THE IMPACT OF DISRUPTIVE INFORMATION TECHNOLOGY INNOVATIONS ON FIRM PERFORMANCE: THE CASE OF RFID ADOPTION AND ITS IMPLICATIONS IN FASHION AND TEXTILES INDUSTRIES

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CERTIFICATE OF ORIGINALITY

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Abstract

Disruptive information technology (IT) innovations provide remarkable opportunities to firms—particularly fashion and textiles firms—for operational efficiency and effectiveness improvement, cost reduction, and customer value enhancement. However, disruptive IT innovations can cause pervasive and radical changes to firms' operations, leading to uncertain impacts on firm performance. Previous studies have examined the impact of non-disruptive IT and suggested that the link between non-disruptive IT and firm performance depends on a range of contingency factors. However, those studies might not be applicable to disruptive IT innovations, and the moderating effects of institutional pressures and upper echelons attributes remain unknown. It is crucial for top managers to understand these issues to respond appropriately to emerging disruptive IT innovations.

This dissertation aims to fill the above research gaps by examining the impact of disruptive IT innovations on firm performance from three perspectives—operational performance, financial performance, and systematic risk—and by investigating how top management team (TMT), firm, and industry level contingency factors affect that impact. We examine the impact of disruptive IT innovations based on the context of radio frequency identification (RFID), a disruptive technology that enables supply-chain business process innovation and thus increasingly utilized in fashion and textiles industries. By employing event study methodology, we examine "abnormal changes" in performance based on U.S.-listed firms that adopted RFID.

The results show that RFID adoption decreased inventory days (-2.92), accounts receivable days (-1.86), and operating cycle (-4.76), improved labor productivity

(USD 3,660 per employee), sales growth (+2.19%), return on assets (+2.00%) and systematic risk (-0.20) over a five-year period (i.e., t - 2 to t + 3). Fashion and textiles RFID adopters and firms in the wholesale and retail industries had greater improvements in supply chain efficiency than did adopters in other industries and firms in manufacturing industries, but not for labor productivity and sales growth performance. The contingency factor analysis indicates that firms experienced higher supply chain efficiency under low institutional pressures. Moreover, firms experiencing coercive pressure, low industry competitiveness, good financial health, low level of business diversification, and high level of geographic diversification showed greater improvements in profitability. Finally, systematic risk was lower under greater TMT pay dispersion resulting from incentives and greater demographic heterogeneity such as age and gender heterogeneity. However, fast fashion and textiles neither obtained higher profitability nor lower systematic risk as a result of RFID adoption, suggesting that these industries must evaluate other contingency factors to improve their financial performance related to RFID adoption.

This dissertation provides a theoretical foundation for the disruptive IT innovations literature by providing some of the first comprehensive and objective evidence of the impact of disruptive IT innovations on firm performance and the moderating effects of external and internal contingency factors. This dissertation also contributes to institutional theory and upper echelons theory by providing empirical evidence of the moderating effects of coercive pressure and TMT heterogeneity. The managerial implications of the contingency frameworks, which helps fashion and textiles firms identify opportunities of a disruptive IT innovation and maximize its benefits through strategic planning, are also applicable to firms in other sectors.

Publications Arising from the Thesis

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CHAPTER 1 INTRODUCTION

1.1 Background

Disruptive information technology (IT) innovation is defined as "an architectural innovation originating in the information technology base that has subsequent pervasive and radical impacts on development processes and their outcomes" (Lyytinen 2003). It is an extension of the theory of disruptive innovation (Christensen and Raynor 2003) and IT innovation (Swanson 1994). Disruptive innovation is "a novel idea or behavior that, when introduced in organization settings, causes dramatic changes in the structure of work process" (Sherif et al. 2006, page 340), whereas IT innovation is innovation in the organizational application of digital and communication technologies (Swanson 1994). An increasing number of fashion and textiles firms are adopting disruptive IT innovations (Azevedo and Carvalho 2012; Kapoor et al. 2009; Loebbecke and Palmer 2006; Moon and Ngai 2008), such as Internet applications, radio frequency identification technology (RFID), and enterprise resource planning (ERP), to cope with intense competition and a rapidly changing environment.

The fashion business is characterized by a wide assortment of highly seasonal products with short life cycles, high levels of impulse purchasing and complicated distribution and logistics operations (Christopher et al. 2004). Thus, fashion and textiles firms have high requirements for operation efficiency and effectiveness such as short lead times and rapid delivery (Moon and Ngai 2008). Disruptive IT innovations help fashion and textiles firms to achieve these requirements. More specifically, such innovations provide remarkable opportunities to fashion and textiles firms to improve their operational efficiency and effectiveness, reduce their costs, enhance customer service value, and create new business opportunities (Brower and Christensen 1995; Lyytinen 2003; Moon and Ngai 2008; Wei et al. 2005). However, disruptive IT innovations also have drawbacks that induce negative impact on firm performance. The innovations entail pervasive and radical changes in both the organization and organizational processes (Lyytinen 2003; Wei et al. 2005). These changes disrupt relationships with employees (Orlikowski 1993) and can lead to failure (Lucas Jr and Goh 2009). Moreover, such innovations are risky and expensive and their benefits are uncertain in the long term (Brower and Christensen 1995).

1.2. Research Motivations and Questions

There is limited understanding about the actual impact of disruptive IT innovations on long-term firm performance. Much of the previous research focuses on studying firm performance and the implications of non-disruptive IT investments (e.g., Hitt and Brynjolfsson 1996; Mithas et al. 2012), which is highly compatible with existing systems or processes with which users are already familiar (Christophe and Detmar 2011). Moreover, previous studies focus on examining the impact of IT innovations on financial return using accounting-based measures or short-term market-based measures. However, risk, a key dimension of firm performance (Brealey and Myers 2002), remains relatively neglected in the IT literature. Studying the impact of disruptive IT innovations is particularly important because of the risky and disruptive nature of those innovations.

Previous studies also suggest that the link between non-disruptive IT and firm performance depends on a range of contingency factors such as firm size, type of IT, time, management support, industry competitiveness, industry clockspeed, and corporate diversification (Clemons and Row 1991; Dehning and Richardson 2002; Hendricks 2007; Kohli and Devaraj 2003; Li and Richard Ye 1999; Melville et al. 2004; Zhu and Kraemer 2002). However, contingency factors such as industry competitiveness, industry clockspeed, and corporate diversification, which moderate the impact of non-disruptive IT innovations, might not applicable to disruptive IT innovations. For instance, although studies suggest that non-disruptive IT innovations provide organizations with enhanced value in a competitive environment (Melville et al. 2007), disruptive IT innovations may negatively impact firms in a competitive environment. Firms in competitive industries require efficient operations to stay ahead of the competition (Scherer and Ross 1990), but disruptive IT innovations disrupt firms' operations. Furthermore, the current literature fails to examine the moderating effects of institutional pressures and upper echelons characteristics (e.g., management team heterogeneity) on the relationship between disruptive IT innovations and firm performance.

The diffusion of disruptive IT innovations is facilitated by institutional pressures in an organizational setting. When managers perform an investment decision on a promising innovation, one of the key criteria they consider is the institutional environment in which their firm is located (Teo et al. 2003). Organizations compete not only for resources and customers but also for political power and institutional legitimacy for social and economic fitness (DiMaggio and Powell 1983). An institutional environment is composed of coercive pressures from regulative bodies, normative pressures from other organizations connected with the focal organization, and mimetic pressures from competitors (Meyer and Rowan 1977; Scott 1987; Scott 1995). These pressures lead to isomorphism or the emergence of institutionalized innovations over time (DiMaggio and Powell 1983). Organizations pursue an institutionalized disruptive IT innovation to gain legitimacy in securing resources for organizational survival (Meyer and Rowan 1977) and financial benefits (Scott 1995). However, conformity to institutional pressures does not necessarily mean that the most effective and efficient option is chosen; therefore, productive success and legitimacy are potentially contradictory goals and may not necessarily result in better firm performance (DiMaggio and Powell 1983). The impact of conformity to institutional pressures remains controversial among institutional theorists. Institutional research provides little resolution to the impact of institutionalized disruptive IT innovations on firm performance.

Disruptive IT innovation also significantly changes the architecture of work practices, and therefore, requires coordination among top managers to generate innovative solutions for such changes. Top management team (TMT) attributes such as heterogeneity (or diversity of member attributes), which affect the relationship among TMT members, are key to the success of disruptive IT innovations. TMT heterogeneity can be a double-edged sword to firms because of its potential to either benefit or disrupt teams and innovation (Bantel and Jackson 1989; Hambrick et al. 1996; Pieterse et al. 2013). However, previous studies focused on examining how environmental and organizational determinants enhance the likelihood of IT innovation success (Clemons and Row 1991; Dehning and Richardson 2002; Hendricks 2007; Kohli and Devaraj 2003; Li and Richard Ye 1999; Melville et al. 2004; Zhu and Kraemer 2002). An upper echelons approach (Hambrick and Mason

1984) would acknowledge how human and social factors at the top of the organization to influence the success of innovation. Several upper echelons studies in strategic management have examined the relationship between TMT heterogeneity and firm outcomes such as innovation and profitability (Devers et al. 2008; Geletkanycz and Sanders 2012; Van Knippenberg et al. 2004), but previous findings are mixed and provide limited implications for disruptive IT innovations.

Thus, this dissertation aims to fill these research gaps by addressing the following three research questions:

1. What is the impact of disruptive IT innovations on firm performance?
2. What are the moderating effects of TMT, firm, and industry level factors on the relationship between disruptive IT innovations and firm performance?
3. What are the managerial insights for top managers in fashion and textiles industries to enhance the performance of disruptive IT innovations?

Based on the case of RFID adoption, we employ event study methodology to examine the impact and contingencies of disruptive IT innovations on firm performance. RFID in the supply chain is an example of disruptive innovation (Fosso Wamba 2011; Krotov and Junglas 2008; Marinos 2005; Raynor 2004; Soon and Gutiérrez 2009) that induces significant changes to adopting firms' supply chain business processes and practices (Fosso Wamba and Chatfield 2011; Whitaker et al. 2007) and has been increasingly applied in various industries, such as fashion and textiles. RFID allows the automated identification of products by embedding chips with wireless antennas into objects (Bose et al. 2009). RFID offers numerous advantages over barcodes, such as absence of the constraint of line-of-sight tracking, simultaneous reading of goods, and reusability (Delen et al. 2007). Because the chips can store relevant information to share over the Internet in real time, RFID also creates complete visibility of inventory movement along the supply chain, from factories to retail outlets, thus leading to improvements in labor cost reduction, inventory management, and supply chain coordination (Lee and Özer 2007). Beginning in 2003, when Walmart launched a mandate requiring its top 100 suppliers (including apparel products suppliers) to use RFID tags on shipment cases or pallets, RFID has received increasing attention from academics and practitioners. A study from ABI Research (2010) reveals that the total RFID market is expected to increase 14% annually, to approximately US$ 8.25 billion by 2014. RFID has been widely applied in 14 areas, including but not limited to food, health, and retailing (Ngai et al. 2008).

The value of RFID technology is particularly valuable to the fashion and textiles industries because the fashion business is characterized by a wide assortment of highly seasonal products with short life-cycles, high levels of impulse-purchasing and complicated distribution and logistics operations (Christopher et al. 2004). In fashion retailing industries, item-based RFID implementation is an emerging trend. RFID tagging of clothing by multinational clothing manufacturers and retailers such as American Apparel and Marks & Spencer is now in the rollout phase, with 200 million RFID labels used globally for clothing in 2009 (Das and Harrop 2009). Clothing manufacturers are also under pressure to adopt RFID due to mandates from giant retailers such as Walmart.

However, RFID is still in the pilot-testing stage and is hindered by problems such as high costs, a lack of standards, the high complexity of system integration with current systems, data accuracy, top management attitude, and staff acceptance (Azevedo and Carvalho 2012; Moon and Ngai 2008; Tsai et al. 2010; Vijayaraman and Osyk 2006). These challenges may have negative impact on firms. Lee and Özer (2007) indicate that a credibility gap exists in reports and whitepapers, and call for more substantive analyses to the fill gap. A number of empirical studies have recently published to access the strategic impact of RFID adoption on firms. However, the actual benefits of RFID adoption remain controversial among academics and practitioners, and most of these studies are survey or case based studies focusing on large retailers or distributors. Little empirical work has been done to substantiate the benefits of RFID using objective data (Visich et al. 2009). Particularly, the benefits to manufacturing firms under pressure of RFID mandates from key customers such as Walmart are unclear (Katz 2005). Therefore, RFID in the supply chain provides a good example for examining the impact and contingencies of disruptive IT innovations on firm performance to help top executives respond appropriately to emerging disruptive IT innovations.

1.3 Theoretical and Managerial Contributions

This dissertation provides a theoretical foundation for the literature on disruptive IT innovations by providing some of the first comprehensive and objective evidence of the impact of a disruptive IT innovation on long-term firm performance along with the moderating effects of external and internal contingency factors. More specifically, our study on the relationship between disruptive IT innovations and risk complements prior IT research, which is primarily concerned with financial return using accounting-based measures or short-term market-based measures. Moreover, our findings show that the moderating effects of some contingency factors (e.g., industry competitiveness and corporate diversification) related to disruptive IT innovations are different from the effects related to non-disruptive IT innovations. This dissertation also contributes to institutional theory and upper echelons theory. It provides the first empirical evidence of the moderating effects of coercive pressure and TMT heterogeneity on the relationship between a disruptive IT innovation and firm performance which have divergent views.

With respect to managerial implications, our results show that RFID enables improvement in operational performance, financial performance, and systematic risk and send an encouraging message to managers to adopt disruptive IT innovations that are similar to the case of RFID. The contingency frameworks we developed based on the findings are applicable to fashion and textiles firms to help managers evaluate their environment to identify opportunities for disruptive IT innovation and to maximize its benefits through strategic planning. Firms should conform to coercive pressure to obtain legitimacy for the improvement of financial performance and systematic risk, and they should be prepared for the potential trade-off of conformity to coercive pressure and efficiency. Firms should also ensure sufficient financial slack and identify opportunities for synergetic effects among business lines for higher financial returns. Moreover, firms should consider redesigning their TMT structures to feature greater pay dispersion from incentive-based pay, along with greater demographic heterogeneity to obtain lower systematic risk. Finally, firms should ensure sufficient financial and labor resources for the adoption to improve financial performance and systematic risk.

1.4 Event Study Methodology

To reveal the causal effect of disruptive IT innovations on firm performance, we adopted the event study approach. An event study is an analytical method that focuses on the impact of a firm-specific event on the market value of the affected firm. Event study methodology was introduced by Fama et al. (1969) to test the abnormal performance of stock prices and is frequently used in accounting and finance research to examine market reactions to announcements or events. Later, Barber and Lyon (1996) proposed a method to examine the long-term impact on the operating performance of a firm event. Event study methodology has become the standard tool for investigating both short- and long-term firm performance. Event study allows researchers to objectively estimate the specific timing and magnitude of abnormal performance before and after the event (i.e., the implementation of RFID) takes place based on objective longitudinal data. Short-term event study captures an immediate abnormal return in market value reflecting investors' response towards an event. However, it does not reflect the actual impact of the event on operating performance in the long term. Therefore, in this dissertation, we focus on employing long-term event study to examine the impact of disruptive IT innovation on long-term firm performance.

1.5 Outline of the Dissertation

This study is organized as follows. Chapter 2 reviews the relevant literature on disruptive IT innovations, institutional theory, upper echelons theory, and RFID adoption. We discuss the event study methodology and data collection procedures in detail in Chapter 3. Based on the research gaps that we identify from previous studies, we conduct three independent but closely related studies, which are reported in Chapters 4, 5, and 6. These three studies use the same methodology of event study. We present our research hypotheses and the corresponding results of our research in Research Part One (Chapter 4), Research Part Two (Chapter 5) and Research Part Three (Chapter 6).

Chapter 4 investigates whether the adoption of disruptive IT innovations contributes to operational performance and tests how the impact of disruptive IT innovation varies across industries (i.e., fashion and textiles industries versus other industries, retailers and wholesalers versus manufacturers).

Chapter 5 focuses on examining whether disruptive IT innovations adoption improves financial performance and on testing a proposed contingency framework (i.e., coercive pressure, industry clockspeed, industry competitiveness, financial health, business diversification, and geographic diversification).

Chapter 6 examines whether disruptive IT innovations reduce systematic risk and investigates how TMT heterogeneity (i.e., pay dispersion and demographic heterogeneity) moderates the relationship between disruptive IT innovations and systematic risk.

Finally, Chapter 7 provides a summary of this dissertation and explains its major theoretical implications for the disruptive IT innovations literature and its managerial implications for fashion and textiles firms.

CHAPTER 2 BACKGROUND AND THEORETICAL DEVELOPMENT

2.1 Disruptive IT Innovations

Disruptive innovations are technologies, products, services, and business models that introduce a performance package of attributes that is different from the mainstream usually valued by customers (Brower and Christensen 1995; Christensen and Raynor 2003). In general, disruptive innovations appear financially unattractive to established firms, and the risk of failure is high because of higher costs and uncertain market reaction over the long term. Moreover, the performance of disruptive innovations never surpasses the capability of the old technology in the early stages, although it can satisfy the requirements of the future market. An example of disruptive innovation is the emergence of smaller disk drives that are slower and have lower capacity than existing disk drives. This compact technology eventually overtook the older market and displaced the established technologies. Other examples applied in fashion and textiles industries include Internet applications, RFID, and ERP.

When a disruptive innovation is new to an organization, its adoption can have a destructive impact on the organization's operation (Christensen and Raynor 2003). Traditionally, disruptive innovations are believed to provide firms with huge financial returns. However, the potential financial return for disruptive innovations is not guaranteed because of high implementation costs and uncertain market reaction. Christensen and Raynor (2003) report that firm resources, processes, and values affect the decision to adopt disruptive innovations. Assink (2006) finds several key inhibitors that hinder large firms' success in developing disruptive innovations. The inhibitors include an inability to unlearn obsolete mental models, a lack of knowledge of how to design the new business concept, a lack of adequate follow-through competencies, and an inability to develop mandatory internal or external infrastructures. Moreover, Christensen and Raynor (2003) note that "disruptive" is a relative term. An idea deemed disruptive by one business may be sustainable for another. In other words, provided adoption is new to an organization, it can have a disruptive impact on that organization.

IT innovation is defined as innovation in the organizational application of digital and communication technologies (Swanson 1994). Swanson (1994) categorizes IT innovation into three broad categories. Type I innovations are process innovations (e.g., new software or hardware architecture) that enhance efficiency and are mainly limited to information system (IS) departments. Type II innovations refer to the use of IS products and services that aim to improve administrative processes (e.g., IT innovations for accounting systems). Type III innovations are service innovations that are of strategic importance to firms because they affect business functions, including an organization's core business processes (e.g., material requirements planning).

Given the disruptive nature of some IT innovations, Lyytinen (2003) leverages the similarity between disruptive innovation and IT innovation and introduces a model of disruptive IT innovation that distinguishes between disruptive and incremental IT innovations. A disruptive IT innovation is an architectural innovation originating from an IT base that subsequently pervades and radically impacts development processes and their outcomes. In other words, disruptive IT innovations dramatically modify an organization's division of labor and require new skills and behavior to sustain competitive advantage. Disruptive IT innovations often encounter resistance from people who believe that their interests would be compromised following the adoption of those innovations (Orlikowski 1993).

2.2 The impact of Disruptive IT Innovations

Although the nature of disruptive IT innovation is well recognized, studies of its impact on firm performance remain underdeveloped. Much of the previous research has focused on studying the firm performance and implications of non-disruptive IT investments (e.g., Hitt and Brynjolfsson 1996; Mithas et al. 2012) that are highly compatible either with existing systems or with processes with which users are already familiar (Christophe and Detmar 2011). Moreover, previous studies focus on examining the impact of IT innovations on financial return using accounting-based measures or short-term, market-based measures. However, risk, which is a key dimension of firm performance (Brealey and Myers 2002), remains relatively neglected in the IT literature. Disruptive IT innovations entail pervasive and radical changes in both the organization and organizational processes (Lyytinen 2003; Wei et al. 2005). These changes consequently cause uncertain effects on the risk portfolio of firms. Therefore, studying the effect of disruptive IT innovations on firm risk is important. Emerging studies have also suggested the importance of the impact and contingencies of IT applications on firm risk (Dewan and Ren 2007; Dewan and Ren 2011; Dewan et al. 2007; Tanriverdi and Ruefli 2004).

Previous research has also suggested that the link between IT innovation and firm performance depends on a range of factors such as industry competitiveness, industry clockspeed, management support, type of IT, time, and firm size (Clemons and Row 1991; Dehning and Richardson 2002; Hendricks 2007; Kohli and Devaraj 2003; Li and Richard Ye 1999; Melville et al. 2004; Zhu and Kraemer 2002). Melville et al. (2004) formulates several propositions based on the resource-based view and posits that IT business value is dependent upon both internal (e.g., organizational resources) and external (e.g., trading partners and industry competitiveness) factors. However, the moderating effect of some contingency factors may not be applicable to disruptive IT innovations because their adoption will result in dramatic changes to a firm's operations (Lyytinen and Rose 2003). For instance, although previous studies suggest that non-disruptive IT innovations provide organizations with enhanced value in competitive environments (Melville et al. 2007), this may might not be the case for disruptive IT innovations. Firms in competitive industries require operations that are more efficient to stay ahead of the competition (Scherer and Ross 1990). However, disruptive IT innovations cause disruptions that may negatively impact firms in competitive environments. Another example is the influence of corporate diversification. Previous studies show that non-disruptive IT investment benefits diversified firms in terms of economies of scale, transfer of technologies across lines of business, and exploiting new use of existing IT resources (Carlo et al. 2011; Clemons and Row 1991). However, this may not be the case for disruptive IT innovations, which are complicated to integrate with existing systems. Diversification implies higher complexity in integration with greater disruptions to operations, and their adoption may thus have a negative impact on firm performance. Furthermore, the moderating effects of institutional pressures and upper echelons attributes on the relationship between disruptive IT innovations and firm performance remain uncertain.

2.2.1 Institutional Theory and Disruptive IT Innovations

From an institutional perspective, organizations compete not only for resources and customers but also for political power and institutional legitimacy for social as well as economic fitness (DiMaggio and Powell 1983). An institutional environment is composed of coercive pressures from regulative bodies, normative pressures from other organizations connected with the focal organization, and mimetic pressures because of uncertainty (Meyer and Rowan 1977; Scott 1995). These pressures lead to isomorphism or the emergence of institutionalized innovations over time (DiMaggio and Powell 1983). An innovation is institutionalized when it is widely understood to be appropriate and necessary for organizations to achieve high efficiency and to maintain their legitimacy through the integration of such innovation into their formal structure (Tolbert and Zucker 1983). Once an innovation is institutionalized, its adoption may not necessarily be justified (Zucker 1987b).

Organizations conform to institutional pressures to gain legitimacy in securing resources for organizational survival (Meyer and Rowan 1977) and financial performance enhancement (Scott 1995). Organizations would be sanctioned otherwise for the lack of perceived legitimacy (DiMaggio and Powell 1983). Legitimacy is defined as "a generalized perception or assumption that the actions of an entity are desirable, proper, or appropriate within some socially constructed system of norms, values, beliefs, and definitions" (Suchman 1995, p574). Legitimacy is critical in accessing various resources from potential exchange partners in the organizational field, such as customers, suppliers, and regulators who a firm needs to survive (Meyer and Rowan 1977). Beyond survival, legitimacy also allows the acquisition of necessary resources that will enhance firm performance (Scott 1995). Legitimacy can be divided into three dimensions under the three pillars or elements of institutions, namely, cognitive, normative, and regulative elements.

Different types of legitimacy can be obtained by three different mechanisms: mimetic, normative, and coercive isomorphism (Scott 1995, page 52). Specifically, mimetic isomorphism obtains cognitive legitimacy by conforming to a common definition of a recognizable practice that emerges from the adoption of innovations utilized by successful organizations or by those confronting high uncertainty and a lack of clear information on technologies. Normative isomorphism obtains normative legitimacy by conforming to shared values, such as accreditations and certifications, arising from pressures related to professional standards (e.g., from trading associations) and social actors (e.g., NGOs). Lastly, coercive isomorphism obtains regulative legitimacy by conforming to formal or informal pressures (i.e., imposition and inducement) from the government or from organizations over dependent organizations (e.g., mandate of RFID adoption from retailers on suppliers) that need resources of legitimacy.

Although conformity to institutional pressures provides firms with the legitimacy needed to secure valued resources for survival and better financial performance (Meyer and Rowan 1977; Scott 1995), conformity to institutional pressures can constrain a firm’s functional autonomy in performing its core work activities, limiting the benefits of the adoption, which have little or no effect on the actual efficiency of organizational operations (Meyer and Rowan 1977; Tolbert and Zucker 1983; Zucker 1987a). Firms that conform to the adoption would also draw resources away from other performance-enhancing activities and then negatively influence performance (DiMaggio and Powell 1983; Meyer and Rowan 1977).

The impact of conformity to institutional pressures on financial performance remains controversial among institutional theorists. However, previous research focused on investigating the effect of institutional pressures on decisions regarding innovation adoption (e.g., Berrone et al. 2013; Teo et al. 2003) rather than examining the effects of conformity to institutionalized innovation adoption on firm performance. Only a few studies related to the effects of conformity to institutionalized innovation adoption on firm performance are found (e.g., Westphal et al. 1997; Yeung et al. 2011; Zhu and Sarkis 2007). As an example, Westphal *et al.* (1997) examined the consequences of conformity on normative adoption (i.e., total quality management accreditation in over 2,700 U.S. hospitals) and stated that adoption was positively associated with legitimacy (e.g., higher ratings on compliance) and negatively associated with firm performance (e.g., return on equity). Yeung *et al.*(2011) examined the effect of ISO 9000 on institutionalized environments with coercive, normative, and mimetic pressures using data on U.S. manufacturers that adopted ISO 9000 from 1994 to 2006 and found that the firms that conformed to institutional pressures obtained benefits of personal legitimacy (e.g., higher CEO compensation), but their performance did not improve (e.g., return on assets). Furthermore, Zhu and Sarkis (2007) conducted a survey involving 341 Chinese manufacturers that conformed to green supply chain management (GSCM) because of mimetic (competitive), normative (customers), and coercive (regulation) pressures to examine whether specific institutional pressures moderate the GSCM practice and the performance improvement relationship. Zhu and Sarkis (2007) identified a positive moderating effect of mimetic pressures on GSCM and economic benefit and a negative moderating effect of regulation and normative pressures on GSCM and economic performance.

In summary, the findings of the aforementioned studies are inconclusive and the impact appears to vary depending on the institutional context. Moreover, these studies focus on examining the impact of administrative innovations, whereas disruptive IT innovations, which may have different effects (Wang 2010), remain a relatively neglected area. Most importantly, there is lack of empirical evidence of the effect of coercive pressure from customer mandate on firm performance.

2.2.2 Upper Echelons Theory and Disruptive IT Innovations

Based on their assertion that organizations are "reflections of the values and cognitive bases of powerful actors in the organization," Hambrick and Mason propose an upper echelons (UE) perspective that suggests that "organizational outcomes—strategic choice and performance levels—are partially predicted by managerial background characteristics" (Hambrick and Mason 1984, page 193). Hambrick and Mason also suggest that demographic characteristics of executives such as age, tenure and functional experience, along with TMT heterogeneity, can be used as proxies for the cognitive base that guides top executive decisions.

