TWO ESSAYS ON RISKS AND RETURNS IN OPERATIONS MANAGEMENT

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Two Essays on Risks and Returns in Operations Management

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Abstract of a Thesis Submitted

Two Essays on Risks and Returns in Operations Management

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Scholars in Operations Management (OM) have traditionally examined the efficacy, performance outcomes, and financial returns of various organizational initiatives such as supplier management, enterprise resource planning, and research and development (R&D) investments. Yet OM scholars often overlook possible "hidden costs" behind these organizational innovations—firm risks associated with organizational strategic initiatives. Some organizational initiatives might improve the financial returns for firms while inducing significant management risks, and others might enhance financial returns and lower risks at the same time. For example, research in marketing showed that investments in customer satisfaction led to lucrative financial returns and lower stock market risks (Fornell et al., 2006).

On the other hand, investments in new products lead to additional financial returns while introducing significant operational and firm risks. Do some organizational or operational investments improve organizational returns at the expense of risks, or do they reduce risks at the same time? If the investments of firms to improve organizational returns are associated with higher financial uncertainty, is there anything that operations managers can do to reduce the risks? This thesis examines two issues associated with the returns and risks of OM.

In the first study, we examine the impact of R&D investments on the financial risks of firms and explore how firms could mitigate these risks through operational improvements (using the stochastic frontier estimation of relative efficiency as a proxy) and quality management initiatives (using Six Sigma implementation as a proxy). R&D investments have been recognized as one of the most important organizational initiatives leading to a sustainable competitive advantage (Danneels, 2002; Kyrgidou and Spyropoulou, 2013). Yet R&D activity is costly and risky, and returns on it are uncertain. Product innovations bring more challenges by inducing market uncertainties and operational disruptions, which might have an adverse impact on the firm's performance outcomes. In particular, previous research on R&D investments focused on investment returns to firms but was less concerned with the associated financial risks of firms.

Based on data from 560 manufacturing firms from 2007-2014 in the United States (U.S.), we constructed the distributed lag model to capture the current-year and 1-year lag effects of R&D investments on firm risks. Using the system generalized method of moments estimator with a 1-year lag, we find that R&D investments significantly increase a firm's financial risks. However, we find that the risks are alleviated when a firm simultaneously invests in operational improvements or quality management. We argue that R&D investments improve a firm's explorative capacity while investments in operational improvements and quality management enhance a firm's exploitative ability. Instead of considering exploitative and explorative as competing, mutually exclusive capabilities, our empirical evidence shows that exploitative and explorative capabilities reinforce each other to mitigate the risks associated with R&D activities, which leads to lower financial uncertainties in regard to R&D investments.

In the second study, we empirically examine the impact of the adoption of business intelligence (BI) systems on firms' operational efficiency and risks (using the volatility in profit returns as a proxy). We examine how the business value of BI systems is enhanced through stakeholder relationships (based on the ratings produced by Kinder, Lydenberg, Domini & Company, Inc., KLD) and process institutionalization (using ISO 9000 certifications as a proxy).

Based on an event study analysis of financial data for a sample of over 200 cases of BI systems adoption from 2005-2014 in the U.S., we find that the adoption of BI systems leads to higher operational efficiency while mitigating firm risks (i.e., leading to lower volatility in profit returns). Additionally, we find that these benefits are significantly higher for firms with better stakeholder relationships and higher process institutionalization. We explore the operational impact on the adoption of

BI systems by firms, and seek to understand the circumstances in which BI systems are more effective. We explore timely OM issues in an age when a huge volume of business data is available through the internet such as web server blogs and social media technologies (i.e., big data).

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List of Abbreviations

2SLS	Two-Stage Least Squares
AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
BI	Business Intelligence
DMAIC	Define, Measure, Analyze, Improve, and Control
ERP	Enterprise Resource Planning
eQQ Max	Maximum values of differences in empirical quantile functions
eQQ Mean	Mean values of differences in empirical quantile functions
eQQ Med	Median values of differences in empirical quantile functions
Gartner	Gartner, Inc.
GMM	Generalized Method of Moments
KBV	Knowledge-Based View
KLD	Kinder, Lydenberg, Domini & Company, Inc.
KM	Knowledge Management
LG	LG Electronics Inc.
Mean Diff	Mean Difference
OB	Organizational Behavior
OLAP	Online Analytical Procession
OM	Operations Management
PSM	Propensity Score Matching
R&D	Research and Development
ROA	Return on Assets
SFE	Stochastic Frontier Estimation
US	United States
WSR	Wilcoxon Signed-Rank

CHAPTER ONE

INTRODUCTION

1.1. Research Background

Traditionally, scholars in operations management (OM) have focused on the efficacy of organizational innovations such as total quality management (Samson and Terziovski, 1999), just-in-time (Sumichrast and Russell, 1990) and enterprise resource planning (ERP; Yen and Sheu, 2004). Typically, academics in our area tend to examine the extent to which organizational innovations result in non-financial indicators such as process defects, customer satisfaction, and employee motivation, which eventually lead to higher profitability and financial returns (Kaynak, 2003). Researchers in OM normally study indicators of financial returns such as return on assets (ROA), sales growth, return on sales, and shareholder value (Huson and Nanda, 1995; Liu et al., 2014). Yet performance indicators of financial returns do not indicate the risks associated with the achievement of potentially higher returns. A classical theory in financial economics suggests that risks and returns are positively associated, and firms often have to increase returns by taking on higher risks (e.g., Petkova and Zhang, 2005). Accordingly, organizations sometimes face a dilemma on whether to make uncertain investments (e.g., by investing in a new product or entering a new market) to maximize the potential returns.

Research and development (R&D) investment is one of these examples. Organizations that make substantial R&D investments often face high uncertainty in their returns. R&D investment is widely recognized as one of the necessary organizational initiatives that firms use to create value and develop sustainable competitive advantages (Capon et al., 1990). Increasing R&D investment is considered critical to preserve production pipelines and maintain a firm’s competitive position in the technology sector (Rhodes and Stelter, 2009). In an increasingly dynamic and competitive global business environment, the product’s life cycle is getting shorter and market opportunity is shrinking. Most firms launch new products and accelerate their R&D process to grasp new business opportunity. However, research shows that almost 80% of R&D projects failed before completion, and over 50% of R&D projects did not generate sufficient returns to cover investment costs (Cooper, 2003).

Thus, it is very important for OM scholars to understand the financial risks associated with R&D and to examine how firms can reduce the financial risks of R&D investments. In fact, given the close relationships and potentially conflicting objectives between a firm’s financial risks and returns, an important and broader empirical research question regarding OM is how, if, and to what extent an organizational innovation will simultaneously lead to risks and returns. If some organizational innovations or investments inevitably lead to a higher risk to firms in pursuit of higher returns, what can firms do? How could firms reduce, mitigate, or reverse the risks associated with organizational initiatives like R&D investments through superior operations?

Another contemporary topic related to risk management in OM concerns the use of a massive amount of data in the mitigation of firm risks in operations. In fact, OM scholars have long emphasized managing certainty using a data-driven, fact-based approach. Principles in quality management, particularly Six Sigma, emphasize extensive process measurements and disciplined, data-driven methods of problem-solving. A fact-based management approach facilitates better strategic investments by firms under various organizational constraints. In the era of big data, firms can acquire and analyze a massive amount of business data through business intelligence (BI) systems to gain business and operational insight. A BI system is a tool to support decision-making by using a data warehouse, data mining, and online analytical procession (OLAP) technology. BI systems retrieve vast quantities of internal and external data that are transferred to the repository for multidimensional analysis, validation, and consolidation (Trkman et al., 2010). Through BI analysis, new knowledge is generated to fit the decision-making purpose, maximizing the value of information (Curko et al., 2007; Rao and Kumar, 2011).

Anecdotal evidence of the benefits of BI systems in the improvement of operations is abundant. For example, Continental Airlines largely improved its business performance and created great value for its customers by adopting a real-time BI system, which saved the firm from bankruptcy (Watson et al., 2006). Likewise, by enhancing information transparency and providing a timely update of shipments to customers using BI systems, Norfolk Southern increased customer satisfaction, improved operations, and created a better strategic position (Wixom and Watson, 2012). Successful stories notwithstanding, the adoption of BI systems presents a great challenge to firms. According to Gartner, Inc. (Gartner), a worldwide leading research and advisory company in information technology, over 50% of BI projects failed to go beyond the pilot test and most of them were eventually abandoned. This failure rate remains very high over the past decade (Goasduff, 2015).

In this thesis, we examine two issues in regard to the returns and risks in OM. In the first study, we examine the impact of R&D investments on the financial risks to firms and explore how firms could mitigate risks through operational improvements and quality management initiatives. We examine the impact of R&D investments on firm risks and study whether the firm's simultaneous investments in operational efficiency and quality management could mitigate the associated financial risks. Based on data from 560 manufacturing firms from 2007-2014 in the United States (U.S.), we construct a distributed lag model to capture the current-year and 1-year lag effects of R&D investments on firm risks. Using the system generalized method of moments (GMM) estimator with a 1-year lag, we find that R&D investments significantly lead to increased financial risks for firms. However, we find that firm risks are alleviated when firms make simultaneous investments in operational improvements or quality management.

In the second study, we examine the returns and risks of BI systems. Based on the event study analysis of the adoption of BI systems from 2005-2014 in the U.S., we empirically examine the impact of BI systems adoption on the operational efficiency of firms and the risks to firms (using the volatility in profit returns as a proxy). Additionally, we examine how the business value of BI systems is enhanced through stakeholder relationships (based on the ratings produced by Kinder, Lydenberg, Domini & Company, Inc., KLD) and process institutionalization (using ISO 9000 certifications as a proxy). Based on an event study analysis of financial data for a sample of over 200 cases of BI systems adoption, we find that the adoption of BI systems leads to higher operational efficiency while mitigating risks (i.e., leading to lower volatility in profit returns). Additionally, we find that the benefits are significantly higher for firms with better stakeholder relationships and higher process institutionalization.

1.2. Literature Review and Research Motivation

1.2.1. R&D Investments

Through R&D activity, firms can create and maintain a sustainable competitive advantage through continuous R&D investments (Capon et al., 1990; Danneels, 2002; Kyrgidou and Spyropoulou, 2013). Although R&D investments lead to long-term competitive advantages for firms, they create significant short-term financial stress due to the immediate increase in expenditures and uncertain return periods (Zhang, 2015). R&D investment is a costly and inherently risky activity that involves tremendous and irretrievable costs in the search, discovery, and development process of a new technology. According to Cooper (2003), almost four-fifths of R&D projects fail before completion, and over half of completed R&D projects cannot cover the initial investment costs. Other studies such as Bloom (2008) and Hall (2002) suggest that R&D involves huge adjustment costs during interim assessments.

