > 0$, because $VA_{T-1,T}(\tilde{q}_T) > 0$ and $U_{T-1,T-1} - (1-\delta)K > 0$.

From $VA_{T-1,T}(\tilde{q}_T) > 0$,

$$s_{T-1}'^{2}(\tilde{q}_T) < \frac{2}{am\alpha(\tilde{q}_T)}\left[\mu_{T-1} + \frac{\ln(1-K+\delta V_T)}{am} - \frac{am\sigma^2}{2}\right] \equiv s_{T-1}^{*2}(\tilde{q}_T).$$

$s'_{T-1}(\tilde{q}_T)$ is below $s_{a,T-1}(\tilde{q}_T)$, in which $VA_{T-1,T}(\tilde{q}_T) > 0$ and $VA_{T-1} - NA_{T-1} > 0$, and then $VA_{T-1} > 0$ for sure **[(c) > 0 and (b) > 0] (same as case 1).** $s'_{T-1}(\tilde{q}_T)$ can be extended by $s_{a,T-1}(\tilde{q}_T)$.

Therefore $s_{T-1}^{Threshold} = s_{a,T-1}(\tilde{q}_T)$, adopt below the threshold.

Let $s'_{T-1}(\tilde{q}_T) = s_{a,T-1}(\tilde{q}_T) + \Delta\,(\Delta > 0)$.

At $s_{a,T-1}(\tilde{q}_T) + \Delta\,(\Delta > 0)$, $VA_{T-1} = U_{T-1,T-1} - (1-\delta)K + \delta VA_{T-1,T}(\tilde{q}_T) < U_{T-1,T-1} - (1-\delta)K$, because $VA_{T-1,T}(\tilde{q}_T) < 0$ and $U_{T-1,T-1} - (1-\delta)K > 0$.

From $VA_{T-1,T}(\tilde{q}_T) < 0$,

$$s_{T-1}'^{2}(\tilde{q}_T) > \frac{2}{am\alpha(\tilde{q}_T)}\left[\mu_{T-1} + \frac{\ln(1-K+\delta V_T)}{am} - \frac{am\sigma^2}{2}\right] \equiv s_{a,T-1}^{2}(\tilde{q}_T).$$

From $U_{T-1,T-1} - (1-\delta)K > 0$,

$$s_{T-1}'^{2}(\tilde{q}_T) < \frac{2}{am}\left[\mu_{T-1} + \frac{\ln(1-K+\delta K)}{am} - \frac{m\sigma^2}{2}\right] \equiv s_{b,T-1}^{2}.$$

When $\tilde{q}_T = 0$ (No one adopts in period T-1), $\alpha(0) = 1$ and then $s_{T-1}^{threshold}$ does not based on $\tilde{q}_T$ any more. At this point, we are back to same estimate as in the prior period and a threshold value is same as $s_{b,T-1}$.

The breakpoint $s_{c,T-1}(\tilde{q}'_T)$ should be placed between $s_{a,T-1}(\tilde{q}_T)$ and $s_{b,T-1}$, $s_{a,T-1}(\tilde{q}_T) < s_{c,T-1}(\tilde{q}_T) < s_{b,T-1}$, where $\tilde{q}'_T > \tilde{q}_T$. $s_{c,T-1}(\tilde{q}'_T)$ can be approximated by

$$s_{c,T-1}^{2}(\tilde{q}'_T) \cong \frac{2}{am\alpha(\tilde{q}'_T)}\left[\mu_{T-1} + \frac{\ln(1-K+\delta V_T)}{am} - \frac{am\sigma^2}{2}\right],\text{ where } \alpha(\tilde{q}'_T) < \alpha(\tilde{q}_T).$$

Therefore, the closed form of threshold in period *T-1* can be defined as

$$s_{T-1}^{threshold,2}(\tilde{q}_T) = \frac{2}{am\alpha(\tilde{q}_T)}\left[\mu_{T-1} + \frac{\ln(1-K+\delta V_T)}{am} - \frac{am\sigma^2}{2}\right], \text{ where } \tilde{q}_T \geq 0.$$

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$s_{T-1}^{threshold}(\tilde{q}_T)$ increases in $\tilde{q}_T$, because $\alpha(\tilde{q}_T)$ decreases in $\tilde{q}_T$.