Recently, TMT heterogeneity has been a central construct in the literature on top management (Hambrick et al. 1996). TMT heterogeneity refers to differences in concentration of valued social assets or resources such as pay and status among group members (Cohen and Levinthal 1990; Nielsen 2010). TMT heterogeneity can be measured from different dimensions, such as demographic characteristic and pay dispersion. TMT heterogeneity can be a double-edged sword to firms because it has the potential to both benefit and to disrupt team and organizational performance (Devers et al. 2008; Geletkanycz and Sanders 2012; Van Knippenberg et al. 2004). Although some studies find that demographic heterogeneity is positively associated with firm performance (Bantel and Jackson 1989; Carpenter 2002; Devers et al. 2007; Jackson 1992), others determine that demographic heterogeneous groups perform less well than homogeneous groups (Pelled et al. 1999; Tsui et al. 1991). TMT with greater diversity of backgrounds may possess a greater breadth of resources (Dutton and Duncan 1987). However, their diversity may also engender conflict and distrust because widely dissimilar team members may have different objectives, values, and perspectives. Therefore, heterogeneity can become a net liability that causes firm performance to suffer.

Pay dispersion is another important dimensions of heterogeneity that is linked to firm performance (Geletkanycz and Sanders 2012) but remains a relatively neglected area in the literature. Pay dispersion refers to divergent compensation among TMT members who are compensated differently for their contributions and effectiveness. A well-designed pay structure can effectively incentivize senior managers and increase firm performance. The key question is whether widely dispersed or tightly dispersed pay is more effective and strategically valuable for organizational performance. However, there are divergent views on pay dispersion (Bloom 1999; Conyon et al. 2001; Fredrickson et al. 2010; Pfeffer and Langton 1993; Shaw et al.

2002; Siegel and Hambrick 2005). Bishop (1987) suggests that dispersed pay offers three benefits. First, it can serve as an incentive for greater employee effort. Second, it helps firms attract more capable and hardworking employees. Third, it reduces the probability of losing the best performers. Similarly, Milgrom (1992) asserts that widely dispersed compensation systems motivate executives who are low performers to perform better so that they will receive large returns. Some researchers find that firm performance is higher when TMT pay is more dispersed (Ehrenberg and Bognanno 1990; Lazear and Rosen 1981; Main et al. 1993; Shaw et al. 2002). However, other scholars find that widely dispersed pay can create disincentives for cooperation, instill feelings of inequity, foster dissatisfaction, and diminish performance (Bloom 1999; Fredrickson et al. 2010; Pfeffer and Langton 1993; Siegel and Hambrick 2005). Previous studies indicate that whether the benefits of pay dispersion outweigh its harmful consequences also appears to depend on certain organizational contingencies such as work context and industry type (Henderson and Fredrickson 2001; Shaw et al. 2002; Siegel and Hambrick 2005). Researchers urge for additional research to help understand the role of pay dispersion in firm performance (Devers et al. 2008).

Studying the effect of TMT heterogeneity on the impact of disruptive IT innovations on firm performance is particularly important because disruptive IT innovations entail pervasive and radical changes in the organization and organizational process (Lyytinen 2003). These changes disrupt existing operations and cause uncertain environments that require coordination among top managers to generate solutions for the disruptions and problems that may have not been considered previously. Although TMT with greater demographic diversity may possess greater breadth of resources such as skills sets and experience (Dutton and Duncan 1987) in the adoption of disruptive IT innovations, it may also engender conflict and distrust that make team coordination difficult. Similarly, pay dispersion motivates members to exert greater effort to obtain higher pay (Main et al. 1993); however, it can also inspire team dysfunction, leading to negative organizational consequences. Because managers may be self-interested and may seek to maximize their own interest, they thus become less committed to organizational goals and their cohesiveness declines (Henderson and Fredrickson 2001). Overall, the existing literature offers little resolution to the question of whether TMT heterogeneity is beneficial to disruptive IT innovations.

2.3 RFID as Disruptive IT Innovation

RFID for supply chain management (SCM) is well recognized as a disruptive technology that induces significant changes to adopting firms' supply chain business processes and practices (Fosso Wamba 2011; Krotov and Junglas 2008; Marinos 2005; Raynor 2004; Soon and Gutiérrez 2009). RFID can replace the existing barcode system and brings radical changes to adopting firms' supply chain operations (Whitaker et al. 2007). RFID allows automated identification products by embedding chips with wireless antennas on objects (Bose et al. 2009). Because the chips can store relevant information to share over the Internet in real time, RFID creates complete visibility of inventory movement along the supply chain, thus leading to improvement in labor cost reduction, inventory management, and supply chain coordination (Lee and Özer 2007). RFID also enables supply-chain business process innovation (Fosso Wamba et al. 2008), and it enables the supply chain to provide new products and services (Leimeister et al. 2009). Moreover, RFID provides real-time intelligence to organizations (Marinos 2005). Real-time intelligence is a new concept that refers to a “communicative object” (Ferguson 2002) that can communicate or even interact with its environment and can be exploited to have a profound impact on both business and society (Krotov and Junglas 2008). For example, it shifts management style from a passive management mode to a more proactive management mode and enables an efficient fight against counterfeit products (Berkhout 2007). Additionally, RFID allows stakeholders in the supply chain to exchange sharing information in real time through the Internet and private networks without constraint on time and location, thus supporting new business model (e.g., B-to-B e-commerce applications) (Lefebvre et al. 2005). The benefits of RFID technology is particularly apparent to the fashion and textiles industries which are characterized by a wide assortment of highly seasonal products with short life-cycles, high levels of impulse-purchasing and complicated distribution and logistics operations (Christopher et al. 2004).

However, RFID systems require new competences that are different from those demanded for installing barcodes (Park 2007). These competences include RFID data analysts, RFID systems technicians, and RFID maintenance officers in the business network to obtain the full potential of RFID (Fosso Wamba et al. 2008). The integration of RFID into a firm’s supply chain processes may also lead to the destruction of its existing competences, leading to the reinvention of its key processes in the business network (Cannon et al. 2008). Furthermore, RFID adoption requires warehouse activities in the supply chain to be completely re-engineered (Lefebvre et al. 2005).

In addition, whereas the barcode is a well-established technology in the supply chain, RFID is relatively new to SCM because it is still in the pilot testing stage and is hindered by problems such as high costs, lack of standards, a high complexity of system integration with current systems, data accuracy, top management attitude, and staff acceptance (Azevedo and Carvalho 2012; Moon and Ngai 2008; Vijayaraman and Osyk 2006). For example, in a study related to RFID technology in the fashion supply chain, Azevedo and Carvalho (2012) show that the primary issues are the difficulties of integrating RFID into current systems and the high costs associated with tags, infrastructure and software systems. Similarly, Sheffi (2004) reports that the disruptive effect of RFID is similar to that of personal computers and televisions whose evolution can be divided into six stages: (1) fog of innovation, (2) life support for existing technologies, (3) stamp of approval, (4) transition from the old technology, (5) ubiquity, and (6) big bang. The benefits of RFID are still unclear and several issues, such as standards, privacy, and security issues, remain unresolved. Sheffi (2004) addresses these problems by classifying RFID development as existing between the first and the third stages of the innovation cycle. Given the disruptive nature of RFID, firms adopting RFID may not immediately experience its benefits (Visich et al. 2009), and it may take as long as two to three years for returns on investment to begin to appear (Kärkkäinen 2003).

2.3.1 The impact of RFID on Firm Performance

RFID has received increasing attention from academics and practitioners since Walmart launched a mandate requiring its top 100 suppliers to use RFID tags on the cases or pallets of shipments in 2003. However, the actual benefits of RFID adoption remain controversial among academics and practitioners. There are studies show that

RFID is beneficial to firms (Fosso Wamba et al. 2008; Kim et al. 2008; Langer et al. 2007; Moon and Ngai 2008). A case study of five Hong Kong fashion retailers by Moon and Ngai (2008) indicate improved operational efficiency and effectiveness and increased sales and profits as major benefits of RFID adoption. In a study of an RFID project in a single supply chain, Wamba et al. (2008) find that RFID adoption improves the performance of certain logistic processes in the retail industry, including "shipping", "receiving", and "put-away". In a comparative survey study of 70 U.S. and 87 Korean retailers, Kim et al. (2008) indicate that RFID adoption improved the inventory management of both the U.S. and the Korean retailers. Langer et al. (2007) conduct a field study for a logistics firm that has adopted RFID. The number of claims filed against the firm is reduced, and efficiency in outbound logistics improved. In a case study of a fashion-industry project involving a leading European retailer and a fashion merchandise manufacturer, Loebbecke and Palmer (2006) find that both partners experience benefits that exceed the RFID costs. They observe time savings and reduced labor costs. Moreover, they find that RFID adoption offers new service to supply chain partners and consumers.

Conversely, there are studies suggest that RFID adoption provides minimal benefit to operational and financial performance. For example, Bottani and Rizzi (2008) reveal that RFID implementation in case-level tagging remains unprofitable for manufacturers in the fast-moving consumer goods supply chain. Yang and colleagues (2008) discuss that most of the suppliers subject to Walmart's mandate suffered from the high cost, unstable technology, and slim benefits gained of RFID adoption. Only a few suppliers, such as Kimberly and P&G, benefited from RFID adoption. Likewise, a recent report by Boston-based AMR Research shows that manufacturers of consumer products that are somehow involved with Walmart are unable to make a business case for using RFID and thus limit their projects to bare-minimum compliance (Katz 2005).

Moreover, most of the previous studies are surveys or case studies focusing on large retailers or distributors. Little empirical work has been done to substantiate these claims using objective data (Visich et al., 2009). Particularly, the benefits to manufacturing firms under pressure of RFID mandates from key customers such as Walmart and the Department of Defense are unclear (Katz, 2005). Some scholars argue that the RFID adoption might only benefits downstream supply chain members (i.e., retailers) but not manufacturers (Wang 2010). The rapid diffusion and market growth of RFID are mainly due to institutional pressures (DiMaggio and Powell 1983; Lai et al. 2006). Therefore, implementing a longitudinal study is important, in order to understand the impact of RFID adoption on the performance of manufacturing firms.

More recently, scholars have used other approaches to estimate the financial impact of RFID more objectively. For example, in a study based on 108 publicly traded firms from various industries and countries that have adopted RFID, Bose et al. (2011) conclude that the relationship between RFID investment announcements and market reaction is negative because investors perceive RFID as a disruptive IT innovation with high risk and cost. Moreover, their sub-sampling analysis shows that U.S.-based firms, late adopters, nonmanufacturing firms, less-diversified firms, financially unhealthy firms, and low-growth-potential firms suffer a more negative impact when firms announce their adoption of RFID. Although short-term event studies provide important insight into the market response to RFID adoption and the factors influencing that impact, the findings merely reflect investors' perception towards RFID investment in the short term, and do not reflect the long-term operating benefits of RFID. Chang (2011) compares 65 manufacturing firms that adopted RFID between 2003 and 2005 to a matched firm that did not adopt RFID to determine changes in profitability over the pre-to-post adoption period. Chang finds that the adopting firms received significant profitability benefits. However, Chang neither focus on examining operational performance, risk performance, nor the moderating effect of contingency factors on that impact.

Drawing on the insights from both disruptive IT innovations and RFID literature, we aim to examine three critical organizational consequences of RFID adoption, namely, operational performance, financial performance, and systematic risk, with a focus on manufacturing firms. Systematic risk is an important dimension of firm performance that has been neglected in the IT literature, which we will discuss further in Chapter 6. We further investigate the effect of a set of contingency factors, such as coercive pressure from customer, which are specific to disruptive IT innovations and RFID adoption.

2.3.2 Institutional Perspective on RFID Adoption

The diffusion of RFID adoption provides an appropriate setting to our research question about the influence of external contingency factor coercive pressure on firm performance. Since 2003 when Walmart required its top 200 suppliers to adopt RFID, the technology has been increasing adopted by firms and it is considered the next wave of IT revolution (Srivastava 2004). By contrast to other IT innovations, such as

ERP and electronic data interchange (EDI), the worldwide diffusion of RFID has been a wave-like phenomenon triggered by the mandate of Walmart in late 2003. Mimetic actions by other major retailers around the globe followed. Government organizations likewise requested their suppliers to adopt RFID, e.g., the U.S. Department of Defense (DOD) in 2005, and the Food and Drug Administration (FDA) in 2006. A firm that joins an RFID-enabled supply chain has no choice but to adopt RFID. Although firms engaging in RFID because of customer mandate(s) could gain legitimacy that offer additional financial benefits (Scott 1995), the adoption might not actually improve their operations because the adoption is mainly driven by institutional forces. Therefore, the effect of coercive pressure from customer mandate on firm performance appears uncertain and worthwhile for an in-depth examination in this dissertation (moderating effect of coercive pressure was examined in Chapter 4, 5, and 6).

2.4 Chapter Summary

We introduced the background of disruptive IT innovations, including benefits and challenges that may lead to an impact and contingencies that are different from non-disruptive IT innovation. We also introduced institutional and upper echelons perspective which may moderate the impact of disruptive IT innovations on firm performance. In addition, this section discussed RFID in the supply chain as an example of disruptive IT innovation and its impact on adopting firms leading to the three empirical studies in Chapter 4, 5, and 6.

CHAPTER 3 RESEARCH METHODOLOGY

3.1 Data Collection

We conducted a comprehensive announcement search covering various databases and around 10,000 listed firms (SIC code 2000-5999) in Standard and Poor's COMPUSTAT. We searched for RFID adoption announcements containing names of publicly listed firm names—keywords such as "RFID," "RF-ID," or "radio frequency identification"─from Factiva for 1992 through 2012. Following the previous literature in both disruptive innovations and RFID technology (e.g., Brower and Christensen 1995; Christensen and Raynor 2003; Lyytinen and Rose 2003; Soon and Gutiérrez 2009), we defined RFID adopters as firms that have applied their first RFID adoption to their supply chain. We focused on the first RFID adoption, which is new to a firm and can have a disruptive impact. A systematic review mechanism was adopted to ensure data validity. We first collected and codified all RFID adoption announcements. We then reviewed all of the announcements and verified any ambiguous cases to ensure that the selection and coding of those announcements are both objective and accurate.

Following the standard practice identified in several previous event studies (Corbett et al. 2005; Naveh and Marcus. 2005), we focused on the first of multiple announcements made by individual firms regarding RFID adoption. Moreover, we eliminated announcements with confounding events such as new firm business, merger and acquisition, and other automatic identification applications (e.g., QR Code) in the supply chain occurring within the five-year confounding window lasting from two years before the event to three years after the event. To ensure that firms do implement RFID, we cross checked announcements collected from Factiva with news from other public sources. For example, lists of manufacturers subject to customer mandates (e.g., Walmart and the Department of Defense), Google News, and related technology periodicals including RFID Journal and the RFID Knowledgebase. The RFID Knowledgebase is acknowledged as the most comprehensive of RFID case study databases to document details of firms' RFID adoption, including implementation scale and RFID solution suppliers for RFID adopters. After extensive and careful filtering, we obtained 410 publicly listed firms (372 manufacturers and 27 wholesalers and retailers) that adopted RFID from 1992 to 2012. Among them, 32 firms are from the fashion and textiles industries. Below are examples of such an announcement.

- *Apr 14, 2008: PR Newswire (U.S.): American Apparel Deploys RFID Solution from Motorola to improve inventory accuracy and streamline operations.*
- *Oct 29, 2004: CMP TechWeb: Nautica, The North Face, and Vanity Fair brands have already begun shipping tagged cases of their products to Wal-Mart's three distribution centers and says that they expect to use approximately 600,000 RFID tags a year initially.*

We obtained firm performance data from COMPUSTAT and stock data from CRSP. We required the performance data to be dated at least two years prior to RFID adoption to match a control firm for further analysis. One hundred sixty firms adopted RFID before becoming listed firms. Therefore, the number of sample firms decreased to 250, 230 of which belong to manufacturing firms (SIC code 2000-3999) and 20 to retail and wholesale firms (SIC code 5000-5999). The entire sample (250) was used in Chapter 4 for comparison among industries, whereas manufacturing sample firms were used in Chapters 5 and 6.

3.1.1 Distribution of Announcements by Industry, Year, and Mandate

Among the 250 RFID announcements that we collected from the Factiva and RFID journals, Figure 3.1 presents the number of RFID announcements among the publicly listed firms. It shows that Food Products (SIC code: 2000) and Chemicals (SIC: 2800) are the two industries with most RFID adoption announcements. Fashion and textiles related industries (SIC: 2200, 2300, 3100, 5600) have 19 announcements. The distribution shows that although RFID technology can provide significant benefits to the fashion and textiles related firms, it is still not commonly adopted in those industries.

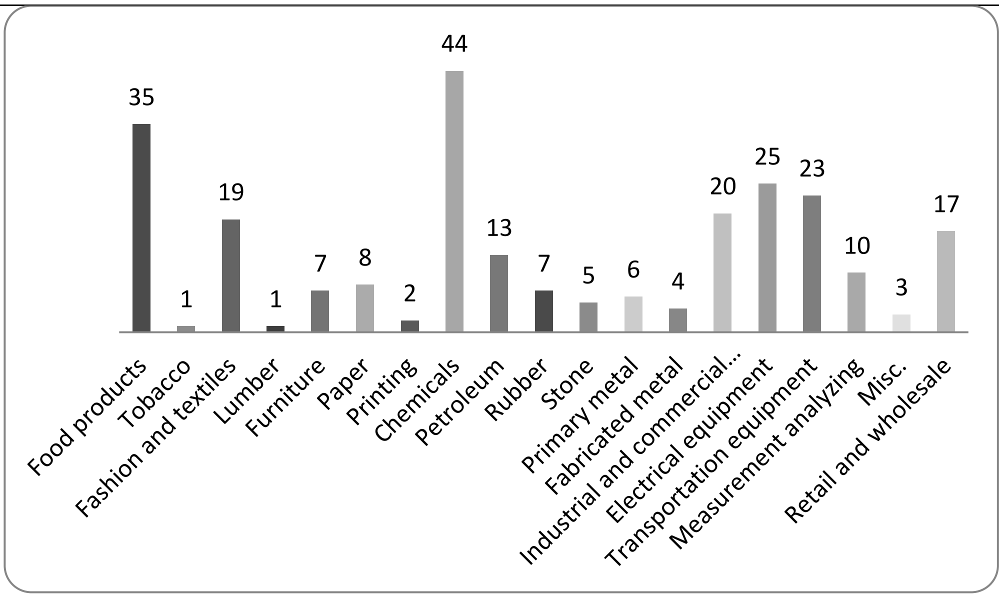

Figure 3.1 Distribution of 250 RFID Announcements by Industry

Table 3.1 shows the year of distribution of the announcements for the 20 retail and wholesale firms and 230 manufacturing firms, respectively. This table also shows that the majority of the RFID adoption announcements in manufacturing industries came in the years 2004, 2005, and 2006 are mainly due to mandates from Walmart in 2003 requesting their top 200 suppliers ship their products with RFID tags by the end of 2006. Specifically, among the 230 announcements from manufacturing industry, nearly 55% (127 out of 230) had adopted RFID through their own initiative in light of the perceived benefits of RFID systems, whereas 45% (103 out of 230) adopted RFID due to customer requirements such as government policies and mandates of business partners. Among the 103 coercive adoptions, 65 firms disclosed the corresponding mandators in their adoption announcements. Among the adopters, 52 stated that retailers were the mandators, such as Walmart for most firms (50 out of 52), whereas 11 reported that the government was the mandator. Below is an example of such an announcement.

- Mar 4 2007: The RFID Knowledgebase: *Shaw Industries Group, a carpet and rug producer, has contracted ODIN Technologies to design and install an RFID system for supply chain optimization and to also comply with* ***Wal-Mart's mandate****.*

Table 3.1 Distribution of 250 RFID Announcements by Year and Mandate			
Whole sample			
Year	Retail and wholesale sample no.	Manufacturing sample No.	Manufacturing firms under coercive adoption
1992		1	
1996		1	
1997		2	
1998		5	
1999		1	
2000		5	
2001		8	
2002	1	6	1
2003	1	15	4
2004	2	47	30
2005	6	65	43
2006	7	37	20
2007	1	20	2
2008	2	7	2
2009		7	1
2010		2	
2011		0	
2012		1	
Total	20	230	103

3.1.2 Fashion and Textiles Industries as Fast Clockspeed Industries

Industry clockspeed represents new product introduction and product obsolescence rate in an industry (Fine 1998). Industry clockspeed classifies industries into three types: fast, median, and slow with an obsolescence rate less than three year, three to 10 years, and more than ten years, respectively (Fine 1998). Accordingly, we classified the sample of manufacturing firms into three groups (i.e., fast, median, and slow). Table 3.2 shows the distribution of industry clockspeed for manufacturing firms. The fashion and textiles industries introduce seasonal products and therefore, they are defined as fast clockspeed industries.

Table 3.2 Description of Fast, Medium, and Slow Clockspeed for 230 Manufacturing Firms

Industry	SIC code	No. of announcements
Fast clockspeed industries		*33*
Fashion and textiles	2200, 2300, 3100	16
Cosmetics	2840, 2844	5
Computer	3570, 3571	4
Semiconductor	3674	5
Misc. (e.g., toys)	3900	3
Medium clockspeed industries		*151*
Food	2000	35
Printing	2700	2
Chemical products [a]	2800	39
Rubber	3000	7
Fabricated metal	3400	4
Industrial equipments [a]	3500	16
Electrical components [a]	3600	20
Transportation [a]	3700	18
Measurement tools	3800	10
Slow clockspeed industries		*46*
Tobacco	2100	1
Lumber & wood	2400	1
Furniture	2500	7
Paper	2600	8
Petrochemicals	2900	13
Stone products	3200	5
Primary metal	3300	6
Aircraft & shipbuilding	3721-3728, 3760	5
Total		230

[a] Exclude SIC code classified as fast or slow clockspeed industries

3.1.3 Details of Fashion and Textiles RFID Adopters

Table 3.3 shows all the announcements of RFID adoption in the fashion and textiles related firms. The table contains the SIC code, the motivation of the adoption, and whether they are Walmart suppliers who face pressure from adoption mandates. The data also shows that a number of famous fashion brands had already adopted RFID in their operations. There were 19 fashion and textiles related firms with financial data from year *t* - 2 (remarked in the last column of Table 3.3).

Table 3.3 List of Fashion and Textiles Firms						
No.	Firm name	SIC	Adoption year	Motivation	Mandator	Financial data
1	American Apparel Inc	2300	2008	Proactive	None	NA
2	Ashworth Inc	2300	2006	Proactive	None	Available
3	Bebe Stores Inc	2300	2004	Reactive	NA	Available
4	Calvin Klein Inc	2300	2005	Proactive	None	NA
5	Fruit of the Loom Ltd	2200	2005	Reactive	NA	NA
6	Fifth & Pacific Companies Inc	2300	2011	Proactive	None	Available
7	Garan Inc	2300	2005	Reactive	NA	NA
8	Jones Apparel Group Inc	2300	2009	Reactive	Walmart	Available
9	Kellwood CO	2300	2004	Proactive	None	Available
10	Levi Strauss & CO	2300	2004	Reactive	Walmart	Available
11	Liz Claiborne Inc	2300	2001	Proactive	None	NA
12	LVMH Moet Hennessy	2300	2001	Proactive	None	Available
13	Maidenform Brands Inc	2300	2012	Proactive	None	Available
14	Mohawk Industries Inc	2200	2005	Proactive	None	Available
15	Nautica Enterprises Inc	2300	2004	Reactive	Walmart	Available
16	Noel Group Inc	2200	2006	Reactive	NA	NA
17	North Face Inc	2300	2004	Reactive	Walmart	NA
18	Pillowtex Corp	2300	2005	Reactive	NA	NA
19	Playtex Apparel Inc	2300	2005	Reactive	NA	NA
20	Polo Ralph Lauren CP	2300	2006	Proactive	None	Available
21	Polymer Group Inc	2200	2005	Proactive	None	Available
22	Russell Corp	2200	2005	Reactive	NA	Available
23	Shaw Industries Inc	2200	2006	Reactive	Walmart	NA
24	Springs Industries	2200	2005	Reactive	NA	NA
25	Sunbeam Corporation	2300	2005	Reactive	NA	NA
26	Tandy Brands Accessories Inc	3100	2005	Reactive	Walmart	Available
27	Tommy Hilfiger Corp	2300	2008	Proactive	None	NA
28	VF Corp	2300	2005	Reactive	Walmart	Available
29	Wolverine World Wide	3100	2005	Reactive	Department of Defense	Available
30	Abercrombie & Fitch	5651	2006	Proactive	None	Available
31	Gap Inc	5651	2005	Proactive	None	Available
32	J Crew Group Inc	5600	2005	Proactive	None	Available

3.2 Event Study Methodology

An event study focuses on the impact of a firm-specific event on the market value of the affected firm. It shows causal relationship between the event and abnormal performance. Event study methodology was introduced by Fama et al. (1969) to test the abnormal performance of stock prices, and is frequently used in accounting and finance research to examine market reaction to announcements or events. Later, Barber and Lyon (1996) proposed a method to examine the long-term impact of a firm event on operating performance. Event study methodology has been commonly used for investigating both short-term and long-term firm performance. Event study allows researchers to objectively estimate the specific timing and magnitude of abnormal performance before and after the event (i.e., the implementation of RFID) takes place based on longitudinal data. In this dissertation, we employ both long-term and short-term event studies to examine the impact of disruptive IT innovation on firm performance.

3.2.1 Long-Term Event Study Methodology

3.2.1.1 Data Analysis

We adopted long-term event study methodology following a number of recent studies (e.g., Corbett et al. 2005; Hendricks 2008). Abnormal changes refer to unusual changes in a sample firm compared to the control firms. In this dissertation, the event study period is period from the RFID implementation to three years after it has been fully implemented. The year of formal RFID adoption was represented as year *t*. Formal RFID adoption indicated that the firm had successfully adopted RFID to its full scale. Previous studies reported that such full-scale integration of RFID into the supply chain system requires approximately one year[1] of implementation (Hendricks 2007; Roberti 2004). Thus, we used *t* - 1 as the initiating time of RFID implementation and year *t* - 2 as the base year that is free from the impact of RFID adoption to match the control firms. We detected the long-term impact of RFID by examining the financial data three years after the RFID adoption (i.e., *t* + 1, *t* + 2, and *t* + 3). Overall, we studied the financial data for the period starting from two years before RFID adoption and three years after RFID adoption (i.e., from *t* - 2 to *t*

[1] We collected RFID announcements with different stages (such as implementation and complete stage) which consistently show implementation time for RFID adoption is one year.

+ 3). We estimated abnormal performance as the sample post-event performance (i.e., actual performance) minus the expected performance. We calculated the expected performance as the sample pre-event performance plus the change of performance of the control firm during the same period (Barber and Lyon 1996). The formula for calculating the abnormal performances as follow:

$$AP_{(t+j)} = PS_{(t+j)} - EP_{(t+j)}$$

$$EP_{(t+j)} = PS_{(t+i)} + [PC(_{t+j)} - PC_{(t+i)}]$$

where AP is the abnormal performance, PS is the actual performance, EP is the expected performance of sample firms, PC is the performance of the control firm, t is the RFID adoption year, i is the base year (i = -2) , and j is the ending year of comparison (j = -1, 0, 1, 2 and 3). In our sample, we included announcements with specified actual adoption dates. While majority of the announcements were made upon or after RFID adoption, only a few of the announcements were disclosed during the implementation stage. Examples of these two types of announcements are shown below.