In our research, we argue that stronger operational and quality management capability is a possible option to mitigate the potential downside risk of R&D investments. From a traditional OM perspective, a firm's process management capability is important to the reduction of the associated operational risks. However, there are conflicting views in the literature regarding operational efficiency in innovation. Some scholars, particularly those from an organizational behavior (OB) perspective, argue that process and quality management techniques are likely conflict with R&D activities. Quality management techniques such as ISO 9001 and Six Sigma aim to coordinate and streamline organizational activities on an ongoing basis, but to reduce mistakes, their requirements and procedures may be too rigid, which impedes creativity and obstructs R&D activities (Benner and Tushman, 2002; Collis, 1994). From an OB perspective, process and quality management innovations are normally a bureaucratic practice in firms.

From a strategic OM perspective, operational and quality management capability is widely accepted as the ability to integrate resources, operational practices, and know-how efficiently and effectively. It plays a vital role in achieving competitive advantages (Li et al., 2010; Tan et al., 2004). Thus, it is important for us to investigate the moderating effect of operational capability when analyzing the relationship between R&D investments and the associated risks. In particular, it is of high interest to discover whether operational efficiency and quality management initiatives can moderate innovation to reduce risks.

The potential moderating impacts of operational and quality management capability on R&D investments can be illustrated by some recent examples. LG Electronics Inc. (LG) tried to differentiate its smartphones and embarked on an R&D project to develop the world’s first modular smartphone. Although the product design itself was successful, LG failed to make a profit due to its poor operational capability (Kang, 2016). LG’s carriers, distributors, and retailers were unable to work together to stock the modules and manage the inventory (Kang, 2016), and LG experienced higher production and supply chain costs. Accordingly, the financial risk of any R&D project depends on the technical achievement of the product, and most important, the firm’s overall operational capability to ensure product delivery. We explore this issue in the current study.

1.2.2. Business Intelligence Systems

BI systems refer to an integrated set of tools, technologies, and software used to collect and explore massive amounts of data originating from different organizational processes and economic activities. BI systems integrate, aggregate, and transform multidimensional data into organized information for managerial decisions (Olszak and Ziemba, 2007; Williams and Williams, 2010). BI shortens the time to analyze structured and unstructured data and provides meaningful information in the right place, at the right time, and in the right format to support better decisions by organizational members (Negash and Gray, 2008). The literature on BI demonstrates that firms used BI systems to improve their profitability, sales, and return on equity (Agarwal and Dhar, 2014; Aral et al., 2012; Davenport and Harris, 2007). Although some proponents believe that BI systems significantly contribute to effective decision-makings, many others question the actual value. Some studies (Fuchs, 2006; Li et al., 2013; Moss and Atre, 2003) point out that the adoption of BI systems is a complex and time-consuming organizational change process, which leads to employee resistance and decreased operational efficiency. The actual benefits of BI systems and the factors that facilitate their implementation are subject to further investigations.

1.3. Research Objectives

In short, the objective of the first part of the thesis is to examine the impact of R&D investments on the financial risks of firms and to explore the possibility of reducing these risks through operational improvements and quality management initiatives. This study aims to address the issues of the hidden risks associated with R&D activity and to understand the operating contexts in which firms' financial risks are likely to be alleviated. We use the stochastic frontier estimation (SFE) of relative efficiency as a proxy of operational efficiency and the implementation of Six Sigma as a proxy of quality management initiatives.

The second main objective is to empirically examine the impacts of adopting BI systems on operational efficiency and the risks to financial returns. We examine how the business value of BI systems vary with stakeholder relationships and process institutionalization of firms. We seek to answer a fundamental question about the business value of BI systems and to understand the circumstances in which a firm can extract additional benefits from the adoption of BI systems.

1.4. Research Approaches and Findings

We focus on stock-listed U.S. manufacturing firms in our first study. Based on the data collected from 560 U.S. manufacturing firms from 2007-2014, we construct a distributed lag model to capture the current-year and 1-year lag effects of R&D investments on firm risks. We employ the system GMM estimator (Arellano and Bond, 1991) to control for endogeneity and unobserved heterogeneity in the data analysis (e.g., Bardhan et al., 2013; Chizema et al., 2015; Uotila et al., 2009).

The system GMM estimator is developed to combine the procedures of the difference GMM estimator with an additional set of moment conditions (Arellano and Bover, 1995; Blundell and Bond, 1998) in which the lagged differences of the endogenous variable as instruments in the levels equation and lagged levels as instruments in the first-differencing equation. There are several advantages to use the system GMM estimator in the data analysis (Alessandri and Seth, 2014; Luo et al., 2015; Wintoki et al., 2012). First, the system GMM estimator controls for the dynamic nature of the endogenous variable and its lagged values. Second, the endogeneity concern is solved by using lagged values of variables as instruments of variable with first differences. Third, the fixed effect of unobserved firm-specific heterogeneity is eliminated by first differences. Last, the system GMM estimator provides better estimates in the presence of potential heteroskedasticity and autocorrelation that easily are found in the dynamic panels.

Using the system GMM estimator with the 1-year lag effect, we find that R&D investments significantly lead to increased financial risks for firms. Yet we find that the financial risks are alleviated when firms simultaneously improve operational efficiency or implement Six Sigma. As a result, our first study demonstrates that as R&D investments improve a firm's explorative capacity, operational efficiency improvements and quality management initiatives enhance a firm's exploitative ability. Instead of considering exploitative and explorative as competing, mutually exclusive capabilities, our empirical evidence shows that exploitative and explorative capabilities reinforce each other to mitigate the risks associated with R&D activities, which leads to lower financial uncertainties for R&D investments.

In our second study, we empirically examine the impacts of the adoption of BI systems on firms' operational efficiency and risks. We use the volatility in profit returns as a proxy for the financial risks of firms. Based on an event study analysis of financial data for a sample of over 200 cases of BI adoptions from 2005-2014 in the U.S., we find that the adoption of BI systems leads to higher operational efficiency and lower firm risks simultaneously (i.e., leading to lower volatility in profit returns). Compared to control firms, the sample firms obtain significantly higher operational efficiency and a reduced risk in profit returns directly after the adoption of BI systems.

Additionally, we conduct a cross-sectional regression analysis to explore the moderating effects of stakeholder relationships and process institutionalization on the adoption of BI systems by firms. We measure stakeholder relationships based on the KLD ratings, and use ISO 9000 certifications as a proxy for process institutionalization. We find that firms with superior stakeholder relationships increase operational efficiency and alleviate firm risks to a greater extent after the adoption of BI systems. Also, firms with a higher institutionalized process show more improvements in operational efficiency and lower volatility of profits after the adoption of BI systems.

We provide empirical evidence that the adoption of BI systems can improve firms' operational efficiency and mitigate risks simultaneously. Strong stakeholder relationships and high process institutionalization following the adoption of BI systems can further enhance firms' operational efficiency and reduce risks. This study sheds light on the importance of BI technology to firms. We also seek to understand the circumstances in which firms are more likely to gain additional benefits from their adoptions of BI systems.

1.5. Research Significance

While studying the returns and risks associated with R&D investments and BI systems, we explore whether firms can simultaneously enhance returns, and lower the risks associated with organizational initiatives, and explore actions that operations managers can do to reduce these risks. Our two studies focus on the impact of R&D investments on the financial risks to firms, the impact of BI systems on operational efficiency, and the risks to financial returns, respectively. Our studies are relevant and significant for firms because new product development through R&D and process improvements through BI systems are contemporary issues operations managers face. As mentioned above, previous research in OM mainly focused on the efficacy, performance outcomes, and financial returns of organizational initiatives but were less concerned with the associated risks. Additionally, it is important for managers to make data-driven, fact-based strategic decisions in a dynamic and competitive global business environment. The availability of big data facilitates a firm's ability to acquire and analyze vast amounts of business data through BI systems and provide support for decision-making. However, the real impact of BI systems is still largely unexplored. Our studies fill the research gaps and lay an important foundation for the future development of the OM field.

In addition to the main impact of R&D investments or BI systems adoption on the returns and risks to firms, our studies also identify the circumstances under which the competitive outcomes of R&D initiatives and BI systems adoption can be strengthened. In our first study, we show the firm risks associated with R&D investments are alleviated when firms simultaneously increase operational and quality management capability. In the second study, we show that the impacts of BI systems adoption on operational efficiency and firm risks are further improved through better stakeholder relationships and higher process institutionalization. These findings provide practical implications. Specifically, firms need to ensure operational and quality management capability alongside their R&D initiatives. Similarly, firms should account for the development of stakeholder relationships and process institutionalization when they embark on a BI project. Firms can reap more benefits of their R&D investments or the adoption of a BI system and reduce firm risks, enhancing the business values of R&D investments and BI systems.

There are some theoretical implications from our research studies. Following Zollo and Winter's (2002) learning mechanisms in organizations, which includes experience accumulation, knowledge articulation and knowledge codification, we consider firms' operational improvements and quality management initiatives as proactive organizational efforts in deliberate learning. Process improvements through operations and quality are inherently routine-based learning. According to Zollo and Winter, the three learning mechanisms have a direct impact on the evolution of operating routines and shape firms' dynamic capabilities. We argue that operational efficiency improvements and quality management practices involve all three learning mechanisms. Therefore, we question the dominant view (e.g., Benner and Tushman, 2002, 2003) that operational and quality improvements are static routines or exploitative activity (March, 1991) that impede exploratory

R&D activities (March, 1991). Our empirical evidence shows that exploitative and explorative are not competing or mutually exclusive capabilities. Instead, they reinforce each other to mitigate firm risks associated with R&D, which leads to lower financial uncertainties of R&D investments.

In the second study, we take a knowledge-based view (KBV) on the competitive outcomes of BI systems. Our empirical evidence shows that BI systems help improve operational efficiency and mitigate risks, which is indicated by the volatility in profits. Most important, we explore the circumstances under which the competitive outcomes from the adoption of BI systems are additional strengthened. We contribute to theory by identifying the role of social capital and process institutionalization in the development of a knowledge-based advantage. Our study advances the understanding of the moderating effects of stakeholder relationships and process institutionalization on the direct impact of the adoption of BI systems on operational efficiency or risks to profits returns. Overall, these two studies present the mechanisms for achieving a high return and low risk for organizational initiatives such as R&D investments and BI systems adoptions.

CHAPTER TWO

STUDY 1:

MITIGATING THE RISKS OF R&D:

DO OPERATIONAL IMPROVEMENTS AND

QUALITY MANAGAGEMENT MATTER?

2.1. Theoretical Background and Hypotheses Development

2.1.1. Organizational Learning and the Knowledge-Based View of Firms

Knowledge is the distinct and strategically important resource of firms (Nonaka and Takeuchi, 1995). By accumulating and developing knowledge, firms can build capabilities to acquire competitive advantages (Conner and Prahalad, 1996; Grant, 1996b; Kale and Singh, 2007). Knowledge can be accumulated over time through learning by doing and is embedded in organizational routines (Nelson and Winter, 2002). With repeated trials, a firm's tacit and experiential wisdom is developed to guide their future actions (Ethiraj et al., 2005; Gavetti and Levinthal, 2000). Learning by doing is related to Zollo and Winter's (2002) "experience accumulation", focusing on a semi-automatic learning process subject to internal and external stimulus, accumulation of tacit knowledge through practical experience, and routines that are related to the element of organizational capabilities.