$s_{T-1}^{threshold}(\tilde{q}_T)$ also increases in $\mu_{T-1}$. As more benefits are known to population, more potential adopters will adopt next period. But, $s_{T-1}^{threshold}(\tilde{q}_T)$ decreases in $m$. It may seem counterintuitive, but it can be explained by the following arguments. If the number of adopters among partners is large, the firm will have larger $\mu_{T-1}$ by network effects. Otherwise, the firm will have less $\mu_{T-1}$.

**Appendix D: Existence of s – thresholds at the initial period ($t=0$)**

If the firm adopts the technology in any period 0, values of adoption is

$VA_0 = [U_0 - K] + \delta U_{0,1}(\tilde{q}_0) + \delta^2 \psi_0$,

where $\psi_0 = \delta^{T-1} V_T + \sum_{i=1}^{T-1} \delta^{i-1} U_{t+1}(q_i^*)$.

Value of non-adoption is

$NA_0 = \delta\pi_1(s_1) = \delta \max\{VA_1, \delta\pi_2(s_2)\}$.

***There exists a threshold $s_0^*$ for each case such that if $s_0 < s_0^*$ then the firm adopts; otherwise, the firm will wait more or never adopt. $s_0^*$ is a non-decreasing function of $\tilde{q}_0$.***

(iii) If $\psi_0 > K$, $s_0^* = s_b$.

(iv) If $\psi_0 \leq K$,

c. if $\tilde{q}_0 < \hat{q}$, $s_0^* = \max\{s_a(\tilde{q}_0), s_c(\tilde{q}_0)\}$, or

d. if $\tilde{q}_0 \geq \hat{q}$, $s_0^* = s_b$. (same as case I)

**Appendix E: Deriving the hazard rates in Weibull and Log-logistic distribution**

(i) If *T* has a Weibull distribution, its *cdf* is given by $F(t) = 1 - \exp\left(-\psi(x_j'\beta)t^{\alpha}\right)$, where $\alpha$ are nonnegative parameters. The density is $f(t) = \psi(x_j'\beta)\alpha t^{\alpha-1}\exp(-\psi(x_j'\beta)t^{\alpha})$. The hazard function is $\lambda(t) = f(t)/S(t) = f(t)/\left(1 - F(t)\right) = \psi(x_j'\beta)\alpha t^{\alpha-1}$. The Weibull distribution allows the hazard rate for a given firm to change monotonically over time. That is, if $\alpha > 1$, the hazard rate is monotonically increasing which, as discussed above, indicates the existence of learning process. If $\alpha < 1$, the hazard is monotonically decreasing. When $\alpha = 1$, the hazard is constant over time.

(ii) If *T* has a log-logistic distribution, *cdf* is given by $F(t) = \gamma t^{\alpha}/(1 + \gamma t^{\alpha})$, where $\alpha$ is a nonnegative parameter. The density is $f(t) = \alpha\gamma t^{\alpha-1}/(1 + \gamma t^{\alpha})^2$. The hazard function is $\lambda(t) = f(t)/S(t) = f(t)/\left(1 - F(t)\right) = \gamma\alpha t^{\alpha-1}/(1 + \gamma t^{\alpha})$. If $\alpha > 1$, the hazard function initially increases until $t' = \left[1/\alpha\gamma\right]^{\alpha-1}$ and then decreases to zero over time. Otherwise, $\alpha \le 1$, the hazard function has a negative duration dependence.