- *Feb 18, 2005: eWeek: Tandy Brands Accessories wasn't part of the 100 suppliers Wal-Mart called on to use RFID tags, but the company has started using them voluntarily in its Wal-Mart shipments. (The adoption date in this case was Feb 18, 2005.)*
- *Jun 28 2004: Home Textiles Today: Mohawk Home later this year will break ground on its seventh finishing and distribution facility, with completion slated for* ***the end of 2005****. Both sites will also be outfitted with state-of-the-art*

technology and equipment, including RFID capabilities, stated Mohawk. (The adoption date in this case was Dec 31, 2005.)

Similar to previous event studies that had aligned the adoption time for announcements (Hendricks et al. 2007) during the implementation stage, such as pilot, trial, and planning phases (unless specified otherwise), we added one year so that the adoption of RFID can be averaged over one year for a full-scale rollout. After confirming the adoption dates of the sample firms, we compared the adoption dates against the dates of the fiscal year end to the estimate year *t*.

Following previous event studies (e.g., Corbett et al. 2005; Yeung et al. 2011), we reported three statistical test results, including the non-parametric Wilcoxon signed-rank (WSR), sign test, and the parametric t-test. Barber and Lyon (1996) had asserted that nonparametric tests were more appropriate than parametric t-test when abnormal performance of the sample firms was not normally distributed. Therefore, we took WSR to be the most appropriate test for our study. The discussion below is based on the WSR statistics. The other statistics contained in the tables indicate similar results. We then applied hierarchical regression to investigate the effects of contingency factors on the relationship between disruptive IT innovations and firm performance.

3.2.1.2 Selection of Control Firms

To select control firms, we used Barber and Lyon's (1996) matching algorithm in Chapter 4, and propensity score matching in Chapter 5 and 6. We used Barber and Lyon (1996) matching method instead of propensity score matching in Chapter 4, because it allows us to include more fashion and textile firms into our sub-sampling analysis to provide meaningful results.

3.2.1.2.1 Barber and Lyon (1996) Matching Algorithm

A rigorous comparison between the sample and the control firms was ensured through matching them based on three criteria, namely, pre-event performance, industry type, and firm size. Barber and Lyon (1996) indicated that controlling pre-event performance is most critical in event studies. They asserted that matching the industry type with 90% to 110% pre-event performance provides the most appropriate matching groups between the sample and the control firms. Previous studies suggested that a two-digit level offers most of the systematic industry characteristics, whereas finer industry delineations provide minimal extra benefits (Clarke 1989; Porac et al. 1999). We initially matched each sample firm to a portfolio of control firms based on at least a two-digit SIC code, 90%-110% of performance, and 50%-200% of the firms' total assets in year t - 2. If no control firm was matched in the previous step, we used at least a one-digit SIC code, 90%-110% of performance, and 50%-200% of the firms' total assets as the matching criteria. If no control firm was matched, we used only 90%-110% of performance and 50%-200% of the firms' total assets as the matching criteria. Finally, if no comparable control firm occurred after the above three steps, we chose the firm with the closest performance.

3.2.1.2.2 Propensity Score Matching

Propensity score matching is an alternative matching method that has been applied extensively in economics and statistics to select control firms (Dehejia and Wahba

2002). Propensity score matching is based on the likelihood that a firm will adopt a particular practice (i.e., RFID in this case) (Rosenbaum and Rubin 1983; Rosenbaum and Rubin 1984). This ensures direct comparisons among firms with similar characteristics (propensity scores) where one firm adopts the disruptive IT innovation and the other does not. Such matching process should substantially reduce any remaining selection bias issues.

We first obtained propensity scores from a logistic regression of an indicator variable equal to one if the firm adopts RFID and zero if the firm does not adopt RFID. Given that matching procedures tend to be invalidated if there are too many regressors (Dehejia and Wahba 2002), we included limited known factors affecting the decision in favor of the disruptive IT innovation based on theories and empirical evidence. The predicting factors were *firm size* (natural logarithm of the total assets), *ROA*, *financial slack* (current assets over total assets), *SGA intensity* (sales and general administrative cost over sales), *leverage* (debt over total assets), *R&D intensity*, *sales growth* (annual sales growth rate), *labor productivity*, and *inventory days* (365 over inventory turnover). All factors were based on data in year t - 2. Firm size, ROA, financial slack and SGA intensity represent the availability of resources for firms to adopt innovations successfully (Damanpour 1987). Firms with more slack resources are more capable of handling disruption and are thus more likely to adopt disruptive IT innovations. Second, we included leverage and R&D intensity to capture managerial risk taking because managerial risk taking is a key determinant of disruptive innovations adoption (Govindarajan and Kopalle 2006). Third, we included the operating performance indicators of *sales growth*, *labor productivity*, and *inventory days*. We expected the motivation behind adopting disruptive innovations by low performance firms to be performance improvement (Chang 2011; Christensen et al. 2004). Finally, we included industry (four-digit SIC) and year fixed effects to match RFID-adopting firms with control firms in the same industry and year. This ensured that the environment of control firms is similar to that of sample firms. Due to a lack of available data, we are not able to control all factors. Those unknown factors not included in the regression are commonly held by all firms and are treated as the error term in the logistic regression model (Chang et al. 2013). In sum, the propensity score was taken as equal to the probability of RFID adoption as calculated by the following logistic model:

$$\Pr(\text{RFID}_{it}) = \alpha_0 + f_{\text{industry}} + f_{t\text{-}2} + \beta_1\text{Firm size}_{it\text{-}2} + \beta_2\text{ROA}_{it\text{-}2} + \beta_3\text{Financial slack}_{it\text{-}2} + \beta_4\text{SGA intensity}_{it\text{-}2} + \beta_5\text{Leverage}_{it\text{-}2} + \beta_6\text{R\&D intensity}_{it\text{-}2} + \beta_7\text{Sales growth}_{it\text{-}2} + \beta_8\text{Labor productivity}_{it\text{-}2} + \beta_9\text{Inventory days}_{it\text{-}2} + e_{it}$$

where t is the adoption year, and Pr (RFID_{it}) is the probability of *i*th firm's RFID adoption in year t.

The logistic regression excluded sample firms with missing related financial data; as a result, the final sample size was reduced from 230 to 205 because the propensity score matching procedure demands all firms to have complete data to estimate the logistic regressions. 2,174 potential control firms from Standard and Poor's COMPUSTAT (SIC code 2000-3999) were identified for these 205 sample firms in manufacturing industries. The pre-match model in Table 3.4 shows the results from this logistic regression. Firms with large size, more financial slack, and high SGA intensity are more likely to adopt RFID. R&D intensity appears to be lower in RFID-adopting firms. RFID-adopting firms also achieved lower performance on sales growth and labor productivity than non-adopting firms' prior RFID adoption. The findings indicate that when firms have more resources and lower performance, less risk-taking firms are more willing to adopt disruptive IT innovation to improve their performance. The pre-match model has a log-likelihood of 1055.64, a Cox & Snell R square of 13.50, a Nagelkerke R square of 30.40, and a Hosmer and Lemeshow Test Chi-square of 10.24 ($p > 0.10$). Moreover, the model has achieved 91.8% correct prediction. The above test statistics demonstrate the appropriateness of the choice of independent variables and the overall fit of our model.

Table 3.4 Determinants of RFID Adoption

Independent variables	
Intercept	-8.42 (0.87)***
Firm size[a]	1.92 (0.13)***
ROA	1.70 (1.31)
Financial slack	2.38 (0.67)***
SGA intensity	2.97 (0.64)***
Leverage	0.45 (0.31)
R&D intensity	-8.98 (1.95)***
Sales growth	-0.85 (0.39)**
Labor productivity[a]	-0.40 (0.23)*
Inventory days[a]	-0.50 (0.32)
Control	2174
Sample	205
Log-likelihood	1055.64
Cox & Snell R square (%)	13.50
Nagelkerke R square (%)	30.40
Hosmer and Lemeshow Test Chi-square (%)	10.24 (*p* value = 0.24)

Note. Unstandardized regression coefficients are shown with standard errors in parentheses.
[a] Logarithm transformed.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$; two-tailed tests.

Having calculated the propensity scores for each firm from the logistic model, we employed a one-to-one nearest neighbor matching without replacement to match RFID-adopting firms to control firms. Specifically, we matched each RFID-adopting firm in the base year (t - 2) to the control firm in the same industry (four-digit SIC) with the most similar propensity score for that year.

We needed to confirm that our matching procedure was indeed providing comparable RFID adopters and non-adopters. Following previous practice, we ran a logistic regression to explain the likelihood of RFID adoption given the variables used in the matching procedure. Table 3.5 presents the matching procedure is successful. Specifically, after applying propensity score matching, the coefficients of most variables experienced sharp decreases in magnitude and became statistically insignificant between the adopter and the matched non-adopter, indicating that they are highly similar. However, we found that the coefficient of firm size was significant because the RFID-adopting firms on our lists were mostly large firms. This result also indicates the need to include firm size as a control in the regression analysis.

Table 3.5 Propensity Score Matching Diagnostics

Independent Variable	Post-match
Firm size[a]	0.73 (0.16)***
ROA	1.18 (1.82)
Financial slack	-0.18 (0.81)
SGA intensity	1.26 (0.89)
Leverage	-0.16 (0.35)
R&D intensity	-1.30 (2.93)
Sales growth	0.14 (0.44)
Labor productivity[a]	-0.04 (0.33)
Inventory days[a]	-0.39 (0.42)
Control	205
Sample	205
Log-likelihood	534.66
Cox & Snell R square	7.90
Nagelkerke R square	10.50
Hosmer and Lemeshow Test Chi-square	9.16 (p value = 0.33)

Note. Unstandardized regression coefficients are shown with standard errors in parentheses.
[a] Logarithm transformed.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$; two-tailed tests.

3.2.2 Short-Term Event Study Methodology

We used short-term event study methodology in Chapter 5 to investigate the impact of RFID adoption on a firm's short-term abnormal stock returns in the days immediately following the announcement of the investment. The abnormal returns for the stock of firm *i* on day *t* are computed as

$$AR_{it} = R_{it} - E(R_{it})$$

where AR_{it} is the abnormal return for firm *i* on day *t*; R_{it} is the actual return for firm *i* on day *t*. To predict the daily returns for each firm *i* over the specific event window, we estimate the market model of each firm's stock returns

$$E(R_{it}) = \alpha_i + \beta_i R_{mt} + \varepsilon_{it}$$

where $E(R_{it})$ is the expected rate of return for firm *i* on day *t*; R_{mt} is the rate of return of market index *m* on day *t*; α_i, and β_i are the market model intercept and slope parameters for firm *i*; and ε_{it} is the error term.

Based on the market model (MacKinlay 1997), we estimated the abnormal returns for three-day event windows (-1, 1), where 0 is the announcement day, -1 is the day before the announcement, and 1 is the day after the announcement. Following the standard practices of event studies (MacKinlay 1997), we calculated the market model using a period of 250 prior trading days (i.e., Day -270 to Day -21), and applied the t-statistics to access whether the abnormal returns are significantly different from 0 (MacKinlay 1997; Patell 1976).

3.3 Chapter Summary

In this section, we described the procedure of data collection and showed the distribution of the 250 sample firms that we collected by industry type (SIC code), industry clockspeed, year, and mandate. This section also discussed the details of both long- and short-term event study methodology, which are used in the following three studies.

CHAPTER 4 RESEARCH PART ONE—DISRUPTIVE IT INNOVATIONS, OPERATIONAL PERFORMANCE, AND INDUSTRY ENVIRONMENT

Based on the case of RFID adoption, this section aims to examine the impact of disruptive IT innovations on operational performance measured as inventory days, accounts receivable days, operating cycle time, labor productivity, and sales growth. We further examine how the impact varies across industries (i.e., fashion and textiles firms versus other adopters, retailers and wholesalers versus manufacturers). Finally, we test the moderating effects of other contextual factors such as coercive pressure from customer mandate.

4.1 The Impact of Disruptive IT Innovations on Supply Chain Efficiency

Supply chain efficiency, measured as inventory days, accounts receivable days, and operating cycle (Lo et al. 2009), reflects the performance of overall supply chain cost, lead performance, inventory level, and delivery promptness for firms (Kojima et al. 2008; Li and O'Brien 1999; Visich et al. 2009). RFID adoption helps to reduce inventory in several ways (Dutta et al. 2007; Lee and Özer 2007; Mikko and Jan 2002; Tajima 2007). First, RFID technology provides higher inventory visibility, which leads to lower inventory discrepancy, forecast error (Dutta et al. 2007; Lee and Özer 2007) and inventory "buffers" (Lee and Özer 2007). Real-time information from upstream and downstream parties also helps firms to reduce the uncertainty of lead time in the replenishment process (Lee and Özer 2007) and to be proactive to create better inventory. The speed and quality control of the production process are also enhanced because parts are easily tracked and located and the information in the RFID tags may help firms monitor assembly work and route the product through the plant. Moreover, RFID technology helps reduce manufacturing bottlenecks (Angeles 2005) and the frequency of production disruptions due to replenishment problems (Mikko and Jan 2002). In summary, through RFID adoption, firms are able to simultaneously increase throughput and quality with lower inventory levels. Therefore, we hypothesize that the time required to convert materials into products should be decreased.

H1: The adoption of disruptive IT innovation significantly reduces inventory days.

RFID technology improves the performance of warehousing and distribution operations and order accuracy by automating operations that used to involve manual handling (Mikko and Jan 2002) and freeing them from human error (Angeles 2005). Problems such as shrinkage and stock outs are reduced at the same time (Lee and Özer 2007). Furthermore, supply chain visibility and the ability to track items with a unique identification not only helps managers identify problematic and exception-handling cases and respond better (Angeles 2005; Mikko and Jan 2002) but also provides more flexible solutions such as redirecting shipments (Mikko and Jan 2002) according to customers' requirements. Overall, order fulfillment time is reduced and customer service quality is increased. The time for firms to collect payments from customers therefore should be shorter. Accordingly, we hypothesize that the accounts receivable days for firms to receive payments from customers decrease.

H2: The adoption of disruptive IT innovation significantly reduces accounts receivable days.

The above hypotheses combined imply a single omnibus prediction that the adoption of RFID will significantly decrease the operating cycle. Operating cycle refers to inventory days (time to convert material into products), and accounts receivable days (time to receive payments from customers) (Eskew and Jensen 1996; Lo et al. 2009). This leads to the following hypothesis:

H3: The adoption of disruptive IT innovation significantly reduces the operating cycle.

4.2 The Impact of Disruptive IT Innovations on Labor Productivity and Sales Growth

Compared with the traditional barcode system, RFID can simultaneously read multiple tags on several packages without the line-of-sight requirement and from longer distances. Therefore, RFID shortens the employee time required to handle order fulfillment. Several practitioners have reported a significant improvement in labor productivity after RFID adoption. For example, Kitchens, Inc. has reported a 35% direct improvement in labor productivity (Angeles 2005). In an experimental research, Saygin (2007) has determined that RFID can lead to savings in labor costs. In a case study on return center logistics, Langer et al. (2007) have learned that RFID can substantially reduce customer claims, thereby reducing the labor resources required to track and correct errors. Therefore, we hypothesize that RFID adoption improves labor productivity.

H4: The adoption of disruptive IT innovation significantly increases labor productivity.

With RFID adoption, intermediate goods, components, and other items at each stage of the supply chain become easier to trace, which ensures higher product availability (i.e., reduced stock-out probability). Industry reports suggest that RFID adoption—particularly item-level RFID tagging in retail supply chains—could increase sales by 2%-7% (Gaukler and Hausman 2007). For manufacturing firms, several major retailers (e.g., Walmart and Tesco) mandate manufacturing firms to use RFID. Adoption not only helps manufacturing firms secure close relationships with retailers but also enables the manufacturing firms to gain a competitive advantage with other customers who favor RFID. Although adoption is not executed in response to a customer mandate, these firms may use RFID to attract the attention of potential RFID-enabled customers. Therefore, we postulate that the adoption of RFID can lead to higher sales performance, measured using the yearly sales growth rate.

H5: The adoption of disruptive IT innovation increases sales performance.

4.3 Data Collection and Methodology

This section analyzed the impact of RFID adoption on operational performance based on panel data from 250 firms (including the retail and wholesale sector and the manufacturing sector) discussed in Chapter 3. We measured inventory days as 365 over inventory turnover, accounts receivable days as 365 over accounts receivable turnover, and operating cycle as the sum of inventory days and accounts receivable days. We estimated labor productivity as operating income over the employee number and sales growth as yearly sales growth rate. Table 4.1 summaries the formulas of these indicators.

Table 4.1. Indicators Definitions

Indicators	Definition
Inventory days	365/Inventory turnover, where inventory turnover is equal to cost of goods sold over average inventory
Accounts receivable days	365/accounts receivable turnover, where accounts receivable turnover is equal to credits sales over average accounts receivable
Operating cycle	Inventory days + accounts receivable days
Labor productivity	Operating income / number of employees
Sales growth	Annual sales growth rate

In this study, we used Barber and Lyon (1996) matching algorithm to match RFID-adopting firms with a portfolio of non-adopting companies based on industry code, company size, and pre-adoption performance (*t* - 2). Table 4.2 is the summary of the operational performance before RFID adoption of the sample and control firms. All the *p*-values show that there was no significant difference in any of the performance indicators between the sample and control groups.

Table 4.2 Descriptive Statistics of Sample and Control Firms on Operational Performance (Year *t* - 2)

	N	Mean	Median	Std. Dev.	Min.	Max.
Sample firms						
Inventory days	248	71.90	60.98	48.05	4.22	346.03
Accounts receivable days	246	52.38	48.64	34.56	0.11	314.54
Operating cycle	240	121.25	111.77	63.43	16.91	423.11
Labor productivity[a]	247	63.51	37.72	86.22	-1.38	688.15
Sales growth[b]	248	10.83	8.26	18.83	-50.50	136.88
Control firms						
Inventory days	248	71.90	60.27	48.15	4.27	327.74
Accounts receivable days	246	52.25	48.83	34.30	0.14	320.62
Operating cycle	240	120.92	112.80	63.53	17.19	448.17
Labor productivity[a]	247	63.20	38.07	85.39	-1.45	661.26
Sales growth[b]	248	10.73	8.24	18.43	-50.25	124.01

[a] In thousands U.S. dollars per employee.
[b] In percent.

4.4 Results

4.4.1 Abnormal Changes in Supply Chain Efficiency, Labor Productivity, and Sales Growth

To test whether inventory days, accounts receivable days, operating cycle, labor productivity, and sales growth of RFID adopters actually improved after adopting RFID, we conducted a long-term event study analysis of the firms' operational performance indicators. Tables 4.3 to 4.7 show the impact of RFID adoption on operational performance. The sample size, N, gradually decreased because of the unavailability of data in the following years. Changes from "t - 3 to t - 2" are reported in the first row to show the existence of any systematic bias prior to the implementation of RFID as well as the abnormal changes in firm performance, i.e., the firms' stronger performance prior to RFID implementation (or weaker performance that led to a mean reverse effect). The second row "t - 2 to t - 1" shows the abnormal changes in the performance of sample firms after the implementation of RFID.

Table 4.3 shows that inventory days significantly ($p < 0.05$) reduced 0.81, 0.93, and 1.81 days after one year (t to t + 1), two year (t + 1 to t + 2), and three year (t + 2 to t + 3) of adoption, respectively. The three-year (t - 2 to t + 1), four-year (t - 2 to t + 2), and five-year (t - 2 to t + 3) cumulative changes in inventory days were -1.28, -2.64, and -2.92, respectively, which are statistically significant ($p < 0.10$). Therefore, H1 is supported.

Table 4.3 Abnormal Changes in Inventory Days

Time period	N	Abnormal mean	Abnormal median	*p*-value (t-test)	*p*-value (WSR test)	*p*-value (sign test)
			Yearly abnormal change			
t - 3 to *t* - 2	250	-0.56	0.56	0.49	0.86	0.57
t - 2 to *t* - 1	248	0.17	0.10	0.83	0.69	0.95
t - 1 to *t*	246	0.16	0.32	0.90	0.49	0.66
t to *t* + 1	229	-5.45	-0.81	0.00***	0.00***	0.03**
t + 1 to *t* + 2	206	-4.23	-0.93	0.01***	0.06**	0.30
t + 2 to *t* + 3	190	-2.78	-1.81	0.04**	0.01***	0.03**
			Cumulative abnormal change			
t - 2 to *t* + 1	229	-4.24	-1.28	0.06*	0.07*	0.02**
t - 2 to *t* + 2	206	-6.15	-2.64	0.01**	0.01***	0.02**
t - 2 to *t* + 3	190	-7.53	-2.92	0.01***	0.00***	0.00***

*p<0.1, **p<0.05, ***p<0.01; two-tailed tests.

Table 4.4 shows that accounts receivable days significantly ($p < 0.05$) reduced 0.56, and 1.23 days after one year (*t* to *t* + 1) and three year (*t* + 2 to *t* + 3) of adoption, respectively. The three-year (*t* - 2 to *t* + 1) and five-year (*t* - 2 to *t* + 3) cumulative changes in accounts receivable days were -0.86, and -1.86, respectively, which are statistically significant ($p < 0.10$). Therefore, H2 is supported as well.

Table 4.4 Abnormal Changes in Accounts Receivable Days

Time period	N	Abnormal mean	Abnormal median	*p*-value (t-test)	*p*-value (WSR test)	*p*-value (sign test)
			Yearly abnormal change			
t - 3 to *t* - 2	249	0.33	0.38	0.53	0.71	0.61
t - 2 to *t* - 1	246	0.69	-0.23	0.28	0.71	0.66
t - 1 to *t*	235	-1.90	0.57	0.43	0.30	0.24
t to *t* + 1	211	-3.26	-0.56	0.00***	0.00***	0.01**
t + 1 to *t* + 2	194	-0.78	-0.19	0.36	0.38	0.62
t + 2 to *t* + 3	156	-1.38	-1.23	0.09*	0.04**	0.23
			Cumulative abnormal change			
t - 2 to *t* + 1	211	-3.09	-0.86	0.02**	0.06*	0.27
t - 2 to *t* + 2	194	-2.25	-0.61	0.13	0.22	0.35
t - 2 to *t* + 3	156	-2.63	-1.86	0.06*	0.04**	0.07*

*p<0.1, **p<0.05, ***p<0.01; two-tailed tests.

Table 4.5 presents that operating cycle significantly ($p < 0.05$) reduced 2.26 and 2.65 days after one year (*t* to *t* + 1) and three year (*t* + 2 to *t* + 3) of adoption, respectively.

The five-year (t - 2 to t + 3) cumulative changes in operating cycle were -4.76, which are statistically significant ($p < 0.05$). Therefore, H3 is supported.

Table 4.5 Abnormal Changes in Operating Cycle

Time period	N	Abnormal mean	Abnormal median	*p*-value (t-test)	*p*-value (WSR test)	*p*-value (sign test)
			Yearly abnormal change			
t - 3 to *t* - 2	249	1.06	0.80	0.40	0.53	0.31
t - 2 to *t* - 1	240	2.43	0.58	0.11	0.42	0.85
t - 1 to *t*	239	0.71	0.81	0.65	0.41	0.44
t to *t* + 1	219	-4.93	-2.26	0.02**	0.01***	0.03**
t + 1 to *t* + 2	196	-4.09	-1.52	0.04**	0.11	0.18
t + 2 to *t* + 3	177	-1.84	-2.65	0.58	0.02**	0.02***
			Cumulative abnormal change			
t - 2 to *t* + 1	219	-1.23	-1.01	0.61	0.45	0.22
t - 2 to *t* + 2	196	-6.34	-2.50	0.06*	0.15	0.28
t - 2 to *t* + 3	177	-6.44	-4.76	0.09*	0.04**	0.13

* p<0.1, ** p<0.05, *** p<0.01; two-tailed tests.

Table 4.6 show that labor productivity significantly ($p < 0.05$) improved 1.41 and 1.79 thousands U.S. dollars per employee after two year (t + 1 to t + 2) and three year (t + 2 to t + 3) of adoption, respectively. The four-year (t - 2 to t + 2) and five-year (t - 2 to t + 3) cumulative changes in labor productivity were 1.21 and 3.66 thousands U.S. dollars per employee, respectively, which are statistically significant ($p < 0.05$). Therefore, H4 is supported.

Table 4.6 Abnormal Changes in Labor Productivity

Time period	N	Abnormal mean	Abnormal median	*p*-value (t-test)	*p*-value (WSR test)	*p*-value (sign test)
			Yearly abnormal change			
t - 3 to *t* - 2	250	-0.39	0.19	0.81	0.28	0.85
t - 2 to *t* - 1	247	-0.59	-0.18	0.79	0.54	0.90
t - 1 to *t*	237	4.53	0.22	0.13	0.58	0.80
t to *t* + 1	220	3.09	0.34	0.17	0.46	0.54
t + 1 to *t* + 2	200	9.51	1.41	0.01**	0.04**	0.18
t + 2 to *t* + 3	176	7.26	1.79	0.05*	0.03**	0.01***
			Cumulative abnormal change			
t - 2 to *t* + 1	222	9.28	0.03	0.04**	0.67	1.00
t - 2 to *t* + 2	200	15.28	1.21	0.01***	0.04**	0.36
t - 2 to *t* + 3	176	17.18	3.66	0.00***	0.01***	0.06*

* p<0.1, ** p<0.05, *** p<0.01; two-tailed tests.

Table 4.7 show that sales growth significantly ($p < 0.10$) increased 2.11% after three year ($t + 2$ to $t + 3$) of adoption. The five-year ($t - 2$ to $t + 3$) cumulative changes in sales growth was 2.19%, which are statistically significant ($p < 0.01$). Therefore, H5 is supported.

Table 4.7 Abnormal Changes in Sales Growth[a]

Time period	N	Abnormal mean	Abnormal median	*p*-value (t-test)	*p*-value (WSR test)	*p*-value (sign test)
			Yearly abnormal change			
t - 3 to *t* - 2	249	-0.83	1.31	0.50	0.64	0.41
t - 2 to *t* - 1	248	-0.13	1.21	0.97	0.91	0.37
t - 1 to *t*	243	-1.24	-2.20	0.45	0.26	0.11
t to *t* + 1	225	2.44	0.69	0.13	0.27	0.55
t + 1 to *t* + 2	207	0.57	0.49	0.75	0.92	0.89
t + 2 to *t* + 3	182	4.20	2.11	0.02**	0.09*	0.16
			Cumulative abnormal change			
t - 2 to *t* + 1	225	2.54	-0.24	0.04**	0.28	0.84
t - 2 to *t* + 2	207	2.35	0.07	0.09*	0.43	0.94
t - 2 to *t* + 3	182	4.03	2.19	0.00***	0.01***	0.09*

[a] In percent.
**p*<0.1, ***p*<0.05, ****p*<0.01; two-tailed tests.

4.4.2 Comparison of Supply Chain Efficiency between Fashion and Textiles Industries and Other Industries

We further compared supply chain efficiency between fashion and textiles RFID adopters and other RFID adopters. Table 4.8 presents fashion and textiles RFID adopters' inventory days drop about 12.89 days over the five year period, while other RFID adopters only drop about 2.47 days. Although both groups show significant changes, the fashion and textiles RFID group has clearly shown much stronger changes over the period. The abnormal changes in accounts receivable days and operating cycle time of fashion and textiles RFID adopters are also significant in some tests, but the changes are less obvious compared to the changes in inventory days. The difference in these two indicators between fashion and textiles RFID and other RFID adopters also show that the fashion and textiles RFID adopter group experienced a much greater improvement in their supply chain efficiency.