In addition to the above procedural organizational learning, organizational effort in deliberate learning is equally important (Zollo and Winter, 2002) to articulate and codify collective knowledge to improve and modify existing operations (Collis, 1996; Nonaka and Takeuchi, 1995; Zollo and Winter, 2002). Knowledge articulation is a deliberate learning process of transmuting tacit knowledge from individuals into explicit knowledge through collective dialogues and discussions (Kale and Singh, 2007; Zollo and Winter, 2002). Individuals in firms are the prime repositories of know-how, skills, values, and cultural beliefs that are most relevant to handle critical tasks (Gore and Gore, 1999; Senge, 1997). From sharing individual experiences and comparing their ideas with those of others, "knowledge becomes crystallized" (Nonaka and Takeuchi, 1995). Such deliberate effort in articulation creates a better common understanding and shared value of new actions and expected performance, and thus results in adaptive improvements to organizational routines (Zollo and Winter, 2002).

Knowledge codification is considered as a documentation to merely store firms' existing knowledge (Kogut and Zander, 1992; Nonaka, 1994). Zollo and Winter (2002) extended the understanding of knowledge codification to a higher proactive and deliberate effort involving creation. Codified knowledge is documented into standard procedures and manuals provided guidelines for doing a repetitive task, facilitating the diffusion of knowledge and the replication of best practices within a firm (Nonaka, 1994; Prencipe and Tell, 2001).

Zollo and Winter (2002)'s learning mechanisms that include experience accumulation, knowledge articulation, and knowledge codification are not unidirectional but overlap. Also, the mechanisms directly impact the evolution of organizational routines and shape firms' dynamic capabilities. In this study, we consider organizational learning occurs when firms invest in the improvement of operational efficiency and the implementation of Six Sigma.

2.1.2. Exploration and exploitation

In the March's (1991) exploration and exploitation framework of organizational learning, exploration implies a firm's activity that is characterized by search, discovery, innovation, variation, risk taking and experimentation. In contrast, exploitation implies a firm's activity that is characterized by refinement, efficiency, production, control, standardization, execution and improvement (March, 1991; Lewin et al., 1999). Thus, the return associated with exploration is uncertain and distant while the return associated with exploitation is predictable and proximate (March, 1991).

Applying March's (1991) view to our study, we define research and development (R&D) as an activity of exploration. R&D is costly, time-consuming and risky activity. At the initial stage of product and process development, a significant amount of capitals and resources is often required to make discoveries. However, the expected return to R&D is subject to high uncertainty. The lead time between project commencement and product commercialization is usually long, and the product life cycle is short in the face of a fast-changing technology (Fung, 2006; Jorde and Teece, 1990; Stockstrom and Herstatt, 2008). On the other hand, we suggest operational efficiency improvement and Six Sigma implementation as exploitation. We suggest that operational efficiency improvement is found in operational capability that is embedded in a bundle of routines to perform a series of tasks repetitively for continuous modifications. This routinization enables a firm to exploit its existing routines and resources, resulting in efficiency improvements. Likewise, the quality management practice as Six Sigma strives for continuous improvements throughout organizational functions by implementing its principles, practices and techniques (Dean and Bowen, 1994; Kaynak, 2003). It emphasizes on a repetitive identification and rectification process in the current situation to reduce variations (Kumar, 2012).

2.1.3. R&D Investments and Firm Risks

R&D is an exploratory activity characterized by search, discovery, innovation, variation, risk taking, and experimentation (Gupta et al., 2006; March, 1991). New product and process development have been recognized as one of the most important organizational initiatives leading to a sustainable competitive advantage (e.g., Calantone et al., 2010; McDermott, 1999). Developing new product and process is vital for firms to maintain their adaptability and the chances of survival (Calantone et al., 2010; McDermott, 1999). With the accelerating technological change and the knowledge dispersion in most industries, a firm tends to dedicate more resources and capital to develop more new products than do its industry peers (Lee et al., 2014; Chen et al., 2016). However, more R&D investments do not guarantee more desirable project outcomes, less exposure to uncertainty (Fung, 2006; Jaruzelski et al., 2011; O'Brien, 2003). Also, a significant amount of capital and resources is often required to make discoveries, but such investments are irreversible (Fung, 2006).

Firm risks refer to financial distress that usually caused by tight cash flow, poor budgeting, heavy business financing, low sales with high costs, or severe financial loss (Sun et al., 2014). R&D activity is costly, time-consuming, and risky (Jorde and Teece, 1990; Stockstrom and Herstatt, 2008). An R&D project can be failed by violating time and budget requirements, late delivery, or components unavailable (Cooper, 2003), as well as a new product can be failed due to poor performance or does not meet reliability and safety requirements (Mackelprang et al., 2015). Product innovations bring more challenges to a firm by inducing both market uncertainties and operational disruptions, which in turn may have an adverse impact on business performance and hurt a firm's survival prospect.

H1. *R&D investments are associated with higher firm risks.*

2.1.4. The Moderating Effect of Operational Efficiency

We hypothesize that the risk associated with R&D can be reduced by improving operational efficiency, which is a firm's relative efficiency in leveraging and converting their resources to operating outcomes (Kim et al., 2011; Miller and Roth, 1994; Roth and Jackson III, 1995). Operational efficiency improvement is related to different sets of firm-specific skills, processes, and routines for incrementally refining existing operations processes and reinforcing efficiency (Peng, 2008; Wu et al., 2010).

Scholars in strategic management (e.g., Peteraf, 1993; Heiens et al., 2007) have focused on unique, heterogeneous, and inimitable resources through firm-specific capabilities to create a sustainable competitive advantage. In fact, operations management (OM) scholars have long studied capabilities from the outcome perspective on cost, flexibility, quality, and delivery performance (e.g., Flynn and Flynn, 2004; White, 1996). Peng et al. (2008) extended the studies on capabilities in OM to organizational processes and routines which are the critical elements in capabilities. They viewed operational capabilities as means to an end, rather than ends in themselves; firms can apply current operational capabilities to exploit new ways of doing work to gain continuous improvement in efficiency (Benner and Tushman, 2003; Peng et al., 2008; Swink and Hegarty, 1998). Recent studies (Wu et al., 2010; Wu et al., 2012) provided a more comprehensive analysis of operational capabilities, which are developed gradually over time through interactions with various resources. A firm's operational capabilities are the capacity to leverage employees' skills to deploy resources in performing jobs that reflect a firm's history, usual practice, and customer preferences (Wu et al., 2010). The firm-specific, tacit, path dependent, and deeply embedded nature of operational capabilities makes them difficult to imitate to differentiate a firm itself in the industry competition, leading to sustainable operating outcomes and improved efficiency (Wu et al., 2010; Wu et al., 2012).

In fact, efficiency improvement process illustrates organizational learning and knowledge creation (e.g., Cheung et al., 2010; Schidt et al., 2005; Zheng et al., 2010). From an organizational learning perspective, repeated operational practice is a learning process that enables individuals to understand a routine better and effectively handle the demands and challenges of everyday operations (Cepeda and Vera, 2007). Individuals accumulate skills by experiential learning (Zollo and Winter, 2002), while a firm with higher operational efficiency develops a stronger knowledge base through which individuals share know-how, cultural norms, and modes of thinking to guide their actions (Cepeda and Vera, 2007; Cohen and Bacdayan, 1994). The knowledge base of firms is a fundamental resource for firms to develop their technological capabilities and competitive outcomes (Liu et al., 2014; Tippins and Sohi, 2003). The depth and breadth of organizational knowledge that is accumulated through experiences benefit a new product development (Katila and Ahuja, 2002; Liu et al., 2014; Van De Ven and Polley, 1992), as well as a renewal of operating routines (Zollo and Winter, 2002). Knowledge codification into operational procedures also makes daily routines more stable by preventing the individuals from repeating the error (Adler et al., 2009; Zollo and Winter, 2002). Firms with efficient and reliable processes and procedures are more likely to obtain a stable condition for search and discovery (Zollo and Winter, 2002), facilitating R&D activities. Also, firms proactively articulate tacit knowledge among individuals to modify existing processes to fit the current situation (Zollo and Winter, 2002), their operations are likely to be more compatible with ongoing innovations. Codification of newly available knowledge configurations, which are the foundation for efficiency improvements (Cepeda and Vera, 2007), enables firms to assimilate the modified routines into existing organizational structure and easily adapt to the new production environment. Firms make proactive efforts to induce organizational learning to improve operational efficiency, streamlining the R&D process and reducing the associated firm risks.

H2. *The negative impact of R&D investments on firm risks is alleviated, or reversed, through higher operational efficiency.*

2.1.5. The Moderating Effect of Quality Management Initiatives

Risk and uncertainty are inherently in R&D projects (Fung, 2006; Pandit et al., 2011), which often fail during the early stages of development (Adams and Brantner, 2010; Cooper, 2003; DiMasi et al., 2016; Stevens, 2014). Managing R&D uncertainty requires firms to pursue process improvement and continuous learning (Senge, 1997). In particular, firms adopted Six Sigma have greater ability to control project implementation process (Anand et al., 2010; Parast, 2011). Six Sigma is a structured and systematic method to identify and eliminate root causes of problems, reducing defect rate while pursuing continuous process improvement (Choo et al., 2007; Kovach and Fredendall, 2013; Linderman et al., 2003; Zu et al., 2008). Also, it forms a parallel-meso organizational structure, involving Six Sigma specialists with a team of employees across multiple functional levels (Schroeder et al., 2008; Sinha and Van de Ven, 2005), as well as using quality tools and techniques to execute a process improvement plan with individuals' contributions (Scholtes et al., 2003; Schroeder et al., 2008; Kovach and Fredendall, 2013). Previous research has shown that learning and knowledge creation in Six Sigma practice enable process improvements (Shah and Ward, 2003; Zu et al., 2008) and enhance communication within a project team to quickly respond to the uncertainty (Zu et al., 2008).

The five phases of Six Sigma structured method are used to define, measure, analyze, improve, and control (DMAIC) variations in operations (Hammer, 2002; Linderman et al., 2006; Schroeder et al., 2008). By repeating DMAIC process, firms' innovation is likely to be embedded in an organizational culture that fosters process analysis (Swink and Jacobs, 2012), as well as effective organizational learning occurs to acquire knowledge (Choo et al., 2007). With experience and knowledge accumulation, firms might develop a stronger problem-solving capability (Kale and Singh, 2007), making a product development process more stable (Kumar, 2012; Sitkin and Stickel, 1996). Also, firms include a diverse Six Sigma team in their R&D projects, they might benefit from combining a variety of individuals' ideas and insights to continuously improve product design (Mader, 2002), reducing risks associated with product failure (Linderman et al., 2003; Treichler et al., 2002).

In addition, using quality tools such as cause-and-effect diagrams and failure mode effects analysis facilitates firms to harness knowledge for R&D (Anand et al., 2010), to develop a common language for organizational members to effectively communicate project status (Choo et al., 2007), and to compare the effects of improving process (Anand et al., 2010; Swink and Jacobs, 2012). Firms documented process refinements might develop a stronger database via which organizational members retrieve the root cause analysis reports as their guidance

(Anand et al., 2010), avoiding repeating errors and reducing the associated risks in R&D.