## Appendix F: Proof of Propositions in Chapter 5

**Proof of proposition 5.1** The rate of adoption is fastest at time $\hat{t}$ such that $\ddot{G}(\hat{t}) = 0$ is satisfied. From $\dot{G}_{\kappa}(t) = p_{\kappa}(t) f_{\kappa}(q(t)),\ t > 0$. Differentiating this, $\ddot{G}(\hat{t}) = Y_2 \dot{p}(\hat{t}) f(q(\hat{t})) + Y_2 p^2(\hat{t}) f'(q(\hat{t})) = 0,\quad \hat{t} > 0.$ Then, $\dot{p}(\hat{t}) = -p^2(\hat{t}) f'(q(\hat{t}))/f(q(\hat{t}))$.

$$\ddot{p}(t_0) = \lambda\left[p(t_0) f(q(t_0)) - \dot{p}(t_0)\right],$$

$$\Theta(t_0) = \ddot{p}(t_0)/\dot{p}(t_0) = \lambda\left(p(t_0) f(q(t_0))/\dot{p}(t_0) - 1\right) = \lambda\left(F'(q(t_0))/\dot{p}(t_0) - 1\right).$$

At time $t_0$, $\Theta(t_0) = 0$ and $\Theta'(t_0) > 0$. Therefore $F'(q(t_0)) = \dot{p}(t_0)$.

$$\Theta'(t_0) = \lambda \cdot \left[F''\left(q(t_0)\right)\dot{p}(t_0) - F'\left(q(t_0)\right)\ddot{p}(t_0)\right]/\dot{p}^2(t_0).$$

To show $\Theta'(t_0) > 0$, we only need the part of numerator in a square bracket because $\lambda / \dot{p}^2(t_0) > 0$. Therefore, $F''\left(q(t_0)\right)\dot{p}(t_0) - F'\left(q(t_0)\right)\ddot{p}(t_0) > 0$. From $F'(q(t_0)) = \dot{p}(t_0)$, we see that $F''(q(t_0)) > \ddot{p}(t_0)$.

**Proof of proposition 5.2** We prove it using contradiction. By contradiction, we assume that $F_H(0) \geq F_L(0)$ and $p_H(0) = p_L(0) = 0$. From the dynamic equations, $\dot{p}_\kappa(t) = \lambda_\kappa\left[F_\kappa\left(\int_0^t p_\kappa(s)ds\right) - p_\kappa(t)\right]$, $\kappa = H, L$. Let $p_H(t)$ and $p_L(t)$ be the solutions. We know that $\dot{p}_H(0) \geq \dot{p}_L(0)$, because $F_H(0) \geq F_L(0)$ by assumption.

Suppose that at any given time $\tilde{t} > 0$, $p_H(\tilde{t}) < p_L(\tilde{t})$. There is a time $\tilde{t}$ such that $p_H(\tau) \geq p_L(\tau)$ for all $\tau \leq \tilde{t}$ and $\dot{p}_H(\tilde{t}) < \dot{p}_L(\tilde{t})$. Therefore $\int_0^{\tilde{t}} p_H(s)ds \geq \int_0^{\tilde{t}} p_L(s)ds$ and $F_H\left(\int_0^{\tilde{t}} p_H(s)ds\right) \geq F_L\left(\int_0^{\tilde{t}} p_L(s)ds\right)$. From the dynamic equations, hence, $\dot{p}_H(\tilde{t}) \geq \dot{p}_L(\tilde{t})$ should be satisfied. This is a contradiction!

# VITA

Daeheon Choi will receive his Ph.D. degree in Business Administration majoring in Operations Management in June 2012 from the University of Washington Seattle. He completed his M.S. degree in Industrial Engineering from the Texas A&M University, and his B.S. degree in Industrial Engineering from Sung Kyun Kwan University in South Korea. In terms of research, Choi mainly conducts research on technology and innovation management in supply chains. His research includes Technology / Innovation Management, information sharing in supply chains, and empirical research in the area of Operations Management. His research has appeared in prestigious conferences such as Manufacturing and Service Operations Management (MSOM), Production and Operations Management (POM), Decision Sciences Institute (DSI), and Annual INFORMS Meetings. Before coming to U.S., he worked as an ERP consultant (certificated by SAP, Inc.) and a manager of Logistics group at SK C&C in South Korea for 30 months and also joined a global internship program in Samsung Electronics in Summer 2005.