Table 4.8 Compare Cumulative Abnormal Changes in Inventory Days, Accounts receivable Days, and Operating Cycle Between Fashion and Textiles Firms and other Adopters

Time period	N	Abnormal mean	Abnormal median	*p*-value (t-test)	*p*-value (WSR test)	*p*-value (sign test)
Fashion and textiles firms						
Inventory days						
t - 2 to *t* + 1	16	-8.62	-11.74	0.07*	0.06*	0.21
t - 2 to *t* + 2	10	-10.00	-7.12	0.06*	0.06*	0.34
t - 2 to *t* + 3	12	-13.75	-12.89	0.05**	0.08*	0.39
Accounts receivable days						
t - 2 to *t* + 1	14	-11.47	-2.82	0.15	0.06*	0.42
t - 2 to *t* + 2	11	-5.36	-4.50	0.02**	0.03**	0.23
t - 2 to *t* + 3	9	-5.19	-3.62	0.12	0.07*	0.18
Operating cycle						
t - 2 to *t* + 1	14	-9.62	-8.81	0.01***	0.01**	0.01**
t - 2 to *t* + 2	10	-5.15	-7.38	0.48	0.39	0.34
t - 2 to *t* + 3	9	-16.2	-14.48	0.08*	0.07*	0.18
Other adopters						
Time period	N	Abnormal mean	Abnormal median	*p*-value (t-test)	*p*-value (WSR test)	*p*-value (sign test)
Inventory days						
t - 2 to *t* + 1	213	-3.92	-1.01	0.10*	0.17	0.04
t - 2 to *t* + 2	196	-7.18	-2.55	0.01**	0.01**	0.02**
t - 2 to *t* + 3	178	-6.10	-2.47	0.04**	0.01***	0.00***
Accounts receivable days						
t - 2 to *t* + 1	197	-2.49	-1.26	0.05*	0.14	0.48
t - 2 to *t* + 2	183	-2.04	-0.29	0.19	0.44	0.66
t - 2 to *t* + 3	147	-3.94	-1.66	0.06*	0.07*	0.16
Operating cycle						
t - 2 to *t* + 1	205	-1.53	-0.59	0.62	0.81	0.58
t - 2 to *t* + 2	186	-6.40	-1.67	0.07*	0.20	0.42
t - 2 to *t* + 3	168	-5.90	-3.65	0.13	0.09*	0.25

*$p<0.1$, **$p<0.05$, ***$p<0.01$; two-tailed tests.

4.4.3 Comparison of Supply Chain Efficiency between Retail and Wholesale Industries and Manufacturing Industries

We also compared the changes of supply chain efficiency between retailer and wholesaler samples with the manufacturing sample. As shown in Table 4.9, although the wholesalers and retailers is a much smaller sample size, the abnormal changes in inventory days and operating cycle time are clearly statistically significant. In contrast, manufacturing firms only experienced significant changes in inventory days but not the operating cycle.

Table 4.9 Compare Cumulative Abnormal Changes in Inventory Days, Accounts receivable Days, and Operating Cycle between Wholesale & Retail Firms and Manufacturing Firms

Time period	N	Abnormal mean	Abnormal median	*p*-value (t-test)	*p*-value (WSR test)	*p*-value (sign test)
Retail and wholesale firms						
Inventory days						
t - 2 to *t* + 1	20	-4.65	-4.31	0.02**	0.02**	0.01**
t - 2 to *t* + 2	17	-4.72	-6.30	0.00***	0.01***	0.05**
t - 2 to *t* + 3	17	-3.91	-5.62	0.04**	0.04**	0.05**
Accounts receivable days						
t - 2 to *t* + 1	16	-1.62	-1.67	0.09	0.11	0.21
t - 2 to *t* + 2	16	-2.17	-0.99	0.12	0.22	0.45
t - 2 to *t* + 3	12	-5.03	-5.24	0.04**	0.06*	0.15
Operating cycle						
t - 2 to *t* + 1	17	-6.19	-4.61	0.01***	0.01***	0.01**
t - 2 to *t* + 2	16	-6.72	-4.73	0.03**	0.02**	0.08*
t - 2 to *t* + 3	16	-8.97	-6.27	0.01***	0.01***	0.08*
Manufacturing firms						
Time period	N	Abnormal mean	Abnormal median	*p*-value (t-test)	*p*-value (WSR test)	*p*-value (sign test)
Inventory days						
t - 2 to *t* + 1	209	-5.62	-1.01	0.04**	0.11	0.07*
t - 2 to *t* + 2	189	-5.88	-2.49	0.03**	0.03**	0.06*
t - 2 to *t* + 3	175	-9.26	-2.47	0.02**	0.00***	0.00***
Accounts receivable days						
t - 2 to *t* + 1	195	-2.63	-1.42	0.04**	0.10	0.39
t - 2 to *t* + 2	178	-1.35	-0.84	0.31	0.36	0.50
t - 2 to *t* + 3	144	-1.68	-1.66	0.19	0.11	0.11
Operating cycle						
t - 2 to *t* + 1	202	-1.39	-0.42	0.58	0.76	0.73
t - 2 to *t* + 2	180	-4.45	-0.72	0.16	0.40	0.71
t - 2 to *t* + 3	161	-3.86	-4.03	0.27	0.18	0.43

* p<0.1, ** p<0.05, *** p<0.01; two-tailed tests.

4.4.4 Comparison of Labor Productivity and Sales Growth Between Fashion and Textiles industries and Other Industries

As shown in Table 4.10, fashion and textiles RFID adopters show no significant impact on labor productivity and sales growth in any of the cumulative periods. Conversely, the abnormal changes in the labor productivity and sales growth of other RFID adopters show significant results over the five-year period (*t* - 2 to *t* + 3). These results indicate that non-fashion-and-textiles RFID adopters experienced better improvement in labor productivity and sales growth.

Table 4.10 Compare Cumulative Abnormal Changes in Labor Productivity and Sales Growth between Fashion and Textiles Firms and other Adopters

Fashion and textiles firms						
Time period	N	Abnormal mean	Abnormal median	*p*-value (t-test)	*p*-value (WSR test)	*p*-value (sign test)
Labor productivity						
t - 2 to *t* + 1	15	4.56	2.84	0.16	0.28	1.00
t - 2 to *t* + 2	12	5.11	2.08	0.14	0.21	0.39
t - 2 to *t* + 3	12	0.98	3.91	0.80	0.43	0.39
Sales growth (%)						
t - 2 to *t* + 1	15	0.43	2.99	0.10	0.13	0.67
t - 2 to *t* + 2	12	1.61	-1.54	0.67	1.00	0.74
t - 2 to *t* + 3	10	2.99	0.80	0.49	0.51	1.00
Other adopters						
Time period	N	Abnormal mean	Abnormal median	*p*-value (t-test)	*p*-value (WSR test)	*p*-value (sign test)
Labor productivity						
t - 2 to *t* + 1	207	7.57	-0.22	0.12	0.99	0.78
t - 2 to *t* + 2	188	15.90	0.73	0.01***	0.07*	0.61
t - 2 to *t* + 3	164	18.27	3.54	0.00***	0.01***	0.10
Sales growth (%)						
t - 2 to *t* + 1	210	2.20	-0.35	0.09*	0.47	0.68
t - 2 to *t* + 2	195	1.91	0.53	0.21	0.53	0.83
t - 2 to *t* + 3	172	4.52	2.37	0.00***	0.01***	0.06*

**p*<0.1, ***p*<0.05, ****p*<0.01; two-tailed tests.

4.4.5 Comparison of Labor Productivity and Sales Growth Between Retail and Wholesale Industries and Manufacturing Industries

Table 4.11 demonstrates that the abnormal changes labor productivity and sales growth of manufacturing RFID adopters were USD 4,610 per employee and 3.46%, respectively, over the five-year period (*t* - 2 to *t* + 3). Retail and wholesale RFID adopters only significantly improved labor productivity to USD 2,960, an increase that is less than that of manufacturing firms. The results indicate that manufacturing firms have better labor productivity and sales growth then wholesalers and retailers.

Table 4.11 Compare Cumulative Abnormal Changes in Labor Productivity and Sales Growth between Wholesale & Retail Firms and Manufacturing Firms

Time period	N	Abnormal mean	Abnormal median	*p*-value (t-test)	*p*-value (WSR test)	*p*-value (sign test)
Retail and wholesale firms						
Labor productivity						
t - 2 to *t* + 1	19	3.75	-1.06	0.17	0.49	0.65
t - 2 to *t* + 2	17	5.45	1.29	0.15	0.16	0.33
t - 2 to *t* + 3	17	7.02	2.96	0.10**	0.04**	0.05**
Sales growth (%)						
t - 2 to *t* + 1	20	0.52	0.71	0.88	0.82	0.82
t - 2 to *t* + 2	19	0.07	0.97	0.97	0.97	1.00
t - 2 to *t* + 3	17	-3.14	-1.53	0.27	0.31	0.63
Manufacturing firms						
Time period	N	Abnormal mean	Abnormal median	*p*-value (t-test)	*p*-value (WSR test)	*p*-value (sign test)
Labor productivity						
t - 2 to *t* + 1	203	7.72	0.10	0.12	1.00	1.00
t - 2 to *t* + 2	183	16.18	1.13	0.01***	0.06*	0.55
t - 2 to *t* + 3	159	18.25	4.61	0.00***	0.02**	0.20
Sales growth (%)						
t - 2 to *t* + 1	205	2.66	-0.28	0.04	0.30	0.73
t - 2 to *t* + 2	188	2.51	0.00	0.10	0.43	1.00
t - 2 to *t* + 3	165	4.18	3.46	0.00***	0.01***	0.04**

* p<0.1, ** p<0.05, *** p<0.01; two-tailed tests.

4.4.6 Hierarchical Regression Analysis of Abnormal Supply Chain Efficiency

We further analyzed whether the level of abnormal supply chain efficiency was contingent upon contextual factors such as firm characteristics and industry factors. In particular, we are interested in testing the moderating effect of coercive pressure. We used the manufacturing sample firms' abnormal operating cycle over the five-year period (*t* - 2 to *t* + 3) as the dependent variable. To measure coercive pressure, we created a dummy variable called *coercive adoption* and coded it as 1 for firms that adopted RFID due to customers' mandate; otherwise, we used 0. We predicted that firms conforming to coercive pressure would lead to lower supply chain efficiency because they might sacrifice their technical efficiency to conform to that adoption. We also included time of adoption, i.e., the year a firm formally adopts RFID. We expected that early adopters who faced less institutional pressures from their external environment to adopt RFID would have more autonomy to customize the adoption to meet their needs and capabilities, thus obtaining higher supply chain efficiency from RFID adoption. We further included firm-level characteristics such as *firm size* (logarithm of the total assets), *previous operating cycle of the firm* (i.e., operating cycle in *t* - 2), *R&D intensity* (R&D expenses over sales), *capital investment* (capital expenses over total assets), and *current ratio* (current assets over total assets). All of these variables were obtained from the data in *t* - 2. For industry-level variables, we created a dummy variable called *fast industry clockspeed*, which was coded as 1 if a firm belongs to a fast industry clockspeed and 0 otherwise. We included *market share*, measured as the sales of the sample firm over all firms that operate in the same 2-digit SIC industry. We included the *change of the operating cycle of control firms* in the five-year period. This variable represents specific changes in the operating cycle of the industry of the control firms during the same period. We included *industry sales growth* measured as the average performance change in industry sales between *t* - 2 and *t* + 3. We created a dummy variable called *source* and coded it as 1 to represent the sources of technology periodicals such as RFID Journal and RFID Knowledgebase, and 0 otherwise. Finally, we created a dummy variable for *announcements after implementation stage*, which equaled 1 for announcements published when the implementation of RFID had been completed, and 0 otherwise.

Table 4.12 indicates the results of the hierarchical regression. Overall, the F values are greater than 5 for all models with significance at the 1% level or higher. Adjusted R square ranges from 24.57% to 28.18%. Models 2 to 3 in Table 4.12 depict that firms with coercive RFID adoption are significantly related to firms' abnormal operating cycle ($p < 0.05$). This result indicates that proactive RFID-adopting firms could achieve higher reduction in operating cycle than firms with coercive adoption. The time of adoption is significantly related to abnormal operating cycle in Model 3 ($p < 0.05$), indicating early adopters obtained higher reduction in operating cycle.

As shown in Models 1 to 3 in Table 4.12, fast clockspeed industries such as fashion and textiles industries appeared to obtain greater decreases in the abnormal operating cycle. Firm size is negatively related to abnormal ROA. Therefore, large firms could obtain more reduction in their operating cycle after RFID adoption. The previous magnitude of the operating cycle is negatively related to abnormal operating cycle, suggesting that firms with poor performance in operating cycle before RFID adoption were able to enjoy higher improvement after RFID adoption. R&D intensity and capital investment are positively associated with abnormal operating cycle, indicating that firms with fewer technologies investments had more room to benefit from the adoption, thus obtaining a greater reduction in the abnormal operating cycle. The change in control firms' operating cycle is also negatively related to the abnormal operating cycle, which suggests that firms could obtain a greater reduction in operating cycle from RFID adoption when the operating cycle of the industry of the control firms is higher.

Table 4.12 Hierarchical Regression Analysis of the Impact of Contingency Factors on Abnormal Operating Cycle (*t* - *2* to *t* + *3*)

Variable	Model 1: Base model	Model 2: Coercive pressure Model	Model 3: Time of adoption model
Intercept	46.15 (0.05)*	38.84 (0.10)	-6,631.96 (0.04)**
Firm size[a]	-11.74 (0.03)**	-10.79 (0.04)**	-10.35 (0.05)**
Previous operating cycle of the firm	-0.09 (0.09)*	-0.10 (0.06)*	-0.10 (0.06)*
Change of the operating cycle of control firms (*t* - 2 to *t* + 3)	-0.33 (0.00)***	-0.33 (0.00)***	-0.34 (0.00)***
R&D intensity	508.47 (0.00)***	503.22 (0.00)***	485.59 (0.00)***
Capital investment	148.59 (0.05)*	174.53 (0.02)**	190.55 (0.01)**
Current ratio	-2.35 (0.43)	-3.00 (0.31)	-3.09 (0.29)
Fast industry clockspeed [b]	-10.21 (0.28)	-11.65 (0.21)	-13.00 (0.16)
Market share	73.61 (0.24)	77.92 (0.20)	99.07 (0.11)
Industry sales growth (*t* - 2 to *t* + 3)	-8.08 (0.61)	-15.65 (0.33)	-12.01 (0.46)
Source	-10.42 (0.15)	-14.32 (0.05)*	-17.91 (0.02)**
Announcements after implementation stage	-10.77 (0.15)	-7.58 (0.31)	-4.03 (0.60)
Coercive adoption		14.77 (0.03)**	13.31 (0.05)**
Time of adoption			3.33 (0.03)**
Model F value	5.74***	5.79***	5.83***
R square (%)	29.75	31.96	34.10
Adjusted R square (%)	24.57	26.44	28.18
R square change (%)	29.75	2.20	2.05
F change	5.74***	4.80**	4.57**

Note. N = 161; *t* is the year of RFID adoption; unstandardized regression coefficients are shown with the *p*-value in parentheses.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$; two-tailed tests.
[a] In logarithm.
[b] Results remain consistent when using fashion and textiles industries only.

4.5 Discussion

This section provides quantitative evidence of the impact of a disruptive IT innovation (in this case, RFID adoption in the supply chain) on operational performance. RFID adoption clearly has a positive impact on operational performance in the long term. These results are consistent with the observations and empirical evidence from previous studies of RFID (e.g., Delen et al. 2007; Fosso Wamba et al. 2008; Kim et al. 2008; Langer et al. 2007; Moon and Ngai 2008).

We further examined how the impact varied across industries and found that fashion and textiles RFID adopters show improved supply chain efficiency over adopters in other industries, but not for labor productivity and sales growth. The fashion and textiles industries introduce products every season and have high requirements for operation efficiency and effectiveness, such as short lead times and rapid delivery (Moon and Ngai 2008). Thus, improvement in fashion supply chain efficiency is particularly apparent to fashion and textiles firms because RFID provides visible material flow along the fashion supply chain.

Moreover, we found that the benefits of RFID in supply chain efficiency are more apparent at the downstream (i.e., retailers) of the supply chain. In the past, traditional supply chains typically applied the push method in which products are produced by manufacturers and pushed to the retailers. Retailers, who rely on manufacturers to provide information to manage their inventory, commonly stock up on costly inventory to create buffer and slack in the system. However, RFID adoption enables retailers to collect actual sales and product visibility, leading to operations that are more efficient and enhanced customer services that reduce inventory days and accounts receivable days. In addition, our findings show that manufacturers show more improvement in labor productivity and sales growth than do retailers. These findings shed light on concerns that RFID adoption provides a greater benefit to downstream supply chain members (i.e., retailers) than to manufacturers (Whang 2010).

Our further regression analysis indicates that the impact of RFID on supply chain efficiency is contingent upon contextual factors. More specifically, we found that firms experienced weaker improvement in supply chain efficiency under coercive adoption and late adoption. From an institutional perspective, these findings suggest that early adopters, free from coercive adoption and motivated by the opportunity for efficiency gains, can obtain more benefits from the adoption because they can adjust adoption to leverage their competencies and to compensate for weaknesses (Angeles 2005; Westphal et al. 1997). In contrast, late adopters who are exposed to coercive adoption or are persuaded to adopt RFID due to mimetic pressures from competitors are more concerned with their social fitness instead of the work outcomes of the adoption (Meyer and Rowan 1977). More specifically, firms under coercive adoption have fewer options but to conform to that pressure, regardless of whether the adoption is disruptive and unsuitable to the firms' specific product systems. Given that firms are less flexible in customizing the adoption to one more suitable for their particular environment (Berrone *et al.*, 2013), they show less improvement in efficiency (Westphal et al. 1997; Zhu and Sarkis 2007). Therefore, manufacturers such as fashion and textiles manufacturing firms that demand high supply chain efficiency should become first movers in adopting RFID. However, they should be cautious about adopting when facing increasing pressure from customers such as Walmart to adopt RFID.

4.6 Chapter Summary

In this section, we examined the impact of disruptive IT innovations on operational performance based on the case of RFID adoption. The results show that RFID adoption significantly improved inventory days, accounts receivable days, operating cycle, labor productivity, and sales growth. The sub-sampling analysis indicates that the impact of these indicators depends on the industry type of the adopting firms. More specifically, fashion and textiles RFID adopters and firms in retail and wholesale industries improved supply chain efficiency more than adopters in other industries and firms in manufacturing industries; however, this is not the case for labor productivity and sales growth. Similarly, the regression analysis indicates that the impact of disruptive IT innovation on supply chain efficiency is moderated by contextual factors such as coercive pressure and firm characteristics.

In the next section, we will extend the study of this section by examining the impact of RFID on financial performance, which is most firms' ultimate goal. Because as shown in Chapter 4, fashion and textiles firms appear to have weaker performance in revenue-related indicators such as labor productivity and sales growth from RFID adoption than firms in other industries, we will thus develop a contingency model that focuses on external and internal factors such as coercive pressure to identify how contingency factors enhance or diminish financial performance.

CHAPTER 5 RESEARCH PART TWO—DISRUPTIVE IT INNOVATIONS AND FINANCIAL PERFORMANCE: A CONTINGENCY FRAMEWORK FOR SUCCESS

This section addresses two research questions based on RFID adoption: (1) What is the long-term impact of a disruptive IT innovation on financial performance? and (2) What are the contingency factors that magnify or diminish the impact of disruptive IT innovations on financial performance? More specifically, drawing on the insights from both disruptive IT innovations and RFID literature, we focus on examining six contingency factors, including coercive pressure, industry clockspeed, industry competitiveness, financial health, business diversification, and geographic diversification, which may moderate financial performance. The findings of the contingency model are applicable not only to fashion and textiles firms but also firms in other sectors.

5.1 The Impact of Disruptive IT Innovations on Financial Performance

In the case of RFID adoption, the adoption is an expensive investment involving high initial setup costs for purchasing of hardware and software, and requires a significant amount of financial and labor resource for implementation (Whitaker et al. 2007). RFID adoption could also lead to resistance from employees who perceive it as a threat to their positions (Wang et al. 2010; Yang et al. 2008). Moreover, particularly in the early days when the technology is less stable and mature, RFID often causes disruptions to business operations (Yang et al. 2008). However, a successful RFID adoption offers two major advantages. First, it automates manual tracking processes, thus improving data accuracy as well as labor efficiency (Jones 1999). Second, it provides real-time information that can help in saving labor, improving supply chain coordination, reducing inventory, and increasing product availability (Lee and Özer 2007). Due to increased information visibility, firms are also able to provide quicker and more effective response to customers (Angeles 2005; Mikko and Jan 2002). Indeed, previous studies have suggested that RFID increases revenue through improved pricing and fewer out-of-stock situations (Srivastava 2004). Moreover, our findings in Chapter 4 show that RFID adoption improved supply chain efficiency, labor productivity, and sales growth. Therefore, we expect that RFID adoption can enhance financial performance through these attributes.

H1: The adoption of disruptive IT innovation significantly improves financial performance.

5.2 A Contingency Framework for Successful Adoption of Disruptive IT Innovations

A disruption could have a local, regional or global impact. The ripple effects from the disruption would depend on its organizational structure, financial status, industry type, and relationships with supply chain partners. We take a contingency perspective to identify the factors that could moderate the success of a disruptive IT innovation. With specific regard to RFID, we propose the external and internal factors described below that could amplify or reduce the impact of the disruption.

5.2.1 External Contingency Factors

5.2.1.1 Coercive Pressure on RFID Adoption

The adoption of disruptive IT innovations can be forced by customer mandate. Since Walmart's 2003 RFID mandate, RFID has increasingly been institutionalized and used as a supplier selection criterion. Accordingly, even a minimum investment in RFID tags, readers, and monitored processes, which results in limited operational improvement, can give an RFID-adopting firm customer legitimacy. Several previous studies have demonstrated that customers that mandate RFID adoption are in a position to use financial benefits to reward dependent firms for their compliance (Whitaker et al. 2007). Moreover, Scott (1995) argued that conformity to the institutional environment could provide legitimacy to firms, allowing them to secure valued resources that lead to better financial performance. In a related study, Bansal and Clelland (2004) showed that high corporate environmental legitimacy experienced reduced stock market risk, because firms obtained environmental legitimacy when their performance related to the natural environment conformed to stakeholders' expectations. Similarly, in a longitudinal study of commercial banks, Deephouse (1999) discussed that bank should conform to institutional pressures to obtain legitimacy that resulting in increased financial performance. Therefore, we postulate that coercive adoption of RFID can have a positive moderating effect on financial performance.

H2: The benefit of disruptive IT innovation is higher under coercive pressure.

5.2.1.2 Industry Clockspeed

Industry characteristics such as industry size, industry efficiency, and supply chain structure can affect RFID utilization. Industry clockspeed represents an industry's new product introduction and product obsolescence rate (Fine 1998). Firms operating in fast clockspeed industries continually introduce numerous new products, which require more responsive and more visible supply chains that can track inventories more efficiently compared with firms in an industry with limited new products. For example, the fashion industry introduces products every season, and the visibility of material flow along the fashion supply chain is particularly important. An RFID tag is attached to each item or pallet of products, and thus firms in fast clockspeed industries should obtain higher utilization rates and additional benefits from RFID adoption. Therefore, RFID adoption is likely to have a stronger impact on financial performance in fast clockspeed industries such as the fashion and textiles industries. Therefore, we propose the following hypothesis.

H3: The benefit of Disruptive IT innovation is higher for fast clockspeed industries.

5.2.1.3 Industry Competitiveness

Previous studies suggest that non-disruptive IT innovations provide organizations with enhanced value in competitive environments (Melville et al. 2007). However, this may not be the case for disruptive IT innovations that dramatically change a firm's operations and demand more slack in financial and labor resources to implement the adoption (Soon and Gutiérrez 2009). Firms in highly competitive industries experience greater environmental uncertainty and require much larger amounts of market information for analysis in a very short period (Dess and Beard

1984). These firms require operations that are more efficient to stay ahead of the competition (Scherer and Ross 1990) and therefore, it is imperative that they have lower levels of slack in terms of time and financial and labor resources while implementing the innovation. Thus, the adoption becomes more costly and more risky for these firms because disruptions could lead to failures in meeting fast-changing customer demands and eventually hurt their long-term profitability. Conversely, in an industry with low competitiveness, competitive interactions are predictable (Xue et al. 2012). Firms operating in a context of low competitiveness could have more slack in their financial and labor resources and use them to implement a disruptive IT innovation, thus obtaining more financial benefits from the adoption.

H4: The benefit of disruptive IT adoption is higher in a low-competition environment.

5.2.2 Internal Contingency Factors

5.2.2.1 Financial health

Disruption can be more severe for firms experiencing greater financial resource uncertainty. Firms that are in poor financial health are more likely to have financial distress, which refers to a firm's low cash flow state while incurring losses without being insolvent (Purnanandam 2008). Such a firm therefore finds it difficult to fulfill its financial obligations (Purnanandam 2008). However, successful disruptive innovation adoption requires sufficient resources and management commitment (Christensen and Raynor 2003). For example, RFID implementation requires a large amount of investment and time commitments during the implementation stage, which may last several years for a large-scale adoption, while there may be no immediately observable returns in the short term. Because a firm in poor financial health requires its management to pay attention to the use of its limited financial resources to improve business operations, such a firm has limited financial slack to fully implement a disruptive IT innovation. Consequently, the benefits of the adoption are limited. Moreover, a firm in poor financial health may not able to provide job security to its employees, leading to lower morale. Low-morale employees resist the disruptive IT innovation more strongly because the innovation may further threaten their job security (Beaudry and Pinsonneault 2005; Lapointe and Rivard 2005). Conversely, firms with a good financial status provide a more stable environment for top managers to commit to the adoption. Moreover, these firms have a higher level of financial resources to support the continuous progress of RFID adoption, which may last several years. Therefore, we formulate the following hypothesis.

H5: The benefit of disruptive IT adoption is higher in firms that are in good financial health.

5.2.2.2 Corporate Diversification

Corporate diversification refers to the pursuit of superior performance through the configuration and coordination of activities across multiple businesses of the corporation (Collis and Montgomery 1997). Non-disruptive IT investment benefits diversified firms in terms of economies of scale, transfer of technologies across lines of business, and exploiting new use of existing IT resources (Clemons and Row 1991). However, this may not be applicable to disruptive IT innovations. A disruptive IT innovation could disrupt the existing configuration and coordination, which make the implementation costly and difficult in a high diversified firm with more complicated configuration in the organizational structure. The benefits of disruptive IT innovation are thus subject to the degree of compatibility amongst the business units, systems and processes. For a firm exhibiting a high level of diversification, the cost of modification for use across multiple businesses is likely to be higher (Montgomery and Singh 1984). Therefore, we argue that the benefits of a disruptive IT innovation depend on the level of diversification (Chari et al. 2008) which could be of two types, (1) *business diversification*, i.e., the extent to which the corporation's activities are spread across different lines of businesses; and (2) *geographic diversification*, i.e., the extent to which the same are spread across different countries or regions.