H3. *The negative impact of R&D investments on firm risks is alleviated, or reversed, through quality management initiatives.*

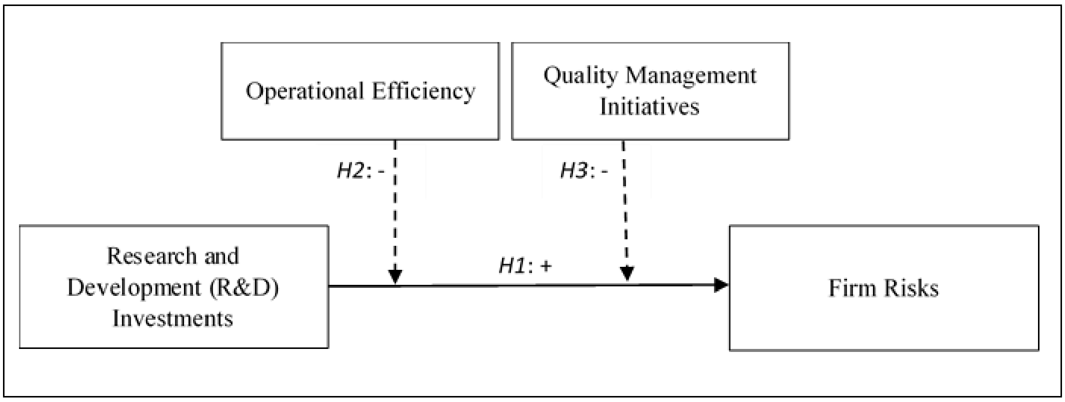


Figure 2.1. Conceptual Framework for Research Model of R&D Investments

2.2. Methodology

2.2.1. Sample and Data Collection

In this study, we focus on firms in the manufacturing sector listed in the U.S. (SIC code: 2000-3999). We obtained financial information from the Standard and Poor's COMPUSTAT and corporate 10-K reports from 2007-2014 on 1,157 U.S.-listed firms with sufficient information in firm-risks measures. Among them, 560 U.S. firms with a total of 3,920 firm-year observations had data available for the measurements of firm risks, R&D investments, operational efficiency, and their 1-year lagged values. The 560 firms represent 19 industries in 2-digit SIC codes.

Table 2.1 shows the first 13 industries of our sample, which includes a wide variety of manufacturing sectors. The top four sectors are (a) electronic and other electric equipment, (b) chemicals and allied products, (c) instruments and related products, and (d) industrial machinery and equipment, representing 78.04% of the total sample.

2-Digit SIC codes	Industries	Number	Percent of sample
36	Electronic and other electric equipment	127	22.68
28	Chemicals and allied products	119	21.25
38	Instruments and related products	104	18.57
35	Industrial machinery and equipment	87	15.54
37	Transportation equipment	28	5.00
34	Fabricated metal products	18	3.21
26	Paper and allied products	13	2.32
30	Rubber and miscellaneous plastics products	12	2.14
33	Primary metal industries	10	1.79
32	Stone, clay, and glass products	9	1.61
20	Food and kindred products	7	1.25
25	Furniture and fixtures	6	1.07
39	Miscellaneous manufacturing industries	6	1.07
Others	Other industries	14	2.50
Total		560	100

Table 2.1. The Distribution of Sample Firms Across Industries

We used Six Sigma implementation as a proxy for firms' quality management initiatives. Similar to prior studies on Six Sigma (e.g., Swink and Jacobs, 2012), we searched for Six Sigma implementation announcements containing keywords such as names of the U.S.-listed firms, and "Six Sigma" in conjunction with "adoption", "implementation", "introduce", or "deploy" through publicly available documents such as all publication sources in the Factiva, 10-K reports, and corporate websites for each of the 3,920 firm-year observations. We had 201 firms with Six Sigma implementation from 2007 or earlier to 2014. Each announcement was reviewed and verified independently by two members of our research team. Table 2.2 lists some examples of the announcements.

Announcement 1	
Company Name	Air Products & Chemicals (NYSE: APD)
Announced on	9 June 2011
Text extracted from Factiva	We've made a significant investment in people and a process, in training, we're very focused on leveraging lean six sigma for the traditional approaches. But it's not only about cost reduction. That's an important element. It's also about using the design for Six Sigma to help us drive new offerings, to help us drive capacity expansions, to help us drive synergies out of acquisitions when we pursue them.
Announcement 2	
Company Name	PolyOne Corporation (NYSE: POL)
Announced on	7 February 2008
Text extracted from Factiva	We operate large fleets as I showed on the last couple of charts and we are always working on logistics optimizing, Six Sigma, lean manufacturing, low-cost country sourcing.
Announcement 3	
Company Name	Praxair, Inc. (NYSE: PX)
Announced on	17 November 2009
Text extracted from Factiva	Through operational excellence initiatives and implementation of our lean six sigma programs we are generating internal cost savings, with the opportunity to deliver a $50 million improvement in the next three years.

Table 2.2. Examples of the Announcement about Six Sigma Implementation

2.2.2. Measurements

Firm risks. We used a reverse Altman's Z-score for publicly traded companies as a proxy for firm risks. That is, the higher the Altman's Z-score, the higher the firm risks. The Altman's Z-score is a widely accepted method of analyzing the health of firms and determining the likelihood of firms' experiencing financial distress or going into bankruptcy within two years (Altman, 1968; Eidleman, 1995; Miller and Reuer, 1996). This concept of the measurement for a firm-level downside risk has received attention in previous strategic management studies on organizational risks (e.g., D'Aveni and Ilinitch, 1992; Kochhar and Hitt, 1998; Miller and Chen, 2004; Miller and Reuer, 1996), though it is relatively new to OM with limited literature (Craighead et al., 2009) on using the Altman's Z-score for publicly traded companies as a proxy for fiancial risks. The calculation of an Altman's Z-score is based on firms' financial figures (Altman, 1968; Altman et al., 2014). We measured risks of a firm *i* in year *t* by following the Altman Z-score's equation (2.1). The equation is composed of five weighted performance ratios to capture different indications of profitability and risks of a firm *i* in year *t*.

$$\begin{aligned}\text{Altman Z-score}_{it} = {} & 1.2\left(\frac{\text{Working Capital}_{it}}{\text{Total Assets}_{it}}\right) \\ & + 1.4\left(\frac{\text{Retained Earnings}_{it}}{\text{Total Assets}_{it}}\right) + 3.3\left(\frac{\text{EBIT}_{it}}{\text{Total Assets}_{it}}\right) \\ & + 0.6\left(\frac{\text{Market Value of Equity}_{it}}{\text{Total Liabilities}_{it}}\right) \\ & + 0.999\left(\frac{\text{Sales}_{it}}{\text{Total Assets}_{it}}\right) \qquad (2.1)\end{aligned}$$

where $\text{Working Capital}_{it}/\text{Total Assets}_{it}$ captures the short-term liquidity risks of a firm *i* in year *t*; $\text{Retained Earnings}_{it}/\text{Total Assets}_{it}$ measures the cumulative profitability of a firm *i* in year *t* by using its assets; $\text{EBIT}_{it}/\text{Total Assets}_{it}$ shows how effectively a firm *i* in year *t* is generating earnings by using its assets; $\text{Market Value of Equity}_{it}/\text{Total Liabilities}_{it}$ captures the long-term solvency risks of a firm *i* in year *t* and shows the market's reaction to the overall financial position of a firm *i* in year *t*; $\text{Sales}_{it}/\text{Total Assets}_{it}$ shows how efficiently a firm *i* in year *t* is generating sales revenue by deploying its assets.

R&D investments. We measured this variable of R&D intensity as a ratio of R&D expenditure to net sales of a firm (e.g., Ehie and Olibe, 2010; Hansen and Hill, 1991; Long and Ravenscraft, 1993). Because the impact of R&D investments in a firm is likely to occur over a number of years rather than during the year (e.g., Bitzer and Stephan, 2007; Esposti and Pierani, 2003; Mudambi and Swift, 2014), we used the distributed lag model (Ahuja and Katila, 2001) to capture the current-year effect and the lag effects of R&D investments. We conducted the optimal lag selection tests, discussed with details in Section 2.3.1. Figures 2.2 and 2.3 show that up to the first lag of R&D investments is optimal; thus, our study captures the impacts of R&D investments in the current year (*t*) and the 1-year lag (*t*-1) on firm risks.

Operational efficiency. Operational efficiency is the relative efficiency of a firm regarding its ability to convert organizational resources into business outputs in comparison with its industry peers (Peng et al., 2008; Swink and Harvey Hegarty, 1998; Winter, 2003). Firms improved operational efficiency is related to their operational capability, which is a firm's ability to use heterogeneous resources, skills, processes, and routines to refine and reinforce the existing operations to achieve desired objectives (Peng et al., 2008; Swink and Harvey Hegarty, 1998). We used the stochastic frontier estimation (SFE) methodology to measure firm's operational efficiency in transforming resources such as the number of employees, capital expenditure, and cost of goods sold into its operating income and measure the efficiency of each firm relative to competitors in the same industry (Carmel and Sawyer, 1998; Dutta et al., 2005; Li et al., 2010). The SFE is a better approach to measure a firm's operational efficiency regarding the transformative framework from various operational inputs into operational outputs. Also, it incorporates a composite error term composed of random effects and pure inefficiency (Aigner et al., 1977). It can isolate any influences from random factors other than inefficient behavior to prevent possible upward bias of inefficiency from the deterministic methods (Vandaie and Zaheer, 2014). Specifically, we used the operations frontier function in Equation (2) to model the output operating income by the operational inputs, including a number of employees, capital expenditure, and cost of goods sold.

$$\begin{aligned}\ln(\text{Operating Income})_{ijt} = \beta_0 &+ \beta_1 \ln(\text{Number of Employees})_{ijt} \\ &+ \beta_2 \ln(\text{Capital Expenditure})_{ijt} \\ &+ \beta_3 \ln(\text{Cost of Goods Sold})_{ijt} + \varepsilon_{ijt} - \gamma_{ijt} \qquad (2.2)\end{aligned}$$

where ε_{ijt} is the purely stochastic random error term affecting operating income, and γ_{ijt} captures the operational inefficiency of a firm *i* in industry *j* (2-digit SIC codes) in year *t*. γ_{ijt} ranges from 0 to 1, with 0 meaning no operational inefficiency (relative to the industry). Thus, γ_{ijt} is a relative measure to indicate how inefficient a firm is in comparison with a corresponding frontier in the same industry and in the same year. The composite error term, $(\varepsilon_{ijt} - \gamma_{ijt})$, is estimated based on the difference between the maximum achieved operating income (in an industry) and the observed operating income so as to obtain a consistent estimate of firm-specific operational inefficiency, $\hat{\gamma}_{ijt}$. Hence, the operational efficiency of a firm *i* in industry *j* in year *t* is

$$\text{Operational efficiency}_{ijt} = \left(1 - \hat{\gamma}_{ijt}\right) \times 100\% \qquad (2.3)$$

Quality management initiatives. We used Six Sigma implementation as a proxy for firms' quality management initiatives. Quality management practices aim to initiate a persistent effort to improve the quality of goods, services, and processes (Linderman et al., 2004). Six Sigma is often recognized as an approach to solve practical problems and foster improvements (Choo et al., 2007; Kovach and Fredendall, 2013) through identifying the root cause of variations and eliminating defects in the process (Linderman et al., 2003; Schroeder et al., 2008). We assigned 1 to firms with Six Sigma implementation and 0 to firms without Six Sigma implementation.

Control variables: At the firm level, we controlled for 1-year prior firm risks, size, age, and leverage as they are highly related to subsequent firm risks in the next year (Baños-Caballero et al., 2014; McAlister et al., 2007; Zhang, 2015). We measured firm size as the natural logarithm of the number of employees (Kull and Wacker, 2010) because larger firms might have more resources than smaller firms to embark on R&D projects (Douglas and Fredendall, 2004), and firm age as the natural logarithm of the number of years from the date of incorporation (Zhang, 2015) because younger firms might lack the knowledge and skills required to manage

R&D tasks than older ones (Czarnitzki and Toole, 2011). In addition, firm leverage as the natural logarithm of the ratio of total debts to total assets (Zhang, 2015) might influence the management in making a decision on R&D investments (Baños-Caballero et al., 2014). We also included industry size as the natural logarithm of all firms' total assets in the same industry based on the 2-digit SIC codes (Lo et al., 2013) because larger industries might have greater abilities to afford product developments (Brunnermeier and Cohen, 2003). Finally, we used time dummy variables to capture the influences of economic factors that firms cannot control and used industry dummy variables (2-digit SIC codes) to control for industry-specific effects.

2.3. Models

2.3.1. Distributed Lag Model

Because the impact of R&D investments in firms grows over a period of time (e.g., Bitzer and Stephan, 2007; Esposti and Pierani, 2003; Mudambi and Swift, 2014), we modelled the R&D investments of firms as time-varying influences on firm risks. Using distributed lag analysis enables us to consider the same-year effect and the lagged values as additional independent variables in one model. Thus, we can examine the time pattern of the R&D effects on firms and the associated risks for several periods after the year that R&D investments were originally made (Ahuja and Katila, 2001; Judge et al., 1982). Recent studies examining the lagged impact of inventory management, process improvement, innovation, and entrepreneurial risk have employed the distributed lag analysis (e.g., Ahuja and Katila, 2001;

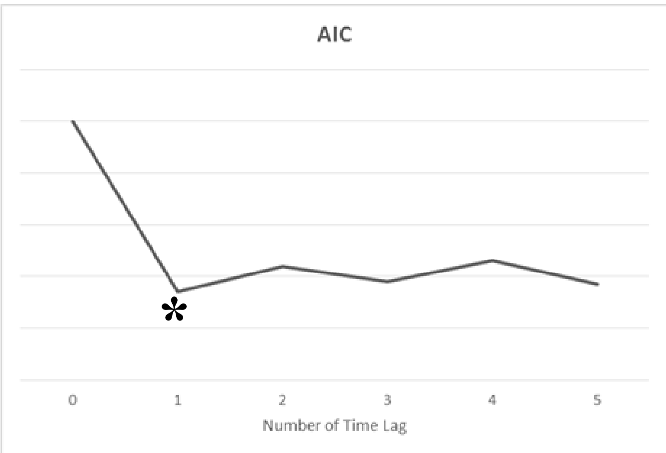
Carrillo and Gaimon, 2000; Joo et al., 2013; Prabhu et al., 2005; Toktay et al., 2000; Wu and Knott, 2006).

R&D is inherently risky because it usually requires firms to invest a huge amount of capital, resources, and time, and such investments are irreversible. Therefore, with a longer lag period to get the investment returns, firms encounter higher risks to maintain business (Rao et al., 2013). Some studies find that the return of R&D investments to firms has a lag period of up to 2 years (Pakes and Schankerman, 1984; Rao et al., 2013). We identified the optimal lag length based on two different approaches using information criteria and residual autocorrelation (Enders, 2008). First, the two most common information criteria are the Akaike information criterion (AIC; Akaike, 1973) and the Bayesian information criterion (BIC; Schwarz, 1978). Both are designed for model selection and take the log-likelihood function with a deterministic penalty term (Yang, 2005). AIC aims at estimating information loss of each candidate model by measuring the Kullback-Leibler divergence between the true distribution. Then the candidate model that can minimize the information loss to the greatest extent is the preferred model, and BIC selects a model with a maximized posterior probability after having all the information from the data (Yang, 2005). AIC and BIC are calculated by (2.4) and (2.5), respectively.

$$\text{AIC} = \text{-2 Log-likelihood} + 2k \tag{2.4}$$

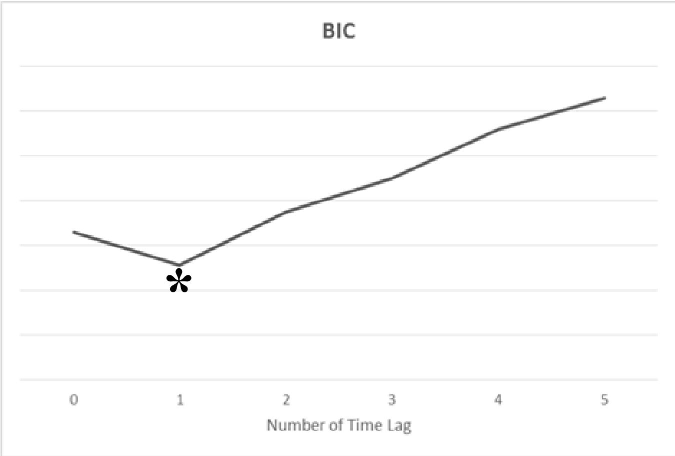
$$\text{BIC} = \text{-2 Log-likelihood} + k\ln(n) \tag{2.5}$$

where k is the number of the estimated parameters and n is the number of observations. The model that gives the smallest AIC or BIC is selected as the preferred model (Wang and Liu, 2006; Yang, 2005). As such, we focused on the model with the smallest AIC or BIC, and identified the optimal lag length accordingly. Figures 2.2 and 2.3 indicate that a 1-year lag is the most appropriate. Another criterion for model selection is related to an elimination of autocorrelation in the residuals. We conducted the Breusch-Godfrey LM test to test the null hypothesis that the residuals are not autocorrelated. Rejecting the null hypothesis indicates that more lags should be added. Table 2.3 shows that the result of the Breusch-Godfrey LM test for R&D investments up to lag 1 was insignificant ($p > 0.05$). As a result, our distributed lag model captures the impacts of R&D investments in the current year (t) and 1 year after the R&D investments were originally made (t-1) in equations (2.6), (2.7), and (2.8).



Notes:
*The lowest value of AIC.

Figure 2.2. Lag selection of R&D investments by AIC



Notes:
*The lowest value of BIC.

Figure 2.3. Lag selection of R&D investments by BIC

	Chi-sq statistics	*p*-value
Breusch-Godfrey LM test for R&D investments up to *t*-1	41.307 (df = 1)	0.190

Note: H_0: The residuals are not autocorrelated; H_a: The residuals are autocorrelated.

Table 2.3. The Breusch-Godfrey LM test for R&D investments up to lag 1

The main impact of R&D investments of firm *i* at current year (*t*) and 1-year lag (*t*-1) on firm risks is

$$\text{Firm Risks}_{it} = \alpha_0 + \alpha_1\text{Firm Risks}_{i(t-1)} + \alpha_2\text{Firm Size}_{it} + \alpha_3\text{Firm Age}_{it} + \alpha_4\text{Firm Leverage}_{it} + \alpha_5\text{Industry Size}_{it} + \alpha_6\text{R\&D Investments}_{it} + \alpha_7\text{R\&D Investments}_{i(t-1)} + \varepsilon_{it} \quad (2.6)$$

The interaction effects of R&D investments and operational efficiency of firm *i* at current year (*t*) and 1-year lag (*t*-1) on firm risks is

$$
\begin{aligned}
\text{Firm Risks}_{it} = \alpha_0 + \ & \alpha_1 \text{Firm Risks}_{i(t-1)} + \alpha_2 \text{Firm Size}_{it} + \alpha_3 \text{Firm Age}_{it} \\
& + \alpha_4 \text{Firm Leverage}_{it} + \alpha_5 \text{Industry Size}_{it} \\
& + \alpha_6 \text{R\&D Investments}_{it} + \alpha_7 \text{R\&D Investments}_{i(t-1)} \\
& + \alpha_8 \text{Operational Efficiency}_{it} + \alpha_9 \text{Operational Efficiency}_{i(t-1)} \\
& + \alpha_{10} \left(\text{R\&D Investments}_{it} \times \text{ Operational Efficiency}_{it} \right) \\
& + \alpha_{11} \left(\text{R\&D Investments}_{i(t-1)} \times \text{ Operational Efficiency}_{i(t-1)} \right) \\
& + \varepsilon_{it} \qquad (2.7)
\end{aligned}
$$

The interaction effects of R&D investments and quality management initiatives of firm *i* at current year (*t*) and 1-year lag (*t*-1) on firm risks is

$$
\begin{aligned}
\text{Firm Risks}_{it} = \alpha_0 + & \alpha_1 \text{Firm Risks}_{i(t-1)} + \alpha_2 \text{Firm Size}_{it} + \alpha_3 \text{Firm Age}_{it} \\
& + \alpha_4 \text{Firm Leverage}_{it} + \alpha_5 \text{Industry Size}_{it} \\
& + \alpha_6 \text{R\&D Investments}_{it} + \alpha_7 \text{R\&D Investments}_{i(t-1)} \\
& + \alpha_8 \text{Quality Management Initiatives}_{i(t-1)} \\
& + \alpha_9 \Big(\text{R\&D Investments}_{it} \\
& \times \text{ Quality Management Initiatives}_{i(t-1)} \Big) \\
& + \alpha_{10} \Big(\text{R\&D Investments}_{i(t-1)} \\
& \times \text{ Quality Management Initiatives}_{i(t-1)} \Big) + \varepsilon_{it} \qquad (2.8)
\end{aligned}
$$

In addition, the cumulative impacts of R&D investments and the interaction effects between R&D investments and operational efficiency or quality management initiatives are likely to be distributed over year *t* and year *t*-1. It may be statistically insignificant in any one period; the cumulative impacts of R&D investments and the interaction effects across time can be obtained by summing up the regression coefficients in the distributed lag model (Gujarati, 2009). We then set a hypothesis as the summed coefficient about the cumulative impact as 0 by performing a *t*-test and checked whether it is statistically significant at the 95% confidence level (Ahuja and Katila, 2001; Greene, 2003; Gujarati, 2009). Accordingly, the distributed lag analysis lets us trace the effects of the R&D investments on the associated risks to firms across time as well as identify the cumulative impact of R&D investments and the interaction effects with operational efficiency or quality management initiatives.