Business Diversification: A reasonable approach to the implementation of disruptive IT innovation is to conduct a pilot project, iron out glitches and bugs, formalize steps to minimize disruption, and then roll out, with due customization, to other processes or business lines. Furthermore, the adoption of a disruptive IT innovation in a highly diversified organization could extend the learning curve with respect to the new technology; because adaptation to the new technology could vary across business lines (e.g., manufacturing and retailing). On the other hand, for a less diversified firm, the roll out of the disruptive IT innovation could be much easier and less expensive, as transferring technology to a similar industry is likely to involve fewer customizations (Montgomery and Wernerfelt 1988). Experience sharing within a similar business line could better reduce employee resistance to the new technology.

H6: The benefit of disruptive IT innovation is higher in firms with less business diversification.

Geographic Diversification: Based on the same rationale, geographically diversified firms are likely to experience longer learning curves compared to geographically centered organizations. Sharing adoption expertise within the same country should be easier than sharing across different countries (e.g., between USA and China). The adoption of the technology can also be a function of the cultural and capability challenges one faces in different regions. Therefore, we argue that the benefits of a disruptive IT innovation would be more beneficial to firms with less geographic diversification.

H7: The benefit of disruptive IT innovation is higher in firms with less geographic diversification.

Figure 5.1 shows the impact of a disruptive IT innovation (as exemplified by RFID adoption) on financial performance, and the four contingency factors that moderate such an impact in the form of the six hypotheses proposed and tested in this study.

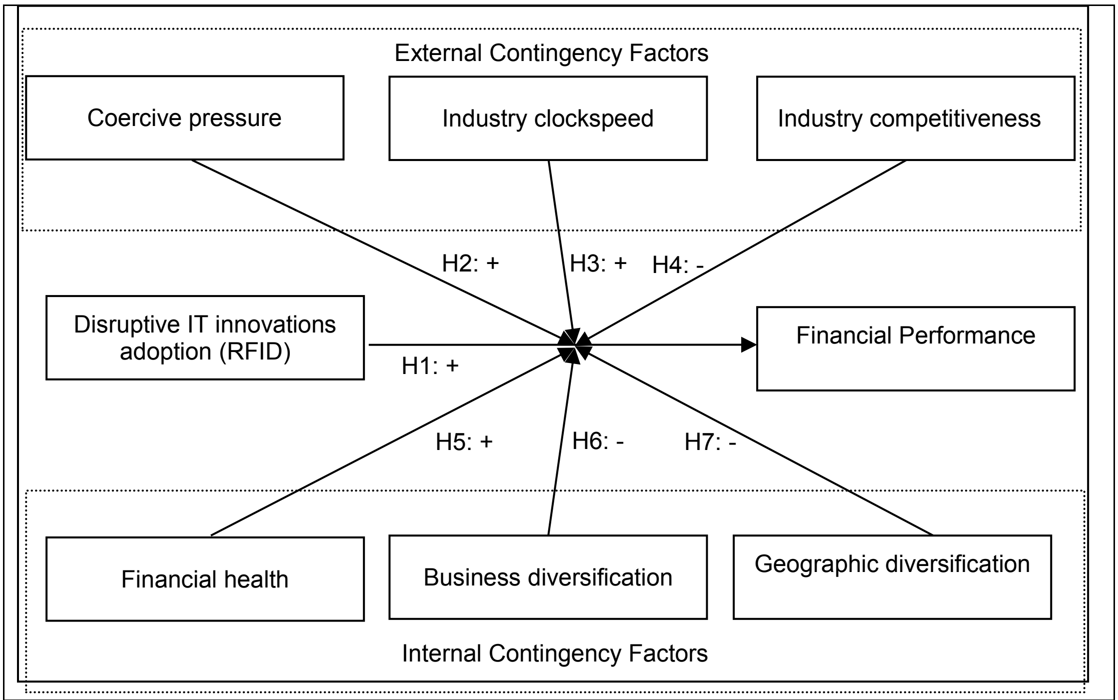

Figure 5.1. Research Framework

5.3 Data Collection and Methodology

This section conducted analysis based on publicly listed manufacturing firms including fashion and textiles firms as having adopted RFID. We used return on assets (ROA), measured as the ratio of operating profit to the firm's total asset to estimate financial performance. We examined abnormal financial performance based on results of propensity score matching discussed in Chapter 3 (section 3.2.1.2.2, page 38-42).

5.4 Results

5.4.1 Abnormal Changes in Financial Performance

Table 5.1 indicates that the abnormal changes in ROA significantly increased 0.74% three years after RFID adoption (i.e., $t + 2$ to $t + 3$; $p < 0.1$), but not during other periods. The three-year ($t - 2$ to $t + 1$), four-year ($t - 2$ to $t + 2$), and five-year ($t - 2$ to *t* + 3) cumulative changes in ROA were 1.03%, 1.17%, and 2.00%, respectively, which are statistically significant ($p < 0.10$).

Table 5.1 Abnormal Changes in ROA[a]

Time period	N	Abnormal mean	Abnormal median	*p*-value (t-test)	*p*-value (WSR test)	*p*-value (sign test)
			Yearly abnormal change			
t - 3 to *t* - 2	204	-0.13	0.39	0.88	0.97	0.53
t - 2 to *t* - 1	182	-0.54	-0.50	0.21	0.19	0.27
t - 1 to *t*	164	0.78	0.26	0.05*	0.12	0.48
t to *t* + 1	147	0.91	0.17	0.08*	0.25	1.00
t + 1 to *t* + 2	130	-0.34	-0.37	0.49	0.23	0.14
t + 2 to *t* + 3	115	0.70	0.74	0.16	0.08*	0.14
			Cumulative abnormal change			
t - 2 to *t* + 1	147	1.52	1.03	0.03**	0.05*	0.10*
t - 2 to *t* + 2	130	1.76	1.17	0.04**	0.03**	0.01**
t - 2 to *t* + 3	115	2.31	2.00	0.01**	0.00***	0.01**

[a] In percent.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$; two-tailed tests.

To test the robustness of the results on ROA, we also used the Barber and Lyon (1996) approach to match sample and control firms based on industry, firm size, and ROA. Consistent with the results based on propensity score matching in Table A1 (in Appendix) shows that ROA significantly increased 1.60% three-year after RFID adoption (i.e., *t* + 2 to *t* + 3; $p < 0.01$). The three-year (*t* - 2 to *t* + 1), and five-year (*t* - 2 to *t* + 3) cumulative changes in ROA were 0.35%, and 1.95%.

5.4.1.1 Sensitivity Analysis

To verify our accounting-based measure of firm performance, we ran an additional test based on abnormal stock returns. We measured the long-term market performance as ($price_{end}$ – $price_{beginning}$ + dividends)/$price_{beginning}$ (Wade et al. 2006). Table 5.2 shows that RFID adoption improved performance over the long term. The abnormal changes in yearly stock return significantly increased 27.43% and 11.82%

during the first and second years of RFID adoption, respectively (i.e., *t* to *t* + 1, *t* + 1 to *t* + 2; $p < 0.05$). We also found that the yearly stock return significantly increased 21.58% during the pilot stage (i.e., *t* - 2 to *t* - 1; $p < 0.05$) indicating that investors evaluated RFID adoption positively when firms started to implement RFID. The three-year (*t* - 2 to *t* + 1), four-year (*t* - 2 to *t* + 2), and five-year (*t* - 2 to *t* + 3) cumulative changes in yearly stock return were 62.68%, 37.42%, and 39.26%, respectively, which are all statistically significant ($p < 0.05$). These findings indicate that the impact of RFID investment on long-term market performance is positive.

Table 5.2 Abnormal Changes in Yearly Stock Return[a]

Time period	N[b]	Abnormal mean	Abnormal median	*p*-value (t-test)	*p*-value (WSR test)	*p*-value (sign test)
			Yearly abnormal change			
t - 3 to *t* - 2	200	86.21	-2.18	0.31	0.79	0.78
t - 2 to *t* - 1	178	134.03	21.58	0.26	0.03**	0.02**
t - 1 to *t*	160	89.90	-12.43	0.32	0.77	0.63
t to *t* + 1	143	144.55	27.43	0.07*	0.00***	0.02**
t + 1 to *t* + 2	126	104.47	11.82	0.13	0.06**	0.33
t + 2 to *t* + 3	111	-159.61	5.10	0.35	0.86	0.70
			Cumulative abnormal change			
t - 2 to *t* + 1	143	481.28	62.68	0.00***	0.00***	0.01***
t - 2 to *t* + 2	126	686.14	37.42	0.00***	0.00***	0.04**
t - 2 to *t* + 3	111	573.85	39.26	0.05*	0.05**	0.18

[a] In percent.
[b] The firm number is different from ROA because 4 outliers of stock returns were deleted. The results remain consistent with the original results.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$; two-tailed test.

In addition, based on the short-term event study discussed in Chapter 3, we examined the impact of RFID adoption on a firm's short-term abnormal returns in the days immediately following the announcement of the investment. As shown in Table 5.3, the abnormal returns for the announcements of RFID adoption during (1), (0, 1) and (-1, 1) were 0.17%, 0.21%, and 0.21%, respectively, which are all statistically significant ($p < 0.10$). All event study analyses (both short-term and long-term) showed that the adoption of RFID had a significant positive impact on financial performance. Therefore, H1 is fully supported.

Table 5.3 Impact of RFID Adoption Announcements on Market Value[a]

Windows	Abnormal Return	t-statistic (*p*-Value)
Daily window return		
(-1)	0.00	0.52 (0.60)
(0)	0.04	0.79 (0.43)
(1)	0.17	1.73* (0.08)
Cumulative window returns		
(-1, 0)	0.05	0.96 (0.34)
(0, 1)	0.21	1.77* (0.08)
(-1, 1)	0.21	1.70* (0.09)

Note. n=187. The number of sample firms in the EVENTUS reduced from 230 to 187, because CRSP database (EVENTUS use stock history in CRSP database to calculated abnormal return) did not have stock performance history for every firm. Previous studies using Eventus also have this similar problem (e.g. Wade et al. 2006).
[a] In percent.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$; two-tailed tests.

5.4.2 Contingency Factors Analysis

We further examined whether the level of abnormal ROA was contingent on the coercive pressure (H2), industry clockspeed (H3), industry competitiveness (H4), financial health (H5), business diversification (H6), and geographic diversification (H7).

5.4.2.1 Coercive Pressure

We created a dummy variable called *coercive adoption* and coded it as 1 for firms adopting RFID due to customers' mandate; otherwise, we used 0.

5.4.2.2 Industry Clockspeed

We created a variable called *industry clockspeed* and assigned it with value of 1, 2, and 3 to represent slow, median, and fast clockspeed industries, respectively.

5.4.2.3 Industry Competitiveness

We used the Herfindahl index (H-index) of industry concentration (Boyd 1995) as an inverse proxy for industry competitiveness. The index was measured as the sum of the squared market shares for all firms in an industry group, and found to range between 0 and 1. A score approaching 0 indicates the presence of many competitors in an industry. Such industries are considered more complex and competitive. We expected firms under high competitive industry (low H-index) obtain smaller profitability from RFID adoption.

5.4.2.4 Financial Health

We used Altman's Z-score (Altman 1968) as a proxy for financial health. A high Z-score indicates good financial health.

5.4.2.5 Corporate Diversification

We measured the business (for H6) and geographic diversification (for H7) of each firm according to its sales reported by different business and geographic segments (Hendricks et al. 2009). We calculated *business diversification* as 1 minus the sum of the square of the ratio of the individual business segment's ratio of annual sales to total sales. Thus, a high score indicates a high degree of business diversification. We calculated *geographic diversification* in a similar way. We expected that a high level of business and greater geographic diversification lead to lower abnormal ROA because RFID adoption in such an environment is more complex due to a high requirement for customization. We collected information from COMPUSTAT

Business Segment data to measure business and geographic diversification (based on international segmentation). Table 5.4 shows the formulas used in estimating each indicator.

Table 5.4 Variable Definitions	
Variable	**Definition**
Financial health	Z-score = 1.2 (WCAP/TA) + 1.4 (RE/TA) + 3.3 (EBIT/TA) + 0.6 (MV/TL) + 0.999 (SALE/TA), Where WCAP is working capital, TA is total assets, RE is retained earnings, EBIT is earnings before interest and taxes, MV is market value of equity, and TL is total liabilities
Industry competitiveness	H-index = $\sum_{i=1}^{N}(\frac{Si}{S})^2$, where Si is the annual sales of the i^{th} firm; S is the total sales of the industry (based on 4-digit SIC code); N is the number of firms in the industry
Business diversification	$1 - \sum_{i=1}^{N}(\frac{Si}{S})^2$, where Si is the annual sales of the i^{th} business segment; S is the total sales of the firm; N is the number of business segments of the firm
Geographic diversification	$1 - \sum_{i=1}^{N}(\frac{Si}{S})^2$, where Si is the annual sales of the ith geographic segment; S is the total sales of the firm; N is the number of geographic segments of the firm

5.4.2.6 Control Variables

We included firm and industry level control variables that could influence the dependent variable *abnormal ROA* (i.e., the sample firm abnormal ROA over the five-year period). We included firm-level characteristics such as *firm size* (total assets), *capital investment* (capital expenditures over total assets), *leverage* (debt-to-equity ratio) and sales growth that could affect financial performance (Hitt and Brynjolfsson 1996). We included further performance variables such as the firm's *previous ROA*, *yearly stock return*, *inventory turnover*, *R&D intensity* and *SGA intensity*. For all these control valuables, we had data starting from year *t* - 2. Third, we controlled *industry sales growth* measured as the average performance change in industry sales between year *t* - 2 and *t* + 3. Furthermore, we created a dummy variable for *announcements after implementation stage* which equaled 1 for announcements published when the implementation of RFID had been completed, and 0 otherwise. Finally, we controlled for the adoption year. Table 5.5 shows the correlations between various indicators.

Table 5.5 Means, Standard Deviations, and Pearson Correlation of Variables in Hierarchical Regression

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1 ROA (*t* -2 to *t* +3)	1																		
2 Firm previous ROA	-0.05	1																	
3 Firm size[a]	0.18*	-0.07	1																
4 Yearly stock return	0.05	0.13	0.72***	1															
5 Leverage	-0.06	-0.10	0.05	-0.01	1														
6 SGA intensity	0.04	0.14	-0.16*	0.04	-0.04	1													
7 R&D intensity	0.09	0.03	0.10	0.19**	-0.07	0.58***	1												
8 Capital investment	-0.05	0.26***	0.15	0.17*	-0.08	-0.17*	0.06	1											
9 Sales growth	-0.06	-0.08	0.06	-0.03	-0.15	-0.17*	0.00	0.28***	1										
10 Inventory turnover	0.33***	0.21**	0.13	0.10	-0.02	-0.06	-0.01	0.08	0.08	1									
11 Industry sales growth (*t* - 2 to *t* + 3)	0.04	0.05	0.23**	0.17*	-0.04	0.00	0.09	-0.08	0.10	-0.00	1								
12 Announcements after implementation stage[b]	-0.04	-0.07	-0.06	-0.02	0.02	-0.07	0.00	-0.02	0.07	-0.02	0.00	1							
13 Adoption year	-0.02	-0.12	0.06	0.07	-0.05	-0.06	0.09	-0.10	0.12	-0.19**	0.19**	-0.24***	1						
14 Coercive adoption[b]	0.09	0.01	-0.11	0.07	0.07	0.22**	0.07	-0.46***	-0.05	-0.13	0.06	-0.10	0.07	1					
15 Industry clockspeed	-0.03	0.12	-0.20*	-0.09	0.09	0.36**	0.19*	-0.03	-0.03	0.04	0.02	0.02	-0.10	-0.02	1.00				
16 Industry competitiveness	0.05	-0.14	-0.11	-0.19**	0.24***	-0.21**	-0.24***	-0.20**	-0.04	-0.09	0.02	-0.01	-0.13	-0.09	0.06	1			
17 Financial health	0.11	0.30***	-0.20**	-0.14	-0.12	-0.34***	-0.39***	0.13	0.16*	-0.28***	-0.10	0.05	-0.11	-0.20**	-0.02	0.03	1		
18 Business diversification	-0.16*	-0.15	0.18**	0.08	0.18*	-0.21**	-0.06	-0.17*	-0.14	-0.20**	0.03	-0.02	0.04	0.00	-0.09	0.14	-0.05	1	
19 Geographic diversification	0.10	-0.02	0.24***	0.23**	0.03	-0.11	0.16*	0.11	-0.05	-0.11	0.06	0.12	0.17*	-0.02	-0.03	-0.16*	-0.17*	0.28***	1
Mean	0.02	0.15	15.58	8.91	3.08	0.22	0.04	0.04	0.12	11.11	0.35	0.71	2004	0.47	0.96	0.27	1.08	0.41	0.79
s.d.	0.09	0.06	26.35	19.78	4.48	0.13	0.06	0.03	0.25	7.54	0.35	0.45	1.86	0.50	0.54	0.19	0.42	0.26	0.14
Mini	-0.23	0.04	0.02	-0.70	-26.64	0.01	0.00	0.01	-0.57	3.61	-0.57	0.00	1998	0.00	1.00	0.06	0.32	0.00	0.00
Maxi	0.24	0.37	177.57	141.76	29.15	0.66	0.39	0.15	1.49	64.62	1.50	1.00	2009	1.00	3.00	0.96	2.44	0.84	0.95

Note. N = 115; *t* is the year of RFID adoption; based on the data in year *t* - 2; * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$; two-tailed tests.

[a] In billion USD.

[b] *Coercive adoption* is coded 1 =”mandate,” 0 = “proactive.” and for *Announcements after the implementation stage* announcement, 1=”yes,” 0 =”no.”

Table 5.6 Hierarchical Regression Analysis of the Impact of Contingency Factors on Abnormal ROA (*t - 2* to *t + 3*)

Variable	Model 1: Base model	Model 2: Coercive adoption model	Model 3: Industry clockspeed model	Model 4: Industry competitiveness model	Model 5: Financial health model	Model 6: Business diversification model	Model 7: Geographic Diversification model
Intercept	-3.55 (0.70)	-4.78 (0.61)	-4.62 (0.62)	-8.43 (0.37)	-9.55 (0.30)	-8.73 (0.34)	-5.39 (0.55)
Firm's previous ROA	-0.14 (0.31)	-0.17 (0.22)	-0.17 (0.23)	-0.16 (0.25)	-0.29 (0.05)*	-0.29 (0.05)**	-0.30 (0.03)**
Firm size	0.00 (0.05)**	0.00 (0.02)**	0.00 (0.02)**	0.00 (0.01)**	0.00 (0.00)***	0.00 (0.00)***	0.00 (0.00)***
Yearly stock return	-0.00 (0.16)	-0.00 (0.06)*	-0.00 (0.06)*	-0.00 (0.05)*	-0.00 (0.02)**	-0.00 (0.02)**	-0.00 (0.02)**
Leverage	-0.00 (0.35)	-0.00 (0.43)	-0.00 (0.43)	-0.00 (0.23)	-0.00 (0.35)	-0.00 (0.48)	-0.00 (0.45)
SGA intensity	0.05 (0.52)	0.05 (0.56)	0.05 (0.53)	0.09 (0.30)	0.14 (0.10)	0.10 (0.23)	0.14 (0.11)
R&D intensity	0.08 (0.67)	0.06 (0.72)	0.06 (0.72)	0.08 (0.67)	0.18 (0.31)	0.22 (0.22)	0.15 (0.38)
Capital investment	-0.08 (0.83)	0.32 (0.43)	0.32 (0.44)	0.51 (0.22)	0.65 (0.12)	0.51 (0.22)	0.40 (0.32)
Sales growth	-0.04 (0.25)	-0.05 (0.14)	-0.05 (0.14)	-0.05 (0.11)	-0.07 (0.03)**	-0.08 (0.02)**	-0.07 (0.04)**
Inventory turnover	0.00 (0.00)***	0.00 (0.00)***	0.00 (0.00)***	0.00 (0.00)***	0.00 (0.00)***	0.00 (0.00)***	0.00 (0.00)***
Industry sales growth (*t* - 2 to *t* + 3)	0.00 (0.95)	0.00 (0.94)	0.00 (0.93)	0.00 (0.95)	0.00 (0.90)	0.00 (0.94)	0.00 (0.91)
Announcements after implementation stage	-0.00 (0.99)	0.01 (0.77)	0.01 (0.77)	0.01 (0.57)	0.01 (0.56)	0.01 (0.64)	0.00 (0.96)
Adoption year	0.00 (0.70)	0.00 (0.61)	0.00 (0.62)	0.00 (0.38)	0.00 (0.31)	0.00 (0.34)	0.00 (0.56)
Coercive adoption (H2)		0.04 (0.05)*	0.04 (0.06)*	0.04 (0.03)**	0.05 (0.01)***	0.05 (0.01)***	0.05 (0.01)***
Industry clockspeed [a] (H3)			-0.00 (0.80)	-0.01 (0.60)	-0.01 (0.58)	-0.01 (0.64)	-0.01 (0.50)
Industry competitiveness (H4)				0.09 (0.06)*	0.09 (0.04)**	0.09 (0.04)**	0.10 (0.02)**
Financial health (H5)					0.06 (0.01)***	0.06 (0.01)***	0.07 (0.00)***
Business diversification (H6)						-0.05 (0.09)*	-0.07 (0.03)**
Geographic diversification (H7)							0.14 (0.02)**
Model F value	1.90**	2.10**	1.93**	2.08**	2.51***	2.58***	2.86***
R square (%)	18.30	21.25	21.30	23.98	29.06	31.11	34.89
Adjusted R square (%)	8.69	11.11	10.28	12. 46	17.48	19.04	22.69
R square change (%)	18.30	2.95	0.05	2.68	5.08	2.05	3.79
F change	1.90**	3.78*	0.06	3.49*	7.02***	2.88*	5.58**

Note. N = 115; *t* is the year of RFID adoption; based on the data in year *t* - 2; unstandardized regression coefficients are shown with the *p*-value in parentheses.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$; two-tailed tests.
[a] Results remain consistent when using fashion and textiles industries only.

Table 5.6 shows the results of the cross-sectional regression. Overall, the F values are greater than 1 for all models with significance at 5% level or higher. Adjusted R square ranges from 8.69% to 22.69%. Models 2 to 7 of Table 5.6 reveal that firms with coercive RFID adoption are related significantly to the abnormal ROA values of the firms (p < 0.10). This indicates that the adopting firms could gain higher abnormal ROA than self-initiated adopters due to coercive adoption; thus, supporting H2. Model 3 to 7 in Table 5.6 show that industry clockspeed is not significantly related to abnormal ROA. Therefore, H3 is not supported. Models 4 to 7 in Table 5.6 show that the H-index is a significant predictor of abnormal ROA (p < 0.10). This suggests that the lower the industry competitiveness faced by the RFID-adopting firms in the industry (higher H-index), the higher the financial benefits. Therefore, H4 is supported.

Models 5 to 7 show that the Z-score is significantly related to abnormal ROA in the long term (p < 0.01). This suggests that RFID-adopting firms with good financial health experienced higher abnormal ROA. Thus, H5 is supported. Models 6 to 7 of Table 5.6 show that business diversification is negatively related to abnormal ROA (p < 0.10), whereas model 6 shows that geographic diversification is significantly and positively related to abnormal ROA (p < 0.05). The finding suggests that RFID-adopting firms with low degree of business diversification and high degree of geographic diversification had higher abnormal ROA over the five-year period. Therefore, H6 is supported, whereas H7 is *not* supported. The direction of geographic diversification works against our prediction in H7. We will discuss this matter further in the discussion section.

As shown in Table 5.6 with respect to Model 7, firm size is related positively to abnormal ROA. This indicates that larger firms benefit more from RFID adoption. Moreover, previous magnitudes of ROA, yearly stock return, and sales growth are negatively related to abnormal ROA, suggesting that firms with lower financial performance before RFID adoption are able to enjoy higher profitability after RFID adoption. Finally, inventory turnover is positively related to abnormal ROA. This suggests that firms with high inventory turnover are able to achieve higher profitability from RFID adoption; because these firms have higher needs for better inventory control.

5.5 Discussion

In this section, we found that the adoption of RFID has a positive impact on financial performance. We neither found significant improvement in profitability during the pilot stage (t - 2 to t - 1) nor in the process of the formal RFID adoption (t - 1 to t + 0). This could be because of increasing costs such as setup costs and training costs for RFID adoption in these periods. Moreover, we found no significant negative impact of RFID adoption on profitability in any of the five-year periods. These findings provide strong support to the proposition that a disruptive IT innovation positively impacts financial performance in general. However, unlike its impact on operational performance which generally show positive impact after one year of adoption (results in Chapter 4), it takes a firm 2 to 3 years to recover from a disruption and realize the financial benefits. The result of this study is consistent with previous studies that had found that the positive link between adoption of IT investment and financial performance lags for several years (e.g., Brynjolfsson and Hitt 1996; Wang et al. 2010). It takes time for a firm to implement new organizational structures and business process complementing the new IT venture before realizing financial benefits from the technologies (Brynjolfsson and Hitt 1996). Another plausible explanation for the major improvement in the third year of RFID adoption is that it reflects the realization of the full benefits derivable from the long-term relationship established with supply chain partners and all this takes times to build and maintain (Mentzer et al. 2001). We also noted that Walmart had shared standardized EPC data with its RFID-enabled suppliers two years after the initial RFID mandate in 2003 (Roberti 2003; Roberti 2005), which might also have delayed the realization of benefits from RFID adoption.

An analysis of coercive adoption requests from major retailers can act as a natural experiment for examining how external pressure moderates the impact of a disruptive IT innovation. As hypothesized, our regression analysis shows that coercive adoption leads to stronger improvement in profitability than self-initiated RFID adoption. From institutional perspective, these results confirm that coercive adoption of RFID offers additional financial benefits to adopting firms because of building a closer and long-term relationship with their mandatory (Lai et al. 2006).

Contrary to our hypotheses, fast industry clockspeed is not positively associated with financial performance. Firms in fast clockspeed industries, such as fashion and textiles, require operations that are more efficient to introduce numerous new products to the market; therefore, it is imperative that they have lower levels of slack in terms of time and resources while implementing the innovation. Although RFID adoption provides firms in fast clockspeed industries with more responsive and more visible supply chains that can track inventories more efficiently, adoption could cause disruptions that lead to failures in meeting fast-changing customer demands, eventually offsetting the benefits of the adoption.

Consistent with our hypotheses, adopting firms exhibit a less positive relationship to financial performance in high competitive industries because they need to avoid disruption in operations for continued competitiveness. The result also implies that if a firm operating in a high-competitive environment adopts disruptive innovations to increase competiveness, it should prepare sufficient slacks in time and resources for better outcome. On the other hand, firms operating in low competitive industries should shift their emphasis from incremental innovations (Tushman and Anderson 1986) to disruptive IT innovations as such a step could offer opportunities for improved profitability.

The observation that good financial health leads to lower abnormal ROA values indicates that slack resources, management commitment, and employee support are essential to successful disruptive IT innovation adoption. Senior management teams should review the availability of slack resources to ensure that resources are adequate to support the implementation process for at least 3 years. Otherwise, the implementation is likely to face great resistance from both the investor and employee in the first two years.