2.3.2. System Generalized method of moments (GMM) Estimator

The above specification does not address endogeneity, which arises due to omitted variables (i.e., unobserved heterogeneity, causality between a predicted value and observed values, and measurement errors in regression covariates). For instance, the sample firms in this study may have inherently different innovativeness and marketing capabilities. Also, the decision to make R&D investments is correlated with unobserved variables such as business strategies or market trends that affect a firm's risks. Thus, endogeneity could lead to over-dispersion in the data and autocorrelation among the residuals of observations from the same firm and finally lead to invalid hypothesis testing and biased inference (Alessandri and Seth, 2014).

A two-stage least squares (2SLS) estimator is commonly used to tackle the endogeneity issue (Bardhan et al., 2013; Greene, 2003). In the first stage of 2SLS, instrumental variables are used and reduced-form regressions are estimated to compute predicted values of the endogenous variables. In the second stage, the predicted values from stage one are used to replace the endogenous variables and then to conduct the second regression analysis for the outcome of interest. A good instrumental variable is uncorrelated with the error term but partially and sufficiently highly correlated with an endogenous variable (Chizema et al., 2015; Tykvová and Borell, 2012). However, it is difficult to obtain such proper exogenous instrumental variables for the endogenous variables other than their lags (Bardhan et al., 2013; Reeb et al., 2012; Wintoki et al., 2012).

In view of the challenge to obtain a valid instrumental variable to deal with endogeneity outside the regression model, some studies have suggested using the GMM estimator (Arellano and Bond, 1991) to control for endogeneity as well as unobserved heterogeneity in data analysis (e.g., Bardhan et al., 2013; Chizema et al., 2015; Uotila et al., 2009). According to Alonso-Borrego and Arellano (1999), the difference GMM estimator suffers from large sample bias if the endogenous variable is highly persistent. Likewise, this study involves the dependent variable of firm risks, which is substantially persistent. Blundell and Bond (1998) explained that the sample bias occurs in the difference GMM estimator because the lagged-level variables are weak instruments for subsequent first differences.

To address the weak instruments concern, the system GMM estimator is developed to combine the procedures of the difference GMM estimator with additional set of moment conditions (Arellano and Bover, 1995; Blundell and Bond, 1998) in which the lagged differences of the endogenous variable as instruments in the levels equation and lagged levels are used as instruments in the first-differencing equation.

Recent studies have mentioned that there are several advantages to using the system GMM estimator in data analysis (e.g., Alessandri and Seth, 2014; Luo et al., 2015; Wintoki et al., 2012). First, the system GMM estimator controls for the dynamic nature of the endogenous variable and its lagged values. Second, the endogeneity concern is solved by using lagged values of variables as instruments of variable with first differences. Third, the fixed effect of unobserved firm-specific heterogeneity is eliminated by first differences. Last, the system GMM estimator provides better estimates in the presence of potential heteroskedasticity and autocorrelation that easily are found in the dynamic panels.

In this study, we carried out the two-step system GMM estimator. First, we transformed the original level equations (2.6), (2.7), and (2.8) by first differencing the equations (2.9), (2.10), and (2.11), removing the fixed effects. For each variable X except the nominal variables in the equations (2.9), (2.10), and (2.11), ΔX_{it} represents $X_{it} - X_{i(t-1)}$ and $\Delta X_{i(t-1)}$ represents $X_{i(t-1)} - X_{i(t-2)}$. Second, the system GMM estimator used the lagged differences and levels of variables as instruments to control for endogeneity.

The main impact of R&D investments of firm i at current year (t) and 1-year lag (t-1) on firm risks is

$$
\begin{aligned}
\Delta\text{Firm Risks}_{it} = \alpha_0 &+ \alpha_1\Delta\text{Firm Risks}_{i(t-1)} + \alpha_2\Delta\text{Firm Size}_{it} + \alpha_3\Delta\text{Firm Age}_{it} \\
&+ \alpha_4\Delta\text{Firm Leverage}_{it} + \alpha_5\Delta\text{Industry Size}_{it} \\
&+ \alpha_6\Delta\text{R\&D Investments}_{it} \\
&+ \alpha_7\Delta\text{R\&D Investments}_{i(t-1)} + \Delta\varepsilon_{it} \qquad (2.9)
\end{aligned}
$$

The interaction effects of R&D investments and operational efficiency of firm i at current year (t) and 1-year lag (t-1) on firm risks is

$$
\begin{aligned}
\Delta\text{Firm Risks}_{it} = \alpha_0 &+ \alpha_1\Delta\text{Firm Risks}_{i(t-1)} + \alpha_2\Delta\text{Firm Size}_{it} + \alpha_3\Delta\text{Firm Age}_{it} \\
&+ \alpha_4\Delta\text{Firm Leverage}_{it} + \alpha_5\Delta\text{Industry Size}_{it} \\
&+ \alpha_6\Delta\text{R\&D Investments}_{it} + \alpha_7\Delta\text{R\&D Investments}_{i(t-1)} \\
&+ \alpha_8\Delta\text{Operational Efficiency}_{it} \\
&+ \alpha_9\Delta\text{Operational Efficiency}_{i(t-1)} \\
&+ \alpha_{10}\Delta(\text{R\&D Investments} \times \text{Operational Efficiency})_{it} \\
&+ \alpha_{11}\Delta(\text{R\&D Investments} \times \text{Operational Efficiency})_{i(t-1)} \\
&+ \Delta\varepsilon_{it} \qquad (2.10)
\end{aligned}
$$

The interactive effects of R&D investments and quality management initiatives of firm i at current year (t) and 1-year lag (t-1) on firm risks is

$$
\begin{aligned}
\Delta\text{Firm Risks}_{it} = \alpha_0 + \ & \alpha_1\Delta\text{Firm Risks}_{i(t-1)} + \alpha_2\Delta\text{Firm Size}_{it} + \alpha_3\Delta\text{Firm Age}_{it} \\
& + \alpha_4\Delta\text{Firm Leverage}_{it} + \alpha_5\Delta\text{Industry Size}_{it} \\
& + \alpha_6\Delta\text{R\&D Investments}_{it} + \alpha_7\Delta\text{R\&D Investments}_{i(t-1)} \\
& + \alpha_8\text{Quality Management Initiatives}_{i(t-1)} \\
& + \alpha_9\Big(\Delta\text{R\&D Investments}_{it} \\
& \times \text{Quality Management Initiatives}_{i(t-1)}\Big) \\
& + \alpha_{10}\Big(\Delta\text{R\&D Investments}_{i(t-1)} \\
& \times \text{Quality Management Initiatives}_{i(t-1)}\Big) + \Delta\varepsilon_{it} \qquad (2.11)
\end{aligned}
$$

2.4. Results

Table 2.4 reports the descriptive statistics and correlations of the study variables. The results show that the variable of firm risks is highly correlated with its lagged value (r = 0.855 for firm risks). Thus, controlling the lagged variable of firm risks in our model is necessary. Also, the lagged values of R&D investments and operational efficiency are highly correlated with their current-year values (r = 0.705 for R&D investments, r = 0.776 for operational efficiency). However, the autocorrelations are removed after the first differences using the system GMM (r = -0.027 for firm risks, r = -0.025 for R&D investments, r = -0.270 for operational efficiency). Table 2.5 presents the system GMM estimator results. Model 1 reports the estimation with only the intercept and the control variables. Model 2 reports the effects of R&D investments. Model 3a considers operational efficiency, and Model 4a takes quality management initiatives into account. Model 3b and Model 4b report the full model of operational efficiency and quality management initiatives as moderating factors, respectively.

The reliability of the system GMM estimator relates to the validity of the instrumental variables. We conduct two specification tests to validate the instrumental variables used in our model. First, the Sargen test is used for testing overidentifying restrictions by analyzing the overall moment conditions. In Table 2.5, the Sargan statistics are not significant ($p > 0.05$) and fail to reject the null hypothesis of the instrumental variables that are uncorrelated with the residuals. The statistics give support to the instrumental variables as being exogenous and appropriate in our model. Second, the Arellano-Bond test is used for testing autocorrelation to the first-difference residuals. As shown in Table 2.5, the results of AR1 are significant ($p < 0.01$) to reject the null hypothesis of the residuals are not serially correlated in the first-order, whereas the results of AR2 are insignificant ($p > 0.05$) and fail to reject the null hypothesis of the residuals are not serially correlated in the second-order. Overall, the test statistics show our model with a proper specification.

According to the Wald Chi-square in Table 2.5, the system GMM estimator results are significant ($p < 0.001$). Three control variables of lagged firm risks, firm size, and firm leverage remain highly significant ($p < 0.001$) in all models. The control variable of the 1-year lagged firm risks are negative to the current-year firm risks, meaning that a firm that has a higher prior 1-year firm risks tends to be negatively related. The variable of firm size is negatively related to firm risks; thus, a firm in a bigger size seems to suffer fewer risks. Also, firm leverage is positively related to firm risks, which indicates that a highly leveraged firm is more likely to suffer more risks.

Model 2 in Table 2.5 shows that the current-year R&D investments ($b = 0.023$, $p < 0.05$) and the 1-year lagged R&D investments ($b = 0.048$, $p < 0.001$) significantly lead to firm risks. Table 2.6 shows the summed coefficients and the related standard deviations for R&D investments, which show that the cumulative effect of R&D investments for years t and t-1 ($b = 0.071$, $p < 0.001$) significantly leads to firm risks. Thus, Hypothesis 1 is supported.

Model 3a in Table 2.5 shows that the current-year operational efficiency ($b = -2.713$, $p < 0.001$) and the lagged operational efficiency ($b = -1.040$, $p < 0.05$) significantly reduce firm risks. Also, Model 3b shows that the interaction between R&D investments and efforts to improve operational efficiency at current year ($b = -0.196$, $p < 0.01$) as well as the interaction between their lagged values ($b = -0.356$, $p < 0.001$) significantly reduce firm risks. Table 2.6 shows that the cumulative impact of the two interactions between R&D investments and operational efficiency for years t and t-1 ($b = -0.552$, $p < 0.001$) significantly reduces firm risks. In addition, Figure 2.4 shows a plot of the significant interaction. For firms with low operational efficiency, a strong negative relationship (simple slope = -0.052, $p < 0.001$) is found between R&D investments and firm risks. In contrast, a strong positive relationship (simple slope = 0.072, $p < 0.001$) is found when firms simultaneously possess high operational efficiency. Thus, Hypothesis 2 is supported because the negative impact of R&D investments on firm risks is reversed through high operational efficiency. Furthermore, we obtain the lowest firm risks when both R&D investments and operational efficiency are at high levels.

As Model 4a in Table 2.5 shows, quality management initiatives (b = -0.175, $p < 0.05$) significantly reduce firm risks. Model 4b shows that the interaction between investments in R&D and quality management initiatives (b = -4.068, $p < 0.001$) as well as the interaction between their lagged values (b = -3.438, $p < 0.001$) are both negative and significant. In Table 2.6, the summed coefficients for quality management initiatives show that the cumulative impact of the interactions between investments in R&D and quality management initiatives for years t and t-1 (b = -7.506, $p < 0.001$) significantly alleviates firm risks. Also, Figure 2.5 shows a strong negative relationship (simple slope = -7.213, $p < 0.001$) between R&D investments and firm risks when Six Sigma is in place. Thus, Hypothesis 3 is supported for the negative impact of R&D investments on firm risks when it is alleviated through quality management initiatives. Additionally, we find the lowest firm risks occurred when R&D investments are high with quality management initiatives.

Variable (Unit)	1	2	3	4	5	6	7	8	9	10	11
1. Firm Risks	1										
2. Lagged Firm Risks	.855**	1									
3. R&D Investments[a]	.107**	.064**	1								
4. Lagged R&D Investments[a]	.096**	.073**	.705**	1							
5. Operational Efficiency	-.180**	-.150**	-.043**	-.020	1						
6. Lagged Operational Efficiency	-.172**	-.184**	-.034*	-.026	.776**	1					
7. Quality Management Initiatives	.050**	.062**	-.067**	-.055**	-.121**	-.129**	1				
8. Firm Size[b]	-.013	.007	-.094**	-.077**	-.191**	-.198**	.530**	1			
9. Firm Age[c]	-.033*	-.011	-.100**	-.079**	-.126**	-.131**	.370**	.517**	1		
10. Firm Leverage	.535**	.492**	-.010	.007	-.247**	-.259**	.298**	.384**	.251**	1	
11. Industry Size[a]	-.001	.002	.091**	.074**	.078**	.077**	-.008	-.042**	-.081**	-.033*	1
Mean	-3.682	-3.950	.571	.676	.721	.720	.330	1.766	1.623	12.988	-.401
Standard deviation	8.989	9.202	5.225	7.715	.110	.114	.470	1.069	.320	1.321	.294
Minimum	-95.249	-95.249	-.020	-.020	.002	.002	.000	.698	.602	5.366	-1.509
Maximum	73.907	94.269	142.225	349.772	.961	.966	1.000	5.863	2.328	14.505	1.085

Note:
*p<0.05 and **p<0.01 (two-tailed).
[a]In millions of U.S. dollars.
[b]In thousands of employees.
[c]In years

Table 2.4. Correlations and Descriptive Statistics

Variables	Model 1	Model 2	Model 3a	Model 3b	Model 4a	Model 4b
Intercept	-2.657 (3.889)	-3.222 (3.308)	-2.160 (4.952)	-4.252 (3.779)	-7.256 (4.693)	-4.949 (4.482)
Lagged Firm Risks	-0.127*** (0.023)	-0.120*** (0.019)	-0.137*** (0.006)	-0.131 *** (0.005)	-0.121*** (0.008)	-0.125*** (0.008)
Firm Size	-6.715*** (0.990)	-6.335*** (0.778)	-5.357*** (0.597)	-5.389*** (0.491)	-5.210*** (0.640)	-5.117*** (0.641)
Firm Age	-1.439 (2.182)	-7.852^{+} (4.567)	-3.561 (3.810)	-2.278 (3.058)	-6.342 (5.154)	-5.553 (5.091)
Firm Leverage	7.481*** (0.390)	7.213*** (0.327)	7.224*** (0.255)	7.654*** (0.180)	7.254*** (0.215)	7.253*** (0.224)
Industry Size	-2.184* (0.997)	-1.473 (1.027)	-1.002 (0.844)	-2.235** (0.809)	-2.723* (1.241)	-2.881* (1.236)
R&D Investments		0.023* (0.010)	0.001 (0.009)	0.107* (0.044)	0.019* (0.009)	0.023* (0.009)
Lagged R&D Investments		0.048*** (0.010)	0.027** (0.010)	0.300*** (0.054)	0.048*** (0.009)	0.050*** (0.009)
Operational Efficiency			-2.713*** (0.557)	-3.180*** (0.526)		
Lagged Operational Efficiency			-1.040* (0.503)	-0.989* (0.481)		
R&D Investments × Operational Efficiency				-0.196** (0.067)		
Lagged R&D Investments × Lagged Operational Efficiency				-0.356*** (0.067)		
Quality Management Initiatives					-0.175* (0.082)	-0.165* (0.080)
R&D Investments × Quality Management Initiatives						-4.068*** (0.312)
Lagged R&D Investments × Quality Management Initiatives						-3.438*** (0.088)
Year Dummies	Included	Included	Included	Included	Included	Included
Industry Dummies	Included	Included	Included	Included	Included	Included
Number of Observations	3920	3920	3920	3920	3920	3920
Wald Chi-square	538.72***	792.67***	3124.92***	9420.27***	3375.49***	6444.87***
Sargan Statistics	p=0.40	p=0.40	p=0.35	p=0.37	p=0.32	p=0.38
AR(1)	p<0.01	p <0.01	p<0.01	p<0.01	p<0.01	p<0.01
AR(2)	p=0.78	p=0.67	p=0.80	p=0.82	p=0.85	p=0.79

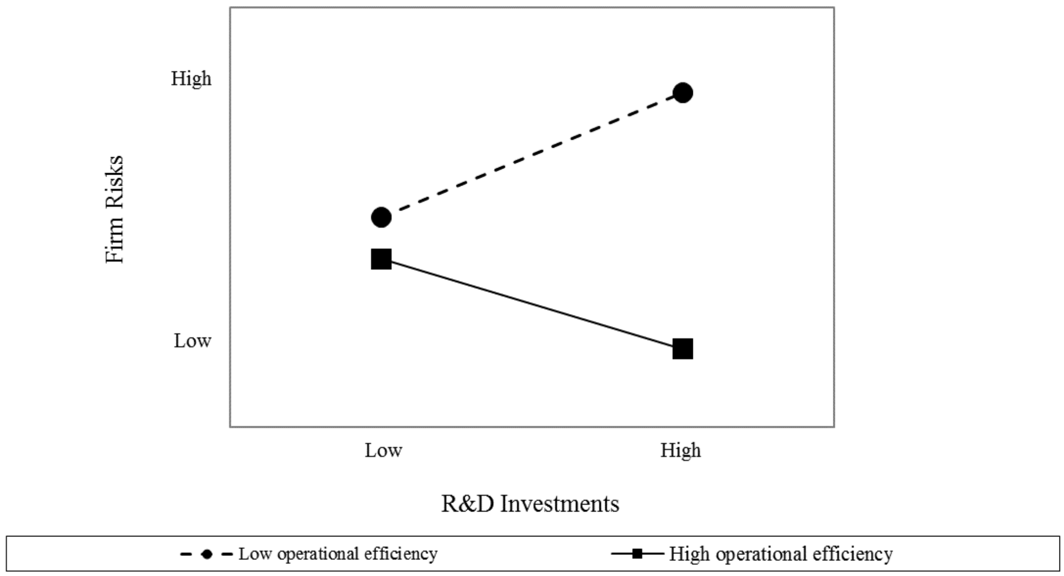
Notes:
$^{+}p<0.1$, $*p<0.05$, $**p<0.01$, and $***p<0.001$ (two-tailed tests); Standard deviation in parentheses.

Table 2.5. System GMM Estimator for Firm Risks with an Interaction of Operational Efficiency or Quality Management Initiatives

Variables	Model 2	Model 3a	Model 3b	Model 4a	Model 4b
R&D Investments	0.023* (0.010)				
Lagged R&D Investments	0.048*** (0.010)				
Operational Efficiency		-2.713*** (0.557)			
Lagged Operational Efficiency		-1.040* (0.503)			
R&D Investments × Operational Efficiency			-0.196** (0.067)		
Lagged R&D Investments × Lagged Operational Efficiency			-0.356*** (0.067)		
Quality Management Initiatives				-0.175* (0.082)	
R&D Investments × Quality Management Initiatives					-4.068*** (0.312)
Lagged R&D Investments × Quality Management Initiatives					-3.438*** (0.088)
Cumulative impact for years *t* and *t*-1 on firm risks	**0.071*** (0.017)**	**-3.753*** (0.825)**	**-0.552*** (0.120)**	**-0.175* (0.082)**	**-7.506*** (0.325)**

Notes:
^{+}p<0.1, *p<0.05, **p<0.01, and ***p<0.001 (two-tailed tests); Standard deviation in parentheses.

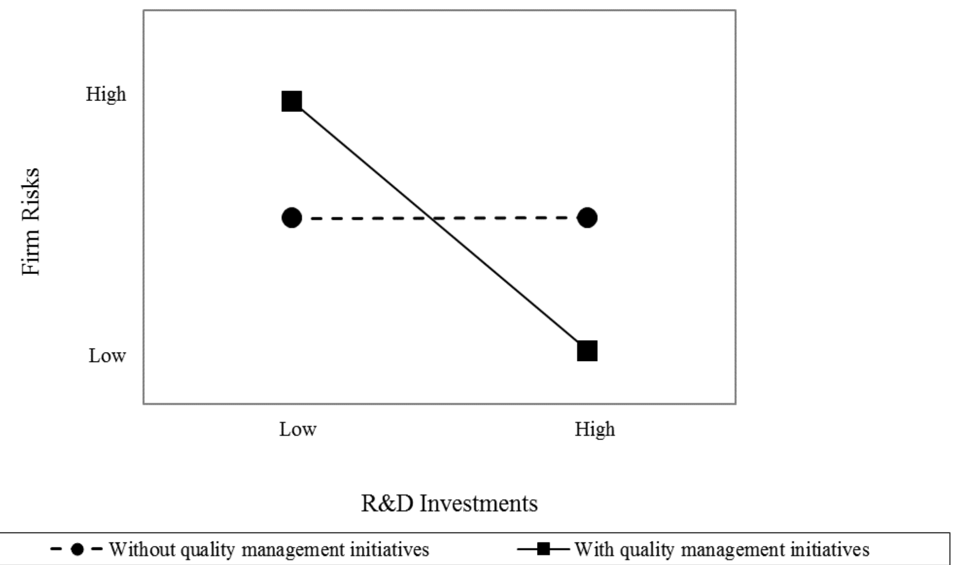
Table 2.6. Cumulative Impacts for Years *t* and *t*-1 on Firm Risks



Gradient of slope for low operational efficiency	**0.072***** **(7.135)**
Gradient of slope for high operational efficiency	**-0.052***** **(-5.543)**

Notes:
^{+}p<0.1, **p*<0.05, ***p*<0.01 and ****p*<0.001 (two-tailed tests);
t-statistics in parentheses.

Figure 2.4. Moderation Effect of R&D Investments on Firm Risks at Low and High Levels of Operational Efficiency



Gradient of slope for no quality management initiatives	**0.005** **(1.039)**
Gradient of slope for quality management initiatives	**-7.213*** ** **(-10.601)**

Notes:
$^{+}p<0.1$, $^{*}p<0.05$, $^{**}p<0.01$ and $^{***}p<0.001$ (two-tailed tests);
t-statistics in parentheses.