Although non-disruptive IT investment literature suggests that IT innovation could benefit diversified firms in terms of economies of scale derived by transferring technologies across lines of business and exploiting new uses of existing IT resources (Clemons and Row 1991), we found that highly diverse businesses could achieve lower profitability than less diversified ones. However, contradicting our hypotheses, we found that geographically diversified firms were able to attain higher profitability than geographic centered firms. There are two plausible explanations for this result. First, since geographically diversified firms can expand into similar business units distributed across different countries, the experience of minimum disruption can carry along. Second, geographically diversified firms have longer and stretched supply chains. Therefore, it is more complex and difficult for a geographically diversified firm to manage its supply chains (Hendricks et al. 2009). RFID adoption offers several advantages to geographically diversified firms including improvement on labor efficiency and real-time information sharing across operations in different countries. As a result, the improvement in supply chain performance to geographically diversified firms from RFID adoption overweighs the costs of customization.

5.6 Chapter Summary

This study has provided empirical evidence to support the proposition that disruptive IT innovations produce a significant and long-term positive impact on firms' financial performance. Our contingency factors analysis indicates that firms under coercive pressure, operating in low-competition industries, in poor financial health, having a low level of business diversification, and having a high level of geographic diversification can enjoy greater improvements in profitability. However, we found that fast clockspeed industries such as fashion and textiles did not benefit more from RFID adoption, suggesting that these industries must evaluate other factors to improve their financial performance related to RFID adoption.

In the next section, we examine the impact of disruptive IT innovations from an alternative perspective on firm performance—i.e., systematic risk and the moderating effect of TMT heterogeneity on systematic risk.

CHAPTER 6 RESEARCH PART THREE—DISRUPTIVE IT INNOVATIONS, SYSTEMATIC RISK, AND TOP MANAGEMENT TEAM HETEROGENEITY

In previous sections, we have shown how disruptive IT innovations enhance performance (i.e., operational and financial performance) and how firm- and industry-level contingency factors moderate that performance. In this section, we will focus on examining the impact of disruptive IT innovations on firm risk and the moderating effect of TMT characteristics. Risk is a key dimension of firm performance (Brealey and Myers 2002) but remains relatively neglected in the IT literature. More specifically, we will examine the impact of disruptive IT innovations on systematic risk, which is highly associated with a firm's market value (Lubatkin and Rogers 1989; McAlister et al. 2007). We believe that an understanding of the impact of disruptive IT innovations on systematic risk is critical to top managers, whose primary task is to maximize shareholder wealth for a given amount of risk. Moreover, top management attributes are key to the success of disruptive IT innovations (Moon and Ngai 2008; Vijayaraman and Osyk 2006). We will examine the effects of two types of TMT heterogeneity: pay dispersion and demographic heterogeneity. These two factors can influence managers' performance behaviors, which in turn affect firm performance.

6.1 Theoretical Background

6.1.1 Risk and Disruptive IT Innovations

IT-enabled disruptive innovation provides new opportunities. However, it also presents uncertain effects on firm risk. Firm risk consists of systematic risk and unsystematic risk (Miller and Bromiley 1990). Systematic risk is the consequence of investor expectations on the future volatility of the total returns of a firm relative to that of the market as a whole (Barton 1988). Systematic risk affects the discount rate used to evaluate investments and value securities (Hendricks and Singhal 2005). Based on portfolio theory, investors can diversify from unsystematic risk by constructing a portfolio of stocks whose returns correlate imperfectly with one another (Lintner 1965; Sharpe 1964). By contrast, systematic risk, which is a market-driven variation in the stock returns of a firm, cannot be diversified. Systematic risk is a standard measure of risk for stock market values (Dewan and Ren 2007; Hendricks and Singhal 2005; McAlister et al. 2007; McGuire et al. 1988). Top managers are particularly concerned with systematic risk because their primary tasks are to maximize shareholder wealth for a given amount of systematic risk.

Emerging studies have started to examine the effects of IT application on firm risk (Dewan and Ren 2007; Dewan and Ren 2011; Dewan et al. 2007; Tanriverdi and Ruefli 2004). In particular, Dewan and Ren (2007) adopted an event study approach to jointly examine the wealth and risk effects associated with electronic commerce announcements from 1996 to 2002. After controlling for contemporaneous risk changes, Dewan and Ren (2007) found that wealth effects are not significant. Total and unsystematic risk showed a significant post-event increase in 1998 and 2000, whereas systematic risk declined in 1996 and 2002 because electronic commerce enabled the use of new online channels and activities that reduce demand uncertainty and the cyclicality of sales revenues. The aforementioned study provides important insights on disruptive IT innovations. Firm risk may be reduced if investors perceive that IT-enabled innovation provides competitive advantages to firms (Lubatkin and Rogers 1989). Moreover, Dewan and Ren (2011) found that the relationship between IT investment and firm risk is moderated by contextual factors. More specifically, the researchers found that IT investment increases firm risk and that suitable firm boundary strategies and vertical integration in supply chain can moderate the effects of IT on firm performance in a manner that increases return and decreases risk at the margins.

6.2 The Impact of Disruptive IT Innovations on Systematic Risk

Disruptive IT innovation revolutionizes operation processes that provide firms with major new growth in business, dramatic improvements, and more efficient unit performance (Kostoff et al. 2004). Engaging in innovation activities also help firms to be aware of the latest developments, to absorb new and related knowledge, and to develop dynamic capabilities that equip firms with the ability to handle dynamic market changes (Cohen and Levinthal 1990; Roberts and Amit 2003; Teece 1982). Previous studies also find empirical evidence that innovations improve firm performance, thus lowering a firm’s systematic risk (Dewan and Ren 2007; McAlister et al. 2007). For instance, Dewan and Ren (2007) find that e-commerce decreases systematic risk because it improves demand uncertainty and the cyclicality of sales revenues. McAlister et al. (2007) examine the impact of a firm’s R&D on the systematic risk of its stock. Their study is based on 644 publicly listed firms and consists of five-year moving windows. Similarly, they find that R&D creates intangible assets that reduce systematic risk.

As a disruptive IT innovation, RFID potentially improves firm performance and its adoption can reduce systematic risk. RFID automates the manual tracking process, thereby improving data accuracy and labor efficiency (Jones 1999). Moreover, RFID offers information visibility that provides firms several advantages in operational performance, such as reduced inventory, increased product availability, and quicker and more effective customer service (Angeles 2005; Lee and Özer 2007; Mikko and Jan 2002). Previous studies also suggest that RFID improves operational efficiency and effectiveness and increases sales and profit (Moon and Ngai 2008). If RFID adoption enhances firms' performance—that is operational performance and profitability—as shown in previous studies, it should help firms insulate themselves from the impact of stock market downturns, thus reducing their systematic risk. Therefore, we propose the following hypothesis.

H1: Disruptive IT innovation significantly reduces systematic risk.

6.3 The Moderating Effects of TMT Heterogeneity

TMT heterogeneity plays a critical role in the success of innovation adoption. In this section, we focus on examining how two important types of TMT heterogeneity, pay dispersion and demographic heterogeneity, moderate the relationship between disruptive IT innovations and systematic risk.

6.3.1 TMT Pay Dispersion

Although pay dispersion motivates members to exert greater effort to obtain higher pay (Main et al. 1993), it can also inspire team dysfunction, leading to negative organizational consequences such as increased turnover, shorter tenures, decreased productivity and collaboration, and lower firm performance (Bloom 1999; Fredrickson et al. 2010; Pfeffer and Langton 1993; Siegel and Hambrick 2005; Wade et al. 2006). Previous studies indicate that TMT members will engage in a series of social comparisons to make sense of the rewards obtained for their performance and to determine whether those rewards are fair and justified (Adams 1965). Executives who obtain far less pay than others may react with an increase in invidious comparisons, increased jealousy, increased feelings of inequity, and lower satisfaction (Bloom 1999; Fredrickson et al. 2010; Pfeffer and Langton 1993; Siegel and Hambrick 2005). Conversely, tightly dispersed pay can be beneficial for group performance because it instills feelings of fairness and common purpose, fosters team-oriented behavior, reduces interpersonal competition, and supports common goal orientations (Cowherd and Levine 1992; Kochan 1994; Milgrom and Roberts 1988; Pfeffer 1994).

Adoption of disruptive IT innovations such as RFID requires long-term support, commitment, and coordination from top managers (Brown and Russell 2007; Moon and Ngai 2008; Ngai and Gunasekaran 2009; Wang et al. 2010). More specifically, top management commitment at the firm and interorganizational levels is required for the coordination and business process reengineering involved in RFID adoption along the supply chain (Sharma et al. 2007). Moreover, to realize the benefits of RFID adoption, managers need to work together to overcome a series of management challenges, such as technology challenges, cost challenges, employees' resistance to change, and business process changes (Brown and Russell 2007; Wu et al. 2006). Therefore, we argue that under widely dispersed pay that inspires team dysfunction, adoption is less likely to be successful and systematic risk is thus higher.

H2: Firms with greater pay dispersion experience higher systematic risk for disruptive IT innovation adoption.

6.3.2 TMT Demographic Heterogeneity

TMT with greater diversity of background may possess greater breadth of information sources, skill sets, values, attitudes, orientations, and experiences to generate more creative, innovative and responsive solutions (Dutton and Duncan 1987), and may be less susceptible to "groupthink", which in turn might limit the generation and assessment of alternatives to problems (Bantel and Jackson 1989; Jackson 1992). Hambrick et al. (1996) suggest that heterogeneous teams perform better under uncertain environments, whereas less heterogeneous team will be more successful in stable environments. Similarly, Murray (1989) indicates that heterogeneous groups perform better under conditions of environmental change because heterogeneous groups have the advantages of improved adaptability and greater creativity (Katz 1982).

Extending the findings and observations of previous studies to demographic heterogeneity in the context of disruptive IT innovations, we expect that greater demographic heterogeneity is more likely to receive a greater benefit from disruptive IT innovations. For example, greater age heterogeneity creates attitudes and values that are more varied to generate new and better solutions to problems. Moreover, age heterogeneity may encourage the exchange of a wide variety of perspectives that can lead to greater acceptance of change. This diversity of opinion might be particularly useful in the case of disruptive IT innovations that are complex in implementation and cause uncertain impact on operations. Similarly, greater gender heterogeneity that includes more women managers offers several benefits when adopting disruptive IT innovations. For instance, women executives are likely to have superior performance in several skill areas, including adapting to change, conflict resolution, and motivating and inspiring others (Brett and Stroh 1999; Eagly and Johnson 1990). These skills are critical to address disruptive IT innovations that create pervasive and radical changes in organizations. In summary, we predict that TMT with a diverse demographic base better equip firms to implement disruptive IT innovations, which in turn leads to lower systematic risk.

H3: Firms with higher demographic heterogeneity experience lower systematic risk for disruptive IT innovation adoption.

Figure 6.1 shows the impact of a disruptive IT innovation (as exemplified by RFID adoption) on systematic risk and the two types of TMT heterogeneity that moderate that impact in the form of the three hypotheses proposed and tested in this section.

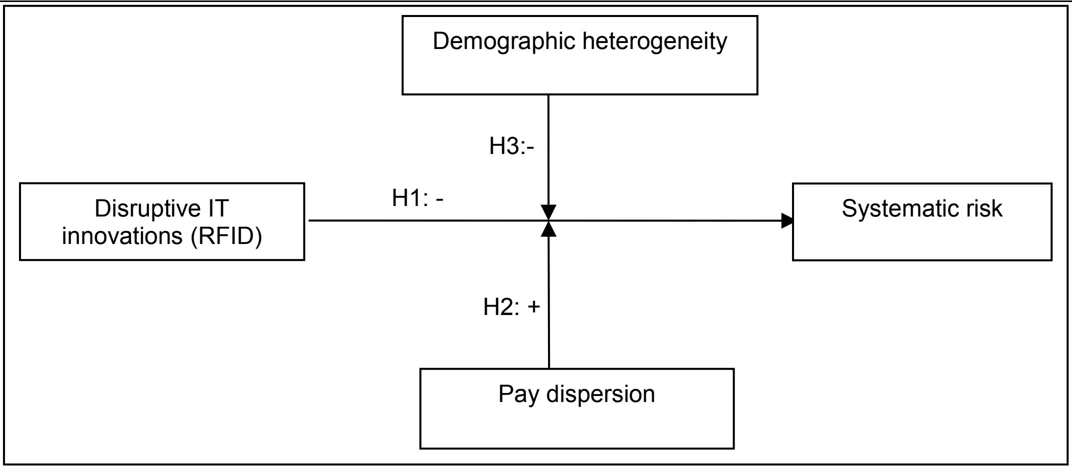

Figure 6.1 Research Framework

6.4 Data Collection and Methodology

This section performed an analysis based on publicly listed manufacturing firms including fashion and textiles firms that have adopted RFID. We measured systematic risk as beta (β_E) from the Capital Asset Pricing Model (CAPM) (Lintner 1965; Sharpe 1964).

$r_E = r_F + \beta_E\,(r_M - r_F)$ where

r_E = expected return of a firm's stock; and

r_F = the risk-free rate; and

r_M = the expected return on the market portfolio; and

$\beta_E = Cov(r_E, r_M)/Var(r_M)$, the covariance of the market's expected return with the individual firm's common stock return divided by the market's variance

Beta was collected from CRSP, whereas TMT compensation and demographic data were collected from EXECUCOMP.

We matched RFID-adopting firms to control firms using the propensity score matching discussed in Chapter 3 (section 3.2.1.2.2, page 38-42). We further included systematic risk in the logistic regression to find the matching control firms that also have similar systematic risk performance prior to RFID adoption. The results of the logistic regression (Appendix Table A2) are similar to that of Table 3.4 (Chapter 3, page 41), and systematic risk is not significantly related to RFID adoption. One hundred and fifty-two sample firms were successfully matched with control firms.

6.5 Results

6.5.1 Abnormal Changes in Systematic Risk

We investigated whether the adoption of disruptive IT innovations significantly reduced systematic risk. The results of effects on systematic risk over a five-year period (from year t - 2 to t + 3) are presented in Table 6.1. Table 6.1 shows that abnormal changes in systematic risk significantly decreased by 0.19 during the pilot stage (t - 2 to t - 1; $p < 0.05$) and 0.10 three (t + 2 to t + 3; $p < 0.10$) years after RFD adoption. The three-year (t - 2 to t + 1), four-year (t - 2 to t + 2), and five-year (t - 2 to t + 3) cumulative effects in systematic risk were -0.11, -0.15, and -0.21, respectively, which are statistically significant ($p < 0.05$). Therefore, H1 is supported.

Table 6.1. Abnormal Changes in Systematic Risk						
Time period	N	Abnormal mean	Abnormal median	*p*-value (t-test)	*p*-value (WSR test)	*p*-value (sign test)
			Yearly abnormal change			
t - 3 to *t* - 2	152	0.03	-0.02	0.83	0.37	0.71
t - 2 to *t* - 1	144	-0.14	-0.19	0.07*	0.01**	0.00***
t - 1 to *t*	136	0.08	0.05	0.23	0.18	0.20
t to *t* + 1	121	-0.08	-0.04	0.09*	0.26	0.59
t + 1 to *t* + 2	106	-0.09	-0.01	0.08	0.28	0.92
t + 2 to *t* + 3	93	-0.13	-0.10	0.01***	0.03**	0.10*
			Cumulative abnormal change			
t - 2 to *t* + 1	121	-0.11	-0.11	0.08*	0.05**	0.05**
t - 2 to *t* + 2	106	-0.15	-0.15	0.02**	0.01**	0.01***
t - 2 to *t* + 3	93	-0.17	-0.21	0.03**	0.01**	0.01**

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$; two-tailed tests.

6.5.2 Analysis of the Effects of TMT Heterogeneity on the Impact of Disruptive IT Innovation on Systematic Risk

We further examined whether the level of abnormal systematic risk was contingent upon TMT pay dispersion (H2) and demographic heterogeneity (H3).

6.5.2.1 TMT Pay Dispersion

We measured pay dispersion using base salary and incentive-based pay. Base salary only includes salary, whereas incentive-based pay includes bonuses, stock options, and restricted stock options. Following previous studies (e.g., Pfeffer and Langton 1993; Siegel and Hambrick 2005), we measured two dimensions of pay dispersion: vertical pay dispersion (pay differences between hierarchical levels) and horizontal pay dispersion (pay differences among peers within the same hierarchical level). We measured vertical pay dispersion, *CEO/level 2*, as the ratio of CEO pay to that of the average pay for level 2 team members (e.g., chief operating officer and chief financial officer). The larger the ratio, the greater the difference between CEO' pay and level 2 managers' pay. We measured horizontal pay dispersion, *CV level 2,* as the coefficient of variation of a level 2 managers' incentives (standard deviation divided by the mean). Similarly, a high ratio implies greater horizontal pay dispersion.

6.5.2.2 TMT Demographic Heterogeneity

We used age and gender heterogeneity as proxies for demographic heterogeneity. Following previous studies (e.g., Bantel and Jackson 1989; Carpenter 2002; Hambrick et al. 1996), we measured age heterogeneity as the coefficient of variation of a TMT's age (standard deviation divided by the mean) and gender heterogeneity using Blau's (1977) index, which is a widely used measure of heterogeneity when categories are used. This index was calculated as $1- \sum P_i^2$, where P is the percentage of members in the *i*th category.

6.5.2.3 Control Variables

We included individual, firm, and industry level control variables that could influence the dependent variable *abnormal systematic risk* (i.e., the sample firm abnormal systematic risk over the five-year period). First, we included firm-level characteristics such as *previous systematic risk of the firm* (i.e., systematic risk in *t* - 2), *firm size* (logarithm of the total assets), *ROE* (operating income over shareholder equity), *R&D intensity* that can affect firm performance, *capital intensity* (capital expenditures over employee number), and *leverage* (debt-to-asset ratio). For all of these control valuables, we had data starting from year *t* - 2. For industry level control variables, we controlled industry clockspeed and assigned the variable with values of 1, 2, and 3 to represent slow, medium, and fast clockspeed industries, respectively. We controlled coercive RFID adoption by creating a dummy variable called *coercive* adoption and coded it as 1 for firms adopting RFID due to customers' mandate; otherwise, we used 0. We controlled *industry sales growth* measured as the average performance change in industry sales between year t - 2 and t + 3. Furthermore, we created a dummy variable for *announcements after implementation stage*, which equaled 1 for announcements published when the implementation of RFID had been completed and 0 otherwise. We controlled for the adoption year. We created a dummy variable called *source* and coded it as 1 to represent the sources of technology periodicals such as RFID Journal and RFID Knowledgebase and 0 otherwise. Finally, we controlled TMT characteristics such as *TMT size* (total number of TMT members), *average salary* (base salary in logarithm), *average incentives* (incentive-base pay in logarithm), *average age*, and *percentage of men* in the management group. Table 6.2 shows the correlations between various indicators.

Table 6.2. Means, Standard Deviations, and Pearson Correlation of Variables in Hierarchical Regression

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1	Systematic risk (*t* -2 to *t* +3)	1																						
2	Firm previous systematic risk	-0.05	1.00																					
3	Firm size[a]	-0.05	0.19	1.00																				
4	ROE	-0.07	-0.15	0.06	1.00																			
5	R&D intensity	0.02	0.26	0.25	-0.07	1.00																		
6	Capital intensity	-0.02	0.15	0.34	-0.01	-0.03	1.00																	
7	Leverage	-0.09	-0.10	0.06	0.15	-0.29	-0.02	1.00																
8	Industry clockspeed	0.10	0.02	-0.11	-0.03	0.27	-0.26	-0.01	1.00															
9	Coercive adoption	-0.23	-0.29	0.00	0.00	0.03	-0.17	0.06	0.19	1.00														
10	Industry sales growth (*t* - 2 to *t* + 3)	-0.27	-0.20	0.21	-0.03	0.10	0.13	-0.24	0.03	0.09	1.00													
11	Announcements After implementation stage	0.16	0.18	-0.09	-0.08	0.07	0.07	0.01	-0.05	-0.19	-0.03	1.00												
12	Adoption year	-0.11	0.15	-0.11	0.03	-0.13	0.10	-0.02	-0.04	0.14	-0.20	-0.17	1.00											
13	Source	0.05	0.21	0.03	-0.28	0.22	-0.11	-0.03	-0.03	0.16	-0.16	0.28	0.14	1.00										
14	Team size	0.19	0.02	0.21	0.04	0.00	0.42	-0.04	-0.08	-0.07	-0.07	0.16	-0.08	-0.06	1.00									
15	Average salary[a]	-0.13	0.17	0.58	0.14	0.16	0.17	0.17	-0.01	-0.07	0.05	-0.08	0.04	-0.07	0.18	1.00								
16	Average incentives[a]	-0.18	0.14	0.48	0.21	0.24	0.15	0.01	0.14	0.16	0.18	-0.17	0.09	0.02	0.29	0.57	1.00							
17	Average age	0.04	-0.14	-0.07	0.04	-0.08	0.00	0.09	-0.01	-0.08	0.05	-0.04	-0.26	-0.23	-0.04	-0.06	-0.22	1.00						
18	CEO/level 2 (salary)	0.22	0.05	-0.01	0.04	-0.11	0.06	-0.07	-0.15	-0.21	-0.10	0.18	0.07	0.00	0.14	0.05	-0.15	-0.03	1.00					
19	CV Level 2 (salary)	0.07	-0.15	-0.06	0.07	-0.13	0.06	0.06	0.01	-0.13	0.08	-0.16	-0.31	-0.20	0.34	0.03	-0.07	0.23	-0.10	1.00				
20	CEO/level 2 (incentives)	-0.18	0.00	-0.12	0.05	-0.07	-0.09	0.03	0.09	0.13	-0.15	0.13	0.03	-0.02	-0.17	-0.01	-0.15	0.04	0.06	-0.30	1.00			
21	CV Level 2 (incentives)	-0.06	-0.12	0.11	0.06	-0.04	0.04	0.06	0.14	-0.03	0.07	0.10	-0.25	-0.09	0.37	0.13	0.12	0.13	-0.10	0.45	-0.19	1.00		
22	Age heterogeneity	-0.03	-0.02	-0.19	-0.05	-0.10	-0.05	-0.08	0.08	-0.17	-0.07	0.11	0.06	0.14	0.01	-0.22	-0.14	-0.11	-0.04	0.07	-0.17	-0.02	1.00	
23	Gender heterogeneity	-0.09	0.00	0.21	0.01	0.03	-0.02	-0.08	0.05	0.02	0.04	-0.09	-0.02	0.02	-0.05	-0.01	0.17	-0.15	-0.17	-0.03	-0.10	-0.05	-0.13	1.00
	Mean	-0.17	1.02	3.73	0.48	0.03	18.32	0.12	1.87	0.48	0.38	0.76	2004	0.37	5.95	2.69	3.18	55.97	2.10	0.21	3.69	0.37	0.09	0.08
	s.d.	0.73	0.50	0.69	0.70	0.04	36.90	0.29	0.53	0.50	0.35	0.43	1.90	0.49	0.92	0.17	0.41	3.74	0.41	0.11	1.63	0.18	0.04	0.15
	Mini	-2.18	0.14	1.56	-3.26	0.00	1.66	-0.71	1.00	0.00	-0.39	0.00	1998	0.00	5.00	1.66	1.51	43.00	1.03	0.03	1.52	0.05	0.00	0.00
	Maxi	2.08	2.34	5.25	3.55	0.19	326.40	1.28	3.00	1.00	1.23	1.00	2009	1.00	10.00	2.97	4.02	68.00	3.15	0.51	13.14	1.01	0.20	0.48

Note. N = 93; *t* is the year of RFID adoption; Correlations ±0.21 or larger are significant at 0.05 (two-tailed). Correlations ±0.27 or larger are significant at 0.01 (two-tailed).
[a] In logarithm.
[*] $p < 0.10$; [**] $p < 0.05$; [***] $p < 0.01$; two-tailed tests.

Table 6.3 shows the results of the hierarchical regression analysis. Overall, the F values are greater than 1 for all models with significance at 5% level or higher. Adjusted R square ranges from 13.79% to 31.56%. Models 2 to 3 in Table 6.3 reveal that pay dispersion results from base salary is positively—but not significantly—associated with abnormal systematic risk. Conversely, the pay dispersion results from incentive-based pay are negatively and significantly related to the firms' abnormal systematic risk ($p < 0.05$). This finding indicates that the higher the pay dispersion resulting from incentive-based pay, the lower the abnormal systematic risk. Thus, H2 is not supported. Model 3 in Table 6.3 shows that age and gender heterogeneity are significantly and negatively related to abnormal systematic risk ($p < 0.10$). The result suggests that greater age and gender heterogeneity offer lower systematic risk. Therefore, H3 is supported.

As shown in Models 1 to 3 in Table 6.3, previous magnitudes of systematic risk are negatively related to abnormal systematic risk, suggesting that firms with high systematic risk before RFID adoption were able to obtain more reduction in systematic risk. Fast clockspeed industries are positively associated with abnormal systematic risk. This result suggests that fast clockspeed industries such as fashion and textiles industries did not experience a greater reduction in systematic risk from the adoption because these industries, which faced rapid market changes, had fewer resources to handle the adoption, and thus obtaining limited benefits. Consistent with previous studies (Bansal and Clelland 2004), coercive adoption is negatively related to abnormal systematic risk ($p < 0.05$), indicating that the adopting firms could obtain coercive legitimacy, which reduced abnormal systematic risk. Moreover, industry sales growth is negatively related to abnormal systematic risk, suggesting that firms in industries with higher sales growth were able to enjoy lower systematic risk after RFID adoption.

Table 6.3. Hierarchical Regression Analysis of the Impact of TMT Heterogeneity on Abnormal Systematic Risk (*t* - *2* to *t* + *3*)

Variable	Model 1: Base model	Model 2: Pay dispersion model	Model 3: Demographic heterogeneity model
Intercept	24.10 (0.79)	60.12 (0.50)	47.56 (0.57)
Firm previous systematic risk	-0.36 (0.04)**	-0.38 (0.03)**	-0.46 (0.01)***
Firm size[a]	0.24 (0.12)	0.25 (0.09)*	0.34 (0.02)**
ROE	-0.05 (0.67)	-0.04 (0.73)	-0.03 (0.78)
R&D intensity	-0.26 (0.90)	-0.97 (0.63)	-2.39 (0.22)
Capital intensity	0.00 (0.75)	0.00 (0.73)	0.00 (0.63)
Leverage	-0.40 (0.16)	-0.43 (0.12)	-0.58 (0.03)**
Industry clockspeed	0.29 (0.06)*	0.40 (0.01)***	0.51 (0.00)***
Coercive adoption	-0.39 (0.02)**	-0.28 (0.09)*	-0.41 (0.01)**
Industry sales growth (*t* - 2 to *t* + 3)	-0.72 (0.01)***	-0.80 (0.00)***	-0.89 (0.00)***
Announcements After implementation stage	0.17 (0.38)	0.30 (0.15)	0.37 (0.06)*
Adoption year	-0.01 (0.79)	-0.03 (0.50)	-0.02 (0.59)
Source	0.08 (0.67)	0.04 (0.84)	0.11 (0.53)
Team size	0.14 (0.16)	0.14 (0.19)	0.12 (0.23)
Average salary[a]	-0.57 (0.35)	-0.38 (0.53)	-0.78 (0.19)
Average incentives[a]	-0.20 (0.44)	-0.20 (0.45)	-0.15 (0.56)
Average age	0.00 (0.91)	0.01 (0.67)	0.00 (0.91)
CEO/level 2 (salary)		0.22 (0.23)	0.11 (0.54)
CV Level 2 (salary)		0.28 (0.74)	0.55 (0.50)
CEO/level 2 (incentives)		-0.12 (0.01)**	-0.15 (0.00)**
CV Level 2 (incentives)		-1.05 (0.02)**	-1.25 (0.00)**
Age heterogeneity			-5.94 (0.00)**
Gender heterogeneity			-1.07 (0.04)**
Model F value	1.92**	2.35***	2.93***
R square (%)	28.78	39.54	47.92
Adjusted R square (%)	13.79	22.74	31.56
R square change (%)	28.78	10.76	8.38
F change	1.92**	3.20**	5.64***

Note. N = 93; *t* is the year of RFID adoption; unstandardized regression coefficients are shown with the *p*-value in parentheses.
[a] In logarithm.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$; two-tailed tests.
Results remain consistent when using fashion and textiles industries only.

6.6 Discussion

Our study in Chapter 5 has shown that disruptive IT innovation has a positive and immediate impact on stock price. The result of this section shows that the impact on stock price has an enduring positive impact on share prices because it improves investors' perception of a firm's systematic risk over the long term. These findings are consistent with Dewan and Ren's (2007) empirical study, which found that e-commerce decreased systematic risk because it improved demand uncertainty and the cyclicality of sales revenues. Our findings also complement prior IT research, which focuses on examining financial return using accounting-based measures or short-term market-based measures. Additionally, these findings add accumulative evidence to the underdeveloped literature area regarding the relationship between IT investment and risk.

Our hierarchical regression results support the notion that firms with greater demographic heterogeneity, such as age and gender heterogeneity obtain lower systematic risk. These findings are consistent with previous studies' assertions and findings (Hambrick et al. 1996; Katz 1982; Murray 1989) that team demographic heterogeneity provides better performance under uncertain environment. We also found mixed evidence for the effects of pay dispersion measures (greater pay dispersion resulting from incentive-based pay but not from base salary leads to lower systematic risk). These findings suggest that studies of pay dispersion and its effects need to be carefully distinguished among dimensions of compensation (i.e., base salary versus incentive-based pay). It is important to recognize that top managers may have different perceptions and reactions to pay dispersion results from different types of compensation. Base salary is a fixed compensation without a link between individual performance and firm performance, but more dependent on the board's valuation. Conversely, incentive-based compensation that includes bonuses, stock options and restricted stock options is primarily linked to firm performance, thus aligning the interest of managers with those of stakeholders. Therefore, pay dispersion resulting from incentive-based pay may motivate greater individual efforts while creating feelings of a common fate and team spirit, which improve organizational performance. However, previous studies examine pay dispersion either using one type of compensation such as salary (Bloom 1999) or total compensation (Siegel and Hambrick 2005), assuming that the effects of pay dispersion resulting from different types of compensation are the same. This may explain why the results of previous studies on the effects of pay dispersion are inconsistent. Therefore, future studies should continue to examine different types of compensation separately.

6.7 Chapter Summary

This study has provided an enriched and deeper understanding of the impact of disruptive IT innovations on systematic risk and moderating effect of TMT heterogeneity on that impact. This study provides empirical evidence supporting the proposition that disruptive IT innovations produce a significant, long-term reduction on systematic risk. The reduction was stronger under greater pay dispersion results from incentive-based pay and demographic heterogeneity, such as age and gender heterogeneity. We also found that firms that conform to coercive adoption could obtain lower systematic risk. However, fast clockspeed industries such as the fashion and textiles industries did not obtain higher systematic risk from the adoption.

CHAPTER 7—CONCLUSION

7.1 Summary of Findings

In chapter 4, we found that RFID adoption clearly has a positive impact on operational performance, such as inventory days, accounts receivable days, operating cycle, labor productivity, and sales growth. The sub-sampling analysis indicates that the impact of the disruptive IT innovations on operational performance depends on the industry type. More specifically, fashion and textiles RFID adopters and firms in retail and wholesale industries improved supply chain efficiency more than adopters in other industries and firms in manufacturing industries, but this result does not hold for labor productivity and sales growth. The regression analysis further indicates that the impact of disruptive IT innovation on supply chain efficiency is moderated by contextual factors such as coercive adoption and firm characteristics.

In chapter 5, we found that RFID adoption provides improvement on long-term financial performance and that the improvement was stronger under coercive adoption, low industry competitiveness, good financial health, low business diversification, and high geographic diversification. However, we found that fast clockspeed industries such as fashion and textiles industries did not benefit more from RFID adoption.

In chapter 6, we found that RFID adoption reduced systematic risk in the long term and that the reduction was stronger for firms with greater pay dispersion resulting from incentive-based pay and greater demographic heterogeneity, such as age and gender heterogeneity. We also found that firms conforming to coercive adoption could obtain lower systematic risk. However, fast clockspeed industries such as the fashion and textiles industries did not obtain lower systematic risk from RFID adoption.

7.2 Limitations and Future Studies

First, we focused our study on publicly listed firms in the U.S. Thus, our findings may not be applicable to other geographical regions or to smaller firms. Future research can extend the analysis to emerging markets or to small- and medium-sized organizations. Moreover, future study can include sample firms across countries to examine contextual factors such as national culture and government policy, which may affect the impact of disruptive IT innovations on firm performance.

Second, announcements were included in our samples because firms publish press releases. Therefore, firms that did not announce their RFID adoption were excluded from this study. Similarly, some selected control firms may have adopted RFID without announcing it to the public. Third, owing to no-availability, certain characteristics related to RFID adoption, e.g., the amount of the investment, were unaccounted in our data. Due the unavailability of data, we were also not able to control all confounding events during the event periods, which may lead to biased results. However, any such bias would be consistent across all firms (both sample and control firms) and therefore should not have compromised the validity of the results.

Fourth, because RFID still has not been widely adopted in some industries such as the fashion and textiles industries, our sample size for some industries is relatively small. However, this should not affect the generalization of our findings for those industries because our sample firms are firms with similar external and internal environments. When RFID becomes more widely adopted, future research may collect sufficient sample firms from these small-sample-size industries to validate the implications of our findings for these industries.

Fifth, we used longitudinal data from listed firms to examine the impact of disruptive IT innovations on firm performance (i.e., operational performance, financial performance, and systematic risk) and the moderating effects of contingency factors (i.e., firm characteristics, industry factors, and TMT heterogeneity) on that impact. Given data availability constraints for public listed firms, we are unable to gain an in-depth understanding of the actual processes in the firms that we studied. Theoretical research using complementary methods (e.g., in-depth interviews, case studies, field studies, and surveys) to validate our indicators and develop a conceptual model related to other elements of disruptive IT innovations will be useful in setting an agenda for further empirical research. For instance, it might be interesting to access the actual behavior of managers and front-line employees in response to disruptive IT innovations.

Additionally, we focused on the case of RFID adoption. Future studies may examine the impact and contingencies of other disruptive IT innovations and determine other aspects of disruptive IT innovations that may differ from non-disruptive IT innovations in terms of adoption determinants, firm performance, and contingency factors.

7.3 Theoretical Implications

This dissertation provides some of the first comprehensive and objective evidence of the impact of disruptive IT innovations such as RFID on firm performance. The direction, magnitude, and timing of the impact of RFID adoption on operational performance, financial performance, and systematic risk are revealed. In particular, this dissertation complements prior IT research, which has focused on examining financial return using accounting-based measures or short-term market-based measures, by adding accumulative evidence to an underdeveloped literature area regarding the relationship between IT investment and risk. Moreover, the moderating effects of the contingency factors on the relationship between a disruptive IT innovation and firm performance are presented and show that the moderating effects of some contingency factors, such as industry competiveness and corporate diversification for disruptive IT innovation, are different from those related to non-disruptive IT innovations.

This dissertation also contributes to institutional theory by providing an empirical account of calculated support for existing institutions. The institutional theory has been applied in the IT adoption literature to explain the antecedents of an IT adoption (e.g., Choi and Hartley 1996, Lai et al. 2006). However, it is important to understand the effect of conformity to institutional pressures on firm performance which remains controversial among institutional theorists. Our examination of the influence of coercive adoption on the performance of the adopting firms fills this gap. Our results indicate that firms conforming to coercive RFID adoption receive legitimacy that leads to stronger financial performance and lower systematic risk; however, they suffer from lower technical benefits (i.e., supply chain efficiency).

These results are consistent with assertions from previous institutional studies that conformity to institutional pressures to obtain legitimacy increases financial benefits (Scott 1995) but has a negative effect on technical efficiency (Meyer and Rowan 1977; Tolbert and Zucker 1983; Zucker 1987a).

Additionally, this dissertation contributes to UE theory by extending heterogeneity research further into the IT domain. Several studies have examined the relationship between TMT heterogeneity and firm outcomes. However, previous findings are mixed and provide few implications for disruptive IT innovations. This dissertation provides empirical evidence of the moderating effects of TMT heterogeneity in terms of pay dispersion and demographic heterogeneity, which previously have not been considered together. It also sheds light on seemingly conflicting perspectives about the effect of TMT heterogeneity on firm performance. Our results show that firms perform better for disruptive IT innovations under greater demographic heterogeneity, such as age and gender heterogeneity. We also found that greater pay dispersion results from incentive-based pay but not from base salaries, leading to lower systematic risk. These findings suggest that studies of pay dispersion and its effects must be careful to distinguish among dimensions of compensation (i.e., base salary versus incentive-based pay). It is important to recognize that top managers may have different perceptions and reactions to pay dispersion resulting from different types of compensation. However, previous studies examine pay dispersion either using one type of compensation such as salary (Bloom 1999) or total compensation (Siegel and Hambrick 2005), assuming that the effects of pay dispersion resulting from different types of compensation are the same. This may explain why the results of previous studies on the effects of pay dispersion are inconsistent. Therefore, future studies should continue to examine different types of compensation separately. Finally, these findings may be helpful for firms to construct reward systems and TMT composition that fit their strategic contexts.

7.4 Managerial Implications to Fashion and Textiles Firms

Disruptive IT innovations are increasingly common in organizational settings and are significantly changing how firms convert and deliver their products and series to customers (Sherif et al. 2006). However, little is known about the actual impact of disruptive IT innovations on long-term firm performance. Therefore, an in-depth understanding of the benefits and contingencies of disruptive IT innovations is essential to help firms formulate an appropriate implementation strategy for adoption to achieve enhanced firm performance. In this dissertation, our results that RFID enables improvement in operational performance, financial performance, and systematic risk send an encouraging message to managers to adopt disruptive IT innovations which are similar to the case of RFID. Based on the findings of contingency factor analysis, we developed contingency frameworks, which are applicable to fashion and textiles firms, to help managers evaluate their environment and identify opportunities for disruptive IT innovation and to maximize its benefits through strategic planning.

Figure 7.1 shows the contingency framework of financial performance for disruptive IT innovations (based on the findings from Chapter 5). Firms in the "Champion" zone are advised to pursue disruptive IT innovation to obtain legitimacy and improve their financial performance; they are also advised to be prepared for the potential trade-off of conformity to coercive adoption and efficiency. Firms in the "Neutralist

1 and 2" zones should formulate different strategies to reach the Champion zone. Firms in the Neutralist 1 zone are under high pressure to adopt. Therefore, they might have no choice but to comply. Although these firms face high industry competiveness and high levels of business diversification, they should take a proactive role in their implementation processes. For example, they should identify opportunities for synergetic effects among closely related or similar business lines for rolling out the innovation. Firms in the Neutralist 2 zone are not guided by coercive adoption from customers, and they have limited financial resources and low levels of geographic diversification. These firms should ensure sufficient financial and labor resources for implementation and ensure that their employee incentives are well aligned with the goal of the implementation. They should also identify opportunities for synergetic effects along geographic lines for rolling out the innovation. Firms in the "Sufferer" zone should either avoid disruptive IT innovations or identify a pathway to the Champion zone. Depending on their external and internal contingency factors, firms in the Sufferer zone should first attempt to move to either the Neutralist 1 or the Neutralist 2 zone.

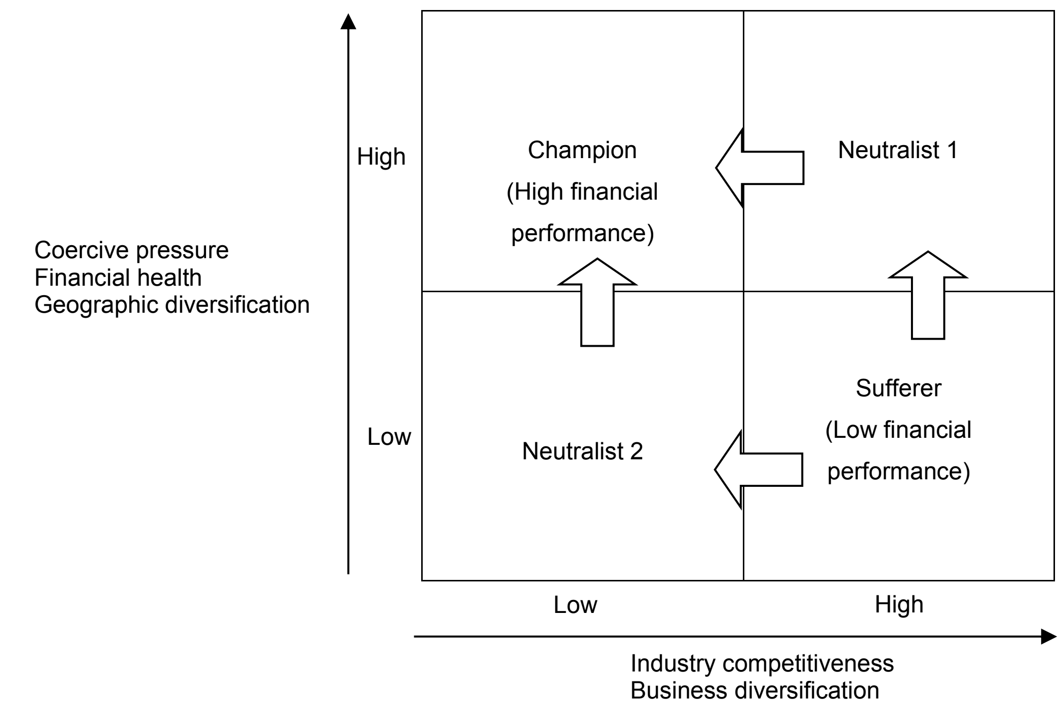

Figure 7.1. Contingency Framework of Financial Performance for Disruptive IT Innovations

Figure 7.2 shows the contingency framework of systematic risk for disruptive IT innovations (based on findings from Chapter 6). Similarly, firms in the Champion zone are advised to pursue disruptive IT innovation to obtain legitimacy and thus improve their systematic risk. Firms in the Neutralist 1 zone have high pay dispersion from incentive-based pay, high demographic heterogeneity, and legitimacy benefits from coercive adoption that help reduce systematic risk, but they are also in fast clockspeed industries such as fashion and textiles. To decrease systematic risk, these firms should ensure sufficient financial and labor resources to avoid negative impact of the adoption. Firms in the Neutralist 2 zone are not fast industry clockspeed firms, but they have low levels of TMT heterogeneity and are not guided by coercive adoption from customers. These firms may use TMT design with greater demographic heterogeneity and greater pay dispersion resulting from incentive-based pay to obtain lower their systematic risk. Firms in the Sufferer zone should either avoid disruptive IT innovations or identify a pathway to the Champion zone.

Given that fashion and textile firms belong to fast clockspeed industries that are associated that with higher systematic risk, it is important that these firms evaluate other beneficial factors such as TMT design with greater demographic heterogeneity and greater pay dispersion resulting from incentive-based pay to lower their systematic risk for disruptive IT innovation adoption. These firms also should identify their product lines that are less fast clockspeed for the adoption.

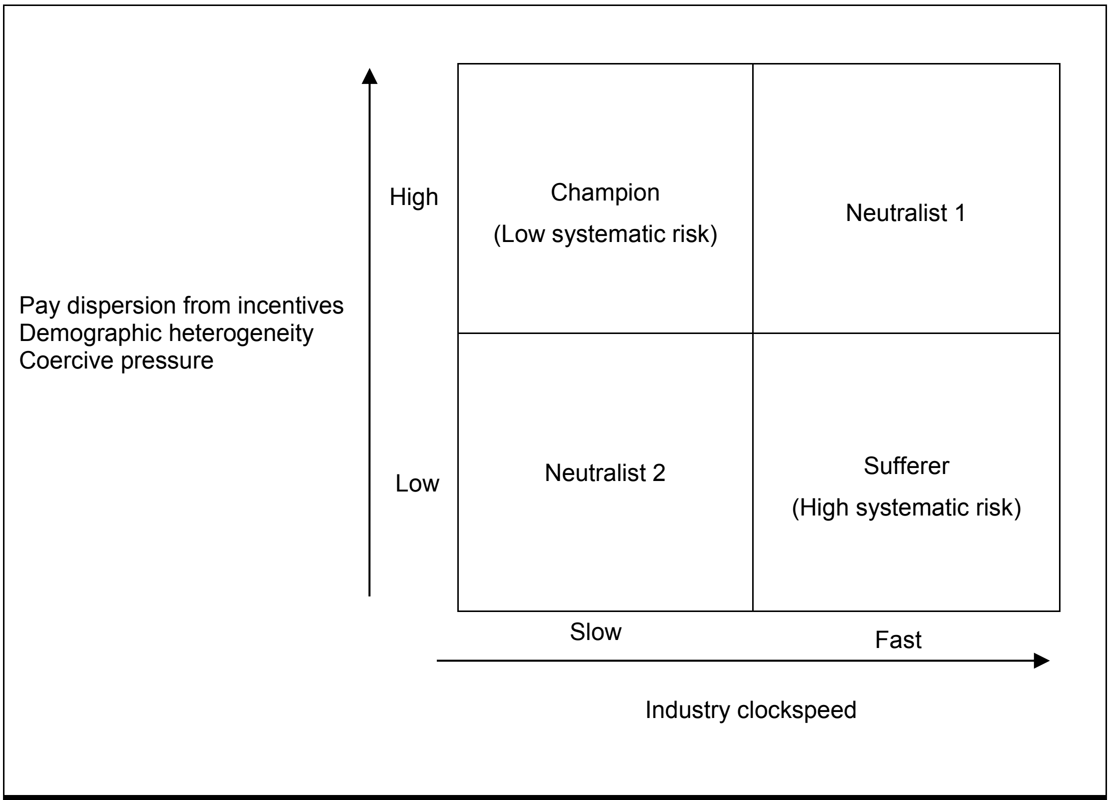

Figure 7.2. Contingency Framework of Systematic Risk for Disruptive IT Innovations

APPENDIX

Table A1 Abnormal Changes in ROA[a] — Barber and Lyon (1996) Matching Approach						
Time period	N	Abnormal mean	Abnormal median	*p*-value (t-test)	*p*-value (WSR test)	*p*-value (sign test)
			Yearly abnormal change			
t - 3 to *t* - 2	225	0.06	-0.27	0.86	0.39	0.42
t - 2 to *t* - 1	216	-0.07	0.10	0.85	1.00	0.28
t - 1 to *t*	211	0.08	0.19	0.83	0.47	0.54
t to *t* + 1	192	0.48	0.10	0.09*	0.59	0.94
t + 1 to *t* + 2	178	0.14	0.03	0.66	0.94	0.94
t + 2 to *t* + 3	165	1.50	1.60	0.00***	0.00***	0.01***
			Cumulative abnormal change			
t - 2 to *t* + 1	192	0.92	0.35	0.05**	0.08*	0.35
t - 2 to *t* + 2	178	0.94	0.37	0.04**	0.15	0.71
t - 2 to *t* + 3	165	2.08	1.95	0.00***	0.00***	0.00***

[a] In percent.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$; two-tailed tests.

Table A2 Propensity Score Matching Diagnostics		
Independent Variable	Pre-Match	Post-Match
Firm Size[a]	1.85 (0.00)***	0.95 (0.00)***
ROA	4.58 (0.01)**	3.37 (0.18)
Financial slack	2.94 (0.00)***	1.08 (0.33)
SGA intensity	2.35 (0.01)**	0.76 (0.51)
R&D intensity	-8.11 (0.00)***	-0.69 (0.87)
Leverage	1.35 (0.00)***	0.41 (0.42)
Sales growth	-1.85 (0.00)***	-0.55 (0.49)
Labor productivity[a]	-0.72 (0.02)**	-0.19 (0.65)
Inventory days[a]	-0.34 (0.46)	-1.02 (0.11)
Systematic risk	0.07 (0.66)	0.15 (0.47)
Control	872	152
Sample	152	152
Log-likelihood	687.58	376.86
Cox & Snell R square (%)	16.00	13.00
Nagelkerke R square (%)	28.00	17.00
Hosmer and Lemeshow test Chi-square (%)	8.00 (*p* value = 0. 43)	7.71 (*p* value = 0.46)

REFERENCES

ABIResearch.com. 2010. "RFID Market to Reach $5.35 Billion This Year." Retrieved May 14, 2011, from http://www.abiresearch.com/press/1618-RFID+Market+to+Reach+$5.35+Billion+This+Year.

Adams, J.S. 1965. *Inequity in Social Exchange*. New York: General Electric Company.

Altman, E. 1968. "Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy," *The Journal of Finance* (23:4), September, pp. 589-609.

Angeles, R. 2005. "RFID Technologies: Supply-Chain Applications and Implementation Issues," *Information Systems Management* (22:1), pp. 51-65.

Assink, M. 2006. "Inhibitors of Disruptive Innovation Capability: A Conceptual Model," *European Journal of Innovation Management* (9:2), pp. 215-233.

Azevedo, S.G., and Carvalho, H. 2012. "Contribution of RFID Technology to Better Management of Fashion Supply Chains," *International Journal of Retail & Distribution Management* (40:2), pp. 128-156.

Bansal, P., and Clelland, I. 2004. "Talking Trash: Legitimacy, Impression Management, and Unsystematic Risk in the Context of the Natural Environment," *Academy of Management Journal* (47:1), pp. 93-103.

Bantel, K.A., and Jackson, S.E. 1989. "Top Management and Innovations in Banking: Does the Composition of the Top Team Make a Difference?," *Strategic Management Journal* (10:S1), pp. 107-124.

Barber, B.M., and Lyon, J.D. 1996. "Detecting Abnormal Operating Performance: The Empirical Power and Specification of Test Statistics," *Journal of Financial Economics* (41:3), pp. 359-399.

Barton, S.L. 1988. "Diversification Strategy and Systematic Risk: Another Look," *Academy of Management Journal* (31:1), pp. 166-175.

Beaudry, A., and Pinsonneault, A. 2005. "Understanding User Responses to Information Technology: A Coping Model of User Adaptation," *MIS Quarterly* (29:3), pp. 493-524.

Berkhout, G. 2007. *The Cyclic Nature of Innovation: Connecting Hard Sciences with Soft Values*. Elsevier.

Berrone, P., Fosfuri, A., Gelabert, L., and Gomez-Mejia, L.R. 2013. "Necessity as the Mother of ‘Green’inventions: Institutional Pressures and Environmental Innovations," *Strategic Management Journal* (34:8), pp. 891-909.

Bishop, J. 1987. "The Recognition and Reward of Employee Performance," *Journal of Labor Economics* (5:4), pp. S36-S56.

Blau, P.M. 1977. *Inequality and Heterogeneity: A Primitive Theory of Social Structure*. Free Press New York.

Bloom, M. 1999. "The Performance Effects of Pay Dispersion on Individuals and Organizations," *Academy of Management Journal* (42:1), pp. 25-40.

Bose, I., Lui, A.K.H., and Ngai, E.W.T. 2011. "The Impact of RFID Adoption on the Market Value of Firms: An Empirical Analysis," *Journal of Organizational Computing and Electronic Commerce* (21:4), pp. 268-294.

Bose, I., Ngai, E.W.T., Teo, T.S.H., and Spiekermann, S. 2009. "Managing RFID Projects in Organizations," *European Journal of Information Systems* (18:6), pp. 534-540.

Bottani, E., and Rizzi, A. 2008. "Economical Assessment of the Impact of RFID Technology and EPC System on the Fast-Moving Consumer Goods Supply Chain," *International Journal of Production Economics* (112:2), pp. 548-569.

Boyd, B.K. 1995. "CEO Duality and Firm Performance: A Contingency Model," *Strategic Management Journal* (16:4), pp. 301-312.

Brealey, R.A., and Myers, S.C. 2002. *Principles of Corporate Finance*. Burr Ridge IL: McGraw-Hill Education.

Brett, J.M., and Stroh, L.K. 1999. "Women in Management How Far Have We Come and What Needs to Be Done as We Approach 2000?," *Journal of Management Inquiry* (8:4), pp. 392-398.

Brower, J.L., and Christensen, C.M. 1995. "Disruptive Technologies: Catching the Wave," *Harvard Business Review* (73), pp. 43-53.

Brown, I., and Russell, J. 2007. "Radio Frequency Identification Technology: An Exploratory Study on Adoption in the South African Retail Sector," *International Journal of Information Management* (27:4), pp. 250-265.

Brynjolfsson, E., and Hitt, L. 1996. "Paradox Lost? Firm-Level Evidence on the Returns to Information Systems Spending," *Management Science* (42:4), pp. 541-558.

Cannon, A.R., Reyes, P.M., Frazier, G.V., and Prater, E.L. 2008. "RFID in the Contemporary Supply Chain: Multiple Perspectives on Its Benefits and Risks," *International Journal of Operations & Production Management* (28:5), pp. 433-454.

Carlo, J.L., Lyytinen, K., and Rose, G.M. 2011. "Internet Computing as a Disruptive Information Technology Innovation: The Role of Strong Order Effects1," *Information Systems Journal* (21:1), pp. 91-122.

Carpenter, M.A. 2002. "The Implications of Strategy and Social Context for the Relationship between Top Management Team Heterogeneity and Firm Performance," *Strategic Management Journal* (23:3), pp. 275-284.

Chang, S.J., Chung, J., and Moon, J.J. 2013. "When Do Wholly Owned Subsidiaries Perform Better Than Joint Ventures?," *Strategic Management Journal* (34:3), pp. 317-337.

Chang, Y. 2011. "Does RFID Improve Firms' Financial Performance? An Empirical Analysis," *Information Technology and Management* (12:3), pp. 273-285.

Chari, M.D.R., Devaraj, S., and David, P. 2008. "The Impact of Information Technology Investments and Diversification Strategies on Firm Performance," *Management Science* (54:1), pp. 224-234.

Christensen, C.M., Anthony, S.D., and Roth, E.A. 2004. *Seeing What's Next: Using the Theories of Innovation to Predict Industry Change*. Boston: Harvard Business Press.

Christensen, C.M., and Raynor, M.E. 2003. *The Innovator's Solution: Creating and Sustaining Successful Growth*. Boston: Harvard Business School Press.

Christophe, M.E.D.C., and Detmar, W.S. 2011. "Opening the Black Box of System Usage: User Adaptation to Disruptive IT," *European Journal of Information Systems* (20:5), pp. 589-607.

Christopher, M., Lowson, R., and Peck, H. 2004. "Creating Agile Supply Chains in the Fashion Industry," *International Journal of Retail & Distribution Management* (32:8), pp. 367-376.

Clemons, E.K., and Row, M.C. 1991. "Sustaining IT Advantage: The Role of Structural Differences," *MIS Quarterly* (15:3), pp. 275-292.

Cohen, W.M., and Levinthal, D.A. 1990. "Absorptive Capacity: A New Perspective on Learning and Innovation," *Administrative Science Quarterly* (35:1), pp. 128-152.

Collis, D.J., and Montgomery, C.A. 1997. *Corporate Strategy: Resources and the Scope of the Firm*. Irwin, Chicago: McGraw-Hill.

Conyon, M.J., Peck, S.I., and Sadler, G.V. 2001. "Corporate Tournaments and Executive Compensation: Evidence from the UK," *Strategic Management Journal* (22:8), pp. 805-815.

Corbett, C.J., Montes-Sancho, M.J., and Kirsch, D.A. 2005. "The Financial Impact of ISO 9000 Certification: An Empirical Analysis," *Management Science* (51:7), pp. 1046-1059.

Cowherd, D.M., and Levine, D.I. 1992. "Product Quality and Pay Equity between Lower-Level Employees and Top Management: An Investigation of Distributive Justice Theory," *Administrative Science Quarterly* (37:2), pp. 302-320.

Damanpour, F. 1987. "The Adoption of Technological, Administrative, and Ancillary Innovations: Impact of Organizational Factors," *Journal of Management* (13:4), pp. 675-688.

Das, R., and Harrop, P. 2009. "RFID Forecasts, Players & Opportunities 2009-2019." Retrieved Jun 8, 2011, from http://www.idtechex.com/research/reports/rfid_forecasts_players_and_opportunities_2009_2019_000226.asp

Deephouse, D.L. 1999. "To Be Different, or to Be the Same? It's a Question (and Theory) of Strategic Balance," *Strategic Management Journal* (20:2), pp. 147-166.

Dehejia, R.H., and Wahba, S. 2002. "Propensity Score-Matching Methods for Nonexperimental Causal Studies," *Review of Economics and statistics* (84:1), pp. 151-161.

Dehning, B., and Richardson, V.J. 2002. "Returns on Investments in Information Technology: A Research Synthesis," *Journal of Information Systems* (16:1), pp. 7-30.

Delen, D., Hardgrave, B.C., and Sharda, R. 2007. "RFID for Better Supply-Chain Management through Enhanced Information Visibility," *Production & Operations Management* (16:5), pp. 613-624.

Dess, G.G., and Beard, D.W. 1984. "Dimensions of Organizational Task Environments," *Administrative Science Quarterly* (29:1), pp. 52-73.

Devers, C.E., Cannella, A.A., Reilly, G.P., and Yoder, M.E. 2007. "Executive Compensation: A Multidisciplinary Review of Recent Developments," *Journal of Management* (33:6), pp. 1016-1072.

Devers, C.E., McNamara, G., Wiseman, R.M., and Arrfelt, M. 2008. "Moving Closer to the Action: Examining Compensation Design Effects on Firm Risk," *Organization Science* (19:4), pp. 548-566.

Dewan, S., and Ren, F. 2007. "Risk and Return of Information Technology Initiatives: Evidence from Electronic Commerce Announcements," *Information Systems Research* (18:4), pp. 370-394.

Dewan, S., and Ren, F. 2011. "Information Technology and Firm Boundaries: Impact on Firm Risk and Return Performance," *Information Systems Research* (22:2), pp. 369-388.

Dewan, S., Shi, C., and Gurbaxani, V. 2007. "Investigating the Risk-Return Relationship of Information Technology Investment: Firm-Level Empirical Analysis," *Management Science* (53:12), pp. 1829-1842.

DiMaggio, P., and Powell, W.W. 1983. "The Iron Cage Revisited: Institutional Isomorphism and Collective Rationality in Organizational Fields," *American Sociological Review* (48:2), pp. 147-160.

Dutta, A., Lee, H.L., and Whang, S. 2007. "RFID and Operations Management: Technology, Value, and Incentives," *Production and Operations Management* (16:5), pp. 646-655.

Dutton, J.E., and Duncan, R.B. 1987. "The Creation of Momentum for Change through the Process of Strategic Issue Diagnosis," *Strategic Management Journal* (8:3), pp. 279-295.

Eagly, A.H., and Johnson, B.T. 1990. "Gender and Leadership Style: A Meta-Analysis," *Psychological Bulletin* (108:2), pp. 233-256.

Ehrenberg, R.G., and Bognanno, M.L. 1990. "The Incentive Effects of Tournaments Revisited: Evidence from the European PGA Tour," *Industrial and Labor Relations Review* (43:3), pp. 74S-88S.

Eskew, R.K., and Jensen, D.L. 1996. *Financial Accounting*. New York: McGraw-Hill.

Fama, E.F., Fisher, L., Jensen, M.C., and Roll, R. 1969. "The Adjustment of Stock Prices to New Information," *International Economic Review* (10:1), pp. 1-21.

Ferguson, G.T. 2002. "Have Your Objects Call My Objects," *Harvard Business Review* (80:6), pp. 138-144.

Fine, C.H. 1998. *Clockspeed: Winning Industry Control in the Age of Temporary Advantage*. Massachusetts: Basic Books.

Fosso Wamba, S. 2011. "Positioning RFID Technology into the Innovation Theory Landscape: A Multidimensional Perspective Integrating Case Study Approach," in: *15th Pacific Asia Conference on Informaiton Systems*. Brisbane, Australia.

Fosso Wamba, S., Lefebvre, L.A., Bendavid, Y., and Lefebvre, E. 2008. "Exploring the Impact of RFID Technology and the EPC Network on Mobile B2B Ecommerce: A Case Study in the Retail Industry," *International Journal of Production Economics* (112:2), pp. 614-629.

Fredrickson, J.W., Davis-Blake, A., and Sanders, W. 2010. "Sharing the Wealth: Social Comparisons and Pay Dispersion in the CEO's Top Team," *Strategic Management Journal* (31:10), pp. 1031-1053.

Gaukler, G.M., Seifert, R. W., and Hausman, W.H. 2007. "Item-Level RFID in the Retail Supply Chain," *Production and Operation Management* (16:1), pp. 65-76.

Geletkanycz, M.A., and Sanders, W. 2012. "New Directions on Compensation and Upper Echelons," *Corporate Governance: An International Review* (20:6), pp. 519-525.

Govindarajan, V., and Kopalle, P.K. 2006. "The Usefulness of Measuring Disruptiveness of Innovations Ex Post in Making Ex Ante Predictions," *Journal of Product Innovation Management* (23:1), pp. 12-18.

Hambrick, D.C., Cho, T.S., and Chen, M.J. 1996. "The Influence of Top Management Team Heterogeneity on Firms' Competitive Moves," *Administrative Science Quarterly* (41:4), pp. 659-684.

Hambrick, D.C., and Mason, P.A. 1984. "Upper Echelons: The Organization as a Reflection of Its Top Managers," *Academy of Management Review* (9:2), pp. 193-206.

Henderson, A.D., and Fredrickson, J.W. 2001. "Top Management Team Coordination Needs and the CEO Pay Gap: A Competitive Test of Economic and Behavioral Views," *Academy of Management Journal* (44:1), pp. 96-117.

Hendricks, K.B., and Singhal, V.R. 2005. "An Empirical Analysis of the Effect of Supply Chain Disruptions on Long-Run Stock Price Performance and Equity Risk of the Firm," *Production and Operations Management* (14:1), pp. 35-52.

Hendricks, K.B., Singhal, V.R., and Zhang, R. 2009. "The Effect of Operational Slack, Diversification, and Vertical Relatedness on the Stock Market Reaction to Supply Chain Disruptions," *Journal of Operations Management* (27:3), pp. 233-246.

Hendricks, K.B., V.R. Singhal. 2008. "The Effect of Product Introduction Delays on Operating Performance," *Management Science* (54:5), pp. 878-892.

Hendricks, K.B., V.R. Singhal, J.K. Stratman. 2007. "The Impact of Enterprise Systems on Corporate Performance: A Study of ERP, SCM, and CRM System Implementations " *Journal of Operations Management* (25:1), pp. 62-82.

Hitt, L.M., and Brynjolfsson, E. 1996. "Productivity, Business Profitability, and Consumer Surplus: Three Different Measures of Information Technology Value," *MIS Quarterly* (20:2), pp. 121-142.

Jackson, S.E. 1992. "Consequences of Group Composition for the Interpersonal Dynamics of Strategic Issue Processing," *Advances in Strategic Management* (8:3), pp. 345-382.

Jones, L. 1999. "Working without Wires," *Industrial Distribution* (88:8), pp. M6-M9.

Kapoor, G., Zhou, W., and Piramuthu, S. 2009. "Challenges Associated with RFID Tag Implementations in Supply Chains," *European Journal of Information Systems* (18:6), pp. 526-533.

Kärkkäinen, M. 2003. "Increasing Efficiency in the Supply Chain for Short Shelf Life Goods Using RFID Tagging," *International Journal of Retail & Distribution Management* (31:10), pp. 529-536.

Katz, J. 2005. "Manufacturers Find Little ROI in RFID." Retrieved Jun 8, 2012, from http://industryweek.digiknow.com/articles/manufacturers_find_little_roi_in_rfid_10892.aspx.

Katz, R. 1982. "The Effects of Group Longevity on Project Communication and Performance," *Administrative Science Quarterly* (27:1), pp. 81-104.

Kim, E.Y., Ko, E., Kim, H., and Koh, C.E. 2008. "Comparison of Benefits of Radio Frequency Indentification: Implications for Business Strategic Performance in the U.S. And Korean Retailers," *Industrial Marketing Management* (37:7), pp. 797-806.

Kochan, T.A. 1994. *The Mutual Gains Enterprise: Forging a Winning Partnership among Labor, Management, and Government*. Harvard Business Press.

Kohli, R., and Devaraj, S. 2003. "Measuring Information Technology Payoff: A Meta-Analysis of Structural Variables in Firm-Level Empirical Research," *Information Systems Research* (14:2), pp. 127-145.

Kojima, M., Nakashima, K., and Ohno, K. 2008. "Performance Evaluation of SCM in JIT Environment," *International Journal of Production Economics* (115:2), pp. 439-443.

Kostoff, R.N., Boylan, R., and Simons, G.R. 2004. "Disruptive Technology Roadmaps," *Technological Forecasting and Social Change* (71:1), pp. 141-159.

Krotov, V., and Junglas, I. 2008. "RFID as a Disruptive Innovation," *Journal of Theoretical and Applied Electronic Commerce Research* (3:2), pp. 44-59.

Lai, K.H., Wong, C.W.Y., and Cheng, T.C.E. 2006. "Institutional Isomorphism and the Adoption of Information Technology for Supply Chain Management," *Computers in Industry* (57:1), pp. 93-98.

Langer, N., Forman, C., Kekre, S., and Scheller-Wolf, A.A. 2007. "Assessing the Impact of RFID on Return Center Logistics," *Interfaces* (37:6), pp. 501-514.

Lapointe, L., and Rivard, S. 2005. "A Multilevel Model of Resistance to Information Technology Implementation," *MIS Quarterly* (29:3), pp. 461-491.

Lazear, E.P., and Rosen, S. 1981. "Rank-Order Tournaments as Optimum Labor Contracts," *Journal of Political Economy* (89:5), pp. 841-864.

Lee, H., and Özer, O. 2007. "Unlocking the Value of RFID," *Production and Operations Management* (16:1), pp. 40-64.

Lefebvre, L.A., Lefebvre, É., Bendavid, Y., Wamba, S.F., and Boeck, H. 2005. "The Potential of RFID in Warehousing Activities in a Retail Industry Supply Chain," *Journal on Chain and Network Science* (5:2), pp. 101-110.

Leimeister, S., Leimeister, J.M., Knebel, U., and Krcmar, H. 2009. "A Cross-National Comparison of Perceived Strategic Importance of RFID for CIOs in Germany and Italy," *International Journal of Information Management* (29:1), pp. 37-47.

Li, D., and O'Brien, C. 1999. "Integrated Decision Modelling of Supply Chain Efficiency," *International Journal of Production Economics* (59:1), pp. 147-157.

Li, M., and Richard Ye, L. 1999. "Information Technology and Firm Performance: Linking with Environmental, Strategic and Managerial Contexts," *Information & Management* (35:1), pp. 43-51.

Lintner, J. 1965. "The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets," *The Review of Economics and Statistics* (47:1), pp. 13-37.

Lo, C.K., Yeung, A.C., and Cheng, T. 2009. "ISO 9000 and Supply Chain Efficiency: Empirical Evidence on Inventory and Account Receivable Days," *International Journal of Production Economics* (118:2), pp. 367-374.

Loebbecke, C., and Palmer, J. 2006. "RFID in the Fashion Industry: Kaufhof Department Stores AG and Gerry Weber International AG, Fashion Manufacturer," *MIS Quarterly Executive* (5:2), pp. 15-25.

Lubatkin, M., and Rogers, R.C. 1989. "Diversification, Systematic Risk, and Shareholder Return: A Capital Market Extension of Rumelt's 1974 Study," *Academy of Management Journal* (32:2), pp. 454-465.

Lucas Jr, H. C., and Goh, J. M. 2009. "Disruptive Technology: How Kodak Missed the Digital Photography Revolution," *The Journal of Strategic Information Systems* (18:1), pp. 46-55.

Lyytinen, K. 2003. "The Disruptive Nature of Information Technology Innovations: The Case of Internet Computing in Systems Development Organizations," *MIS Quarterly* (27:4), pp. 557-595.

Lyytinen, K., and Rose, G.M. 2003. "Disruptive Information System Innovation: The Case of Internet Computing," *Information Systems Journal* (13:4), pp. 301-330.

MacKinlay, A.C. 1997. "Event Studies in Economics and Finance," *Journal of Economic Literature* (35:1), pp. 13-39.

Main, B.G., O'Reilly III, C.A., and Wade, J. 1993. "Top Executive Pay: Tournament or Teamwork?," *Journal of Labor Economics* (11:4), pp. 606-628.

Marinos, G. 2005. "RFID and the Value of Context: How a Disruptive Technology Promises Real-Time Intelligence," *DM Review* (15:5), pp. 38-40.

McAlister, L., Srinivasan, R., and Kim, M. 2007. "Advertising, Research and Development, and Systematic Risk of the Firm," *Journal of Marketing* (71:1), pp. 35-48.

McGuire, J.B., Sundgren, A., and Schneeweis, T. 1988. "Corporate Social Responsibility and Firm Financial Performance," *Academy of Management Journal* (31:4), pp. 854-872.

Melville, N., Gurbaxani, V., and Kraemer, K. 2007. "The Productivity Impact of Information Technology across Competitive Regimes: The Role of Industry Concentration and Dynamism," *Decision Support Systems* (43:1), pp. 229-242.

Melville, N., Kraemer, K., and Gurbaxani, V. 2004. "Review: Information Technology and Organizational Performance: An Integrative Model of IT Business Value," *MIS Quarterly* (28:2), pp. 283-322.

Mentzer, J.T., DeWitt, W., Keebler, J.S., Min, S., Nix, N.W., Smith, C.D., and Zacharia, Z.G. 2001. "Defining Supply Chain Management," *Journal of Business Logistics* (22:2), pp. 1-25.

Meyer, J.W., and Rowan, B. 1977. "Institutionalized Organizations: Formal Structure as Myth and Ceremony," *American Journal of Sociology* (83:2), pp. 340-363.

Mikko, K., and Jan, H. 2002. "Wireless Product Identification: Enabler for Handling Efficiency, Customisation and Information Sharing," *Supply Chain Management: An International Journal* (7:4), pp. 242-252.

Milgrom. 1992. *Economics, Organization and Management*. NJ: Prentice-Hall International.

Milgrom, P., and Roberts, J. 1988. "An Economic Approach to Influence Activities in Organizations," *American Journal of Sociology* (94), pp. S154-S179.

Miller, K.D., and Bromiley, P. 1990. "Strategic Risk and Corporate Performance: An Analysis of Alternative Risk Measures," *Academy of Management Journal* (33:4), pp. 756-779.

Mithas, S., Tafti, A., Bardhan, I., and Mein Goh, J. 2012. "Information Technology and Firm Profitability: Mechanisms and Empirical Evidence," *MIS Quarterly* (36:1), pp. 205-224.

Montgomery, C.A., and Singh, H. 1984. "Diversification Strategy and Systematic Risk," *Strategic Management Journal* (5:2), pp. 181-191.

Montgomery, C.A., and Wernerfelt, B. 1988. "Diversification, Ricardian Rents, and Tobin's Q," *The RAND Journal of Economics* (19:4), pp. 623-632.

Moon, K.L., and Ngai, E.W.T. 2008. "The Adoption of RFID in Fashion Retailing: A Business Value-Added Framework," *Industrial Management & Data Systems* (108:5), pp. 596-612.

Murray, A.I. 1989. "Top Management Group Heterogeneity and Firm Performance," *Strategic Management Journal* (10:S1), pp. 125-141.

Naveh, E., and Marcus., A. 2005. "Achieving Competitive Advantage through Implementing a Replicable Management Standard: Installing and Using ISO 9000," *Journal of Operations Management* (24:1), pp. 1-26.

Ngai, E.W., and Gunasekaran, A. 2009. "RFID Adoption: Issues and Challenges," *International Journal of Enterprise Information Systems* (5:1), pp. 1-8.

Ngai, E.W.T., Moon, K.K.L., Riggins, F.J., and Yi, C.Y. 2008. "RFID Research: An Academic Literature Review (1995-2005) and Future Research Directions," *International Journal of Production Economics* (112:2), pp. 510-520.

Nielsen, S. 2010. "Top Management Team Diversity: A Review of Theories and Methodologies," *International Journal of Management Reviews* (12:3), pp. 301-316.

Orlikowski, W.J. 1993. "Case Tools as Organizational Change: Investigating Incremental and Radical Changes in Systems Development," *MIS Quarterly* (17:3), pp. 309-340.

Park, S. 2007. *Strategies and Policies in Digital Convergence*. IGI Global.

Patell, J.M. 1976. "Corporate Forecasts of Earnings Per Share and Stock Price Behavior: Empirical Test," *Journal of Accounting Research* (14:2), pp. 246-276.

Pelled, L.H., Eisenhardt, K.M., and Xin, K.R. 1999. "Exploring the Black Box: An Analysis of Work Group Diversity, Conflict and Performance," *Administrative Science Quarterly* (44:1), pp. 1-28.

Pfeffer, J. 1994. *Competitive Advantage through People: Unleashing the Power of the Work Force*. Harvard Business Press.

Pfeffer, J., and Langton, N. 1993. "The Effect of Wage Dispersion on Satisfaction, Productivity, and Working Collaboratively: Evidence from College and University Faculty," *Administrative Science Quarterly* (38:3), pp. 382-407.

Pieterse, A.N., Van Knippenberg, D., and Van Dierendonck, D. 2013. "Cultural Diversity and Team Performance: The Role of Team Member Goal Orientation," *Academy of Management Journal* (56:3), pp. 782-804.

Purnanandam, A. 2008. "Financial Distress and Corporate Risk Management: Theory and Evidence," *Journal of Financial Economics* (87:3), pp. 706-739.

Raynor, M.E. 2004. "RFID and Disruptive Innovation." Retrieved Jul 10, 2014, from https://www.rfidjournal.com/purchase-access?type=Article&id=1173&r=%2Farticles%2Fview%3F1173.

Roberti, M. 2003. "Analysis: RFID-Wal-Mart Network Effect." Retrieved May 27, 2011, from http://www.cioinsight.com/c/a/Trends/Analysis-RFID-WalMarts-Network-Effect/.

Roberti, M. 2004. "Best Buy to Deploy RFID." Retrieved May 23, 2011, from http://www.rfidjournal.com/article/view/1104.

Roberti, M. 2005. "Target, Wal-Mart Share EPC Data." Retrieved May 14, 2011, from http://www.RFIDjournal.com/article/articleprint/1928/-1/1.

Roberts, P.W., and Amit, R. 2003. "The Dynamics of Innovative Activity and Competitive Advantage: The Case of Australian Retail Banking, 1981 to 1995," *Organization Science* (14:2), pp. 107-122.

Rosenbaum, P.R., and Rubin, D.B. 1983. "The Central Role of the Propensity Score in Observational Studies for Causal Effects," *Biometrika* (70:1), pp. 41-55.

Rosenbaum, P.R., and Rubin, D.B. 1984. "Reducing Bias in Observational Studies Using Subclassification on the Propensity Score," *Journal of the American Statistical Association* (79:387), pp. 516-524.

Saygin, C. 2007. "Adaptive Inventory Management Using RFID Data," *International Journal of Advanced Manufacturing Technology* (32:9-10), pp. 1045-1051.

Scherer, F.M., and Ross, D. 1990. *Industrial Market Structure and Economic Performance*. Boston: Houghton Mifflin Company.

Scott, W.R. 1987. "The Adolescence of Institutional Theory," *Administrative Science Quarterly* (32:4), pp. 493–511.

Scott, W.R. 1995. *Institutions and Organizations*. Thousand Oak, California: Sage Publications.

Sharma, A., Citurs, A., and Konsynski, B. 2007. "Strategic and Institutional Perspectives in the Adoption and Early Integration of Radio Frequency Identification (RFID)," *40th Annual Hawaii International Conference*, Waikoloa, HI: IEEE, pp. 224c-224c.

Sharpe, W.F. 1964. "Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk*," *The Journal of Finance* (19:3), pp. 425-442.

Shaw, J.D., Gupta, N., and Delery, J.E. 2002. "Pay Dispersion and Workforce Performance: Moderating Effects of Incentives and Interdependence," *Strategic Management Journal* (23:6), pp. 491-512.

Sheffi, Y. 2004. "RFID and the Innovation Cycle," *International Journal of Logistics Management* (15:1), pp. 1-10.

Sherif, K., Zmud, R.W., and Browne, G.J. 2006. "Managing Peer-to-Peer Conflicts in Disruptive Information Technology Innovations: The Case of Software Reuse," *MIS Quarterly* (30:2), pp. 339-356.

Siegel, P.A., and Hambrick, D.C. 2005. "Pay Disparities within Top Management Groups: Evidence of Harmful Effects on Performance of High-Technology Firms," *Organization Science* (16:3), pp. 259-274.

Soon, C.B., and Gutiérrez, J.A. 2009. "Recognizing RFID as a Disruptive Technology," *International Journal of Information Systems and Supply Chain Management* (2:1), pp. 55-68.

Srivastava, B. 2004. "Radio Frequency ID Technology: The Next Revolution in SCM " *Business Horizons* (47:6), pp. 60-68.

Suchman, M.C. 1995. "Managing Legitimacy: Strategic and Institutional Approaches," *Academy of Management Review* (20:3), pp. 571-610.

Swanson, E.B. 1994. "Information Systems Innovation among Organizations," *Management Science* (40:9), pp. 1069-1092.

Tajima, M. 2007. "Strategic Value of RFID in Supply Chain Management," *Journal of Purchasing and Supply Management* (13:4), pp. 261-273.

Teece, D. 1982. "Towards an Economic Theory of the Multiproduct Firm," *Journal of Economic Behavior and Organization* (3:1), pp. 39-63.

Teo, H.H., Wei, K.K., and Benbasat, I. 2003. "Predicting Intention to Adopt Interorganizational Linkages: An Institutional Perspective," *MIS Quarterly* (27:1), pp. 19-49.

Tolbert, P.S., and Zucker, L.G. 1983. "Institutional Sources of Change in the Formal Structure of Organizations: The Diffusion of Civil Service Reform, 1880-1935," *Administrative Science Quarterly* (28:1), pp. 22-39.

Tsai, M.C., Lee, W., and Wu, H.C. 2010. "Determinants of RFID Adoption Intention: Evidence from Taiwanese Retail Chains," *Information & Management* (47:5), pp. 255-261.

Tsui, A.S., Egan, T., and O'Reilly, C. 1991. "Being Different: Relational Demography and Organizational Attachment," *Academy of Management Proceedings*: Academy of Management, pp. 183-187.

Tushman, M.L., and Anderson, P. 1986. "Technological Discontinuities and Organizational Environments," *Administrative Science Quarterly* (31:3), pp. 439-465.

Van Knippenberg, D., De Dreu, C.K., and Homan, A.C. 2004. "Work Group Diversity and Group Performance: An Integrative Model and Research Agenda," *Journal of Applied Psychology* (89:6), pp. 1008-1022.

Vijayaraman, B.S., and Osyk, B.A. 2006. "An Empirical Study of RFID Implementation in the Warehousing Industry," *International Journal of Logistics Management* (17:1), pp. 6-20.

Visich, J.K., Li, S., Khumawala, B.M., and Reyes, P.M. 2009. "Empirical Evidence of RFID Impacts on Supply Chain Performance," *International Journal of Operations & Production Management* (29:12), pp. 1290-1315.

Wade, J.B., O'Reilly III, C.A., and Pollock, T.G. 2006. "Overpaid CEOs and Underpaid Managers: Fairness and Executive Compensation," *Organization Science* (17:5), pp. 527-544.

Wang, Y.M., Wang, Y.S., and Yang, Y.F. 2010. "Understanding the Determinants of RFID Adoption in the Manufacturing Industry," *Technological Forecasting and Social Change* (77:5), pp. 803-815.

Wei, H.L., Wang, E.T., and Ju, P.H. 2005. "Understanding Misalignment and Cascading Change of ERP Implementation: A Stage View of Process Analysis," *European Journal of Information Systems* (14:4), pp. 324-334.

Westphal, J.D., Gulati, R., and Shortell, S.M. 1997. "Customization or Conformity? An Institutional and Network Perspective on the Content and Consequences of TQM Adoption," *Administrative Science Quarterly* (42:2), pp. 366-394.

Whang, S. 2010. "Timing of RFID Adoption in a Supply Chain," *Management Science* (56:2), pp. 343-355.

Whitaker, J., Mithas, S., and Krishnan, M.S. 2007. "A Field Study of RFID Deployment and Return Expectations," *Production and Operations Management* (16:5), pp. 599-612.

Wu, N.C., Nystroma, M.A., Lina, T.R., and Yu, H.C. 2006. "Challenges to Global RFID Adoption," *Technovation* (26:12), pp. 1317-1323.

Xue, L., Ray, G., and Sambamurthy, V. 2012. "Efficiency or Innovation: How Do Industry Environments Moderate the Effects of Firms' IT Asset Portfolios?," *MIS quarterly* (36:2), pp. 509-528.

Yang, X., Kishore, R., and Liu, Z. 2008. "The Institutional Facets of Innovation Diffusion Initiating: The Case of Wal-Mart's RFID Campaign," *ICIS 2008 Proceedings*.

Yeung, A.C.L., Lo, C.K.Y., and Cheng, T.C.E. 2011. "Behind the Iron Cage: An Institutional Perspective on ISO 9000 Adoption and CEO Compensation," *Organization Science* (22:6), pp. 1600-1612

Zhu, K., and Kraemer, K.L. 2002. "E-Commerce Metrics for Net-Enhanced Organizations: Assessing the Value of E-Commerce to Firm Performance in the Manufacturing Sector," *Information Systems Research* (13:3), pp. 275-295.

Zhu, Q., and Sarkis, J. 2007. "The Moderating Effects of Institutional Pressures on Emergent Green Supply Chain Practices and Performance," *International Journal of Production Research* (45:18-19), pp. 4333-4355.

Zucker, L.G. 1987a. "Institutional Theories of Organization," *Annual review of sociology* (13), pp. 443-464.

Zucker, L.G. 1987b. "Normal Change or Risky Business: Institutional Effects on the 'Harzard' of Change in Hospital Organizations, 1959-79," *Journal of Management Studies* (24:6), pp. 671-700.