Figure 2.5. Moderation Effect of R&D Investments on Firm Risks by Quality Management Initiatives

2.5. Discussions and Conclusions

Our results show that although R&D investments significantly lead to the financial risks of firms, the actual impact also depends on firms' operational efficiency and quality management initiatives. Firms with higher operational efficiency or using Six Sigma have significantly lower financial risks among the firms associated with R&D investments.

Specifically, our results show that high operational efficiency alleviates firm risks associated with R&D. As illustrated in Figure 2.1, we observe that firms that simultaneously possess high operational efficiency and significantly invest in R&D investments actually have lower risks. However, a significant negative relationship exists between R&D investments and firm risks when firms' operational efficiency is low. It might indicate that a firm with high operational efficiency has more stable operating routines to carry out repeated tasks. Higher adaptability is a result as firms learn tacit knowledge of individuals to improve the existing routines or produce a new routine. As such, operating routines of the firm with high operational efficiency seem to be more dynamic, facilitating discovery and exploratory activities in product innovation and making the R&D process more manageable.

Additionally, our results show that quality management initiatives such as Six Sigma helps mitigate firm risks associated with R&D investments. Figure 2.2 shows how quality management initiatives alleviate firm risks of R&D investments. Such risks are generally lower when firms employ quality management practices than firms do not. These findings might indicate that a firm with Six Sigma is more likely to have developed systematic, structured practice in problem solving, minimizing errors, and variations in R&D processes.

In particular, our findings on financial risks of firms highlight the interactions of R&D investments and operational efficiency or quality management initiatives. The figures illustrate that the lowest financial risk of firms in the context of product innovation is achieved when investments in R&D and operational efficiency are both at high levels. Likewise, high R&D investments together with quality management initiatives lead to lower financial risks for firms. High operational efficiency or quality management initiatives might not only enhance the evolution of operating routines and shape dynamic capabilities, but also contribute to “organizational renewal” (Danneels, 2002) through the interaction with R&D investments. Organizational renewal is a firm’s evolutionary process, involving the development and improvement of product innovation and organizational capabilities such as operational capability and quality improvement capability, thereby making changes in a firm’s core competencies (e.g., Burgelman, 1991; Floyd and Lane, 2000; Huff et al., 1992). This is particularly important in a dynamic environment in which an ongoing renewal of organizational core competencies nourishes adaptability and flexibility, which are necessary for firms to manage uncertainty in product innovation (Cooper and Smith, 1992; Danneels, 2002). Thus, a firm with higher capacity to maintain continuous renewal of its core competencies is more likely to gain higher adaptability and flexibility in R&D to minimize financial risks.

2.5.1. Theoretical Implications

Instead of examining the financial returns and market competitiveness of R&D investments, we focus on the hidden costs to firms associated with R&D. Our results evidence that R&D is a risk-taking activity with significant financial risks for firms. Yet risks arising from R&D have often been overlooked in previous research, and thus very few have explored possible means to mitigate such risks.

This study demonstrates that operational efficiency and quality management initiatives can help reduce firm risks from R&D investments. We extend understanding of operational efficiency into the routine-based view in operational capability and consider that the improvements in operational efficiency depend on how well a firm enhances each operating routine through learning to produce business outputs from resources. We also argue that quality management practices promote organizational learning through identifying, measuring, analyzing, and rectifying root causes of problems repeatedly in pursuit of continuous improvement. Throughout the routine-based process of operations and quality management practices, a firm accumulates experience and knowledge in problem solving over the time; thereby, its performance becomes more stable and predictable. We take the learning perspective for operational efficiency improvements and quality management initiatives, and our argument is developed based on Zollo and Winter's (2002) learning mechanisms in organizations. The learning mechanisms include experience accumulation, knowledge articulation, and knowledge codification. The authors specifically pointed out that the accumulation process of experience with the deliberate learning process in knowledge articulation and codification directly enhances the evolution of operating routines and facilitates the development of dynamic capabilities for firms. Accordingly, we argue that operational efficiency improvements and quality management practices exhibit the three learning mechanisms, and firms' investments in operational efficiency improvements and quality management initiatives are proactive organizational efforts in deliberate learning. Firms explore more opportunities through articulating tacit knowledge of individuals and the organization, which facilitates incremental improvements and provides a dynamic capability to firms. We demonstrate that financial risks associated with R&D are reduced if firms simultaneously invest in R&D and improve operational efficiency or adopt quality management initiatives. Therefore, our results challenge the dominant view (e.g., Benner and Tushman, 2002, 2003) that operational efficiency and quality management practices are static routines or exploitative activities (March, 1991). We contribute to the theory by demonstrating that exploration and exploitation are not competing or mutually exclusive. Instead, exploration and exploitation reinforce each other to mitigate firm risks, leading to lower financial uncertainties of R&D investments.

Additionally, our study sheds light on the interaction between high R&D investments and operational efficiency or quality management. High R&D investments without substantial operational efficiency improvements or quality management initiatives might lead to high-cost explorations that create hurdles to firms in implementing novel ideas. Meanwhile, high efforts in operational efficiency improvements or quality management initiatives without high R&D investments might result in a competency trap and organizational inertia to reduce innovation performance. We extend our understanding of the interactions of high R&D investments, operational efficiency, or quality management and see them as a firm's evolutionary processes (i.e., organizational renewal; Danneels, 2002), making firms more adaptable and flexible. Overall, our study contributes to theory by providing a dynamic perspective to operational efficiency improvements and quality management practices.

2.5.2. Managerial Implications

Our analysis has significant practical implications for firms investing in product development. We show that R&D investments cause significant firm risks, yet such risks are alleviated through the firms' efforts to improve operational efficiency and initiate quality management practices. Even though the improvements in efficiency and quality are generally recognized as a way to eliminate and rectify problems in operating processes, their value in risks reduction is less explored. Specifically, firms with greater efforts spend to improve operational efficiency might encounter lower risks associated with R&D. Likewise, firms that employ quality management to handle tasks for product developments have lower risks than firms without adopted quality management practices. Having an effective risk-reduction strategy in the product innovation process might depend on the interaction effects of R&D investments with organizational efforts in operational efficiency improvements or quality management initiatives, rather than on developing each of them individually. For example, a firm with high innovation can achieve the first-mover advantage, attractive financial returns, and new market segments by launching novel products frequently. Nevertheless, it might suffer a huge, irreversible loss of what it earned due to operational issues such as resource misallocation, quality defects, or schedule delays if it lacks operational efficiency or quality management techniques with its R&D activity. Thus, we suggest firms simultaneously invested in R&D with operational efficiency or quality management.

2.5.3. Conclusions

Effectively managing and mitigating the risks associated with the R&D process is essential. Yet the extant literature has paid little attention to the potential risks in product developments, and the important roles of operational improvements and quality management initiatives in reducing firm risks from R&D investments. Based on the data from the U.S. manufacturing firms with investments in R&D, we construct the distributed lag model to capture the current-year and 1-year lag effects of R&D investments on firm risks. Using the system GMM estimator with the 1-year lag, we find a significant impact of R&D investments on firm risks. Nevertheless, such R&D-

related firm risks are reversed when firms have high operational efficiency. Firm risks associated with R&D are also alleviated when firms implement quality management practices. Also, firms that spend simultaneous high efforts on R&D and operational improvements reduce firm risks to a greater extent. Similar interaction outcomes occur when firms invest in R&D and adopt quality management practices at the same time.

Moreover, our results extend the understanding of organizational exploration and exploitation. Previous studies have commonly viewed exploration and exploitation as conflicting activities. Instead, our analysis supports the interaction between exploratory R&D activities and exploitative improvement activities of process management. Such interactive effect effectively alleviates firm risks associated with R&D.

CHAPTER THREE

STUDY 2:

RISKS AND RETURNS OF BUSINESS INTELLIGENCE SYSTEMS: A KNOWLEDGE-BASED PERSPECTIVE

3.1. Theoretical Background and Hypotheses Development

3.1.1. The Knowledge-Based View of Firms

The knowledge-based view (KBV) of the firm considers organizational knowledge as a strategic asset (Nonaka and Takeuchi, 1995). A firm's heterogeneous knowledge base and its ability to use such knowledge in operations and produce new knowledge are the critical sources of a firm's sustainable competitive advantage (Pemberton and Stonehouse, 2000; Ranft and Lord, 2002). In this regard, a firm as a knowledge-creating entity exists by means of its effective use of knowledge (Rebolledo and Nollet, 2011). As such, appropriate processes need to be in place in a firm to create and transfer knowledge. Yet not every single process can effectuate valuable knowledge, so the recent advancement of business intelligence (BI) systems could provide a firm a great opportunity in the use and creation of knowledge to gain inimitable resources.

BI systems refer to an integrated set of tools, technologies, and software used to collect and explore massive amounts of data originating from a firm's different sources to integrate, aggregate, and multidimensionally analyze data into one coherent body of knowledge (Bose, 2009; Popovič et al., 2012; Trieu, 2017). Accordingly, data are viewed as highly valuable organizational resources (Wang and Wang, 2008). A firm can make use of BI systems to analyze general economic and market trends as well as internal operations and productions. Through BI systems, meaningful information is available in the right place, at the right time, and in the right format help users make their decisions and to guide their actions (Negash and Gray, 2008). Even though adopting BI systems is a complex activity requiring appropriate organizational structures, resources, data quality, comprehensive training, and engagement of stakeholders over a long period of time (Fuchs, 2006; Li et al., 2013; Moss and Atre, 2003), proponents believe that BI systems leverage information assets to facilitate a firms' making more informed decisions and significantly improve its strategic intelligence and risk management capability (e.g., Agarwal and Dhar, 2014; Yeoh and Koronios, 2010). In this study, we use the KBV for the competitive outcome of BI systems.

3.1.2. A Social Capital View on Information Disseminations

The social capital theory states that social capital is a valuable asset that results from accessing a set of resources through a network of relationships possessed by an individual or a social unit and is identified as a synthesis of three dimensions: structural, relational and cognitive (Nahapiet and Ghoshal, 1998). First, the structural dimension of social capital refers to the pattern of connections among actors. It also can be viewed as social ties (Inkpen and Tsang, 2005), which are the foundation of connecting social capital and act as the conduits to nurture social capital transactions (Adler and Kwon, 2002). Because valuable information is potentially embedded in the social ties (Coleman, 1993), more social interaction will enhance a firm's ability to assimilate and absorb knowledge (Nahapiet and Ghoshal, 1998). Second, the relational dimension of social capital focuses on the strength of personal relationships that actors build with each other over time (Nahapiet and Ghoshal, 1998). The key facet of this dimension is trust (Leana and Van Buren, 1999; Nahapiet and Ghoshal, 1998). Through repeated interactions, trust develops and contributes to knowledge exchange among actors. Third, the cognitive dimension of social capital refers to the perceptions of actors as they interact with one another as a team.

Good social relationships among stakeholders help initiate a common set of goals, sharing values and visions of the firm (Inkpen and Tsang, 2005; Nahapiet and Ghoshal, 1998). Each of these dimensions of social capital is likely to enhance social interactions, facilitating knowledge transfer and knowledge diffusion. According to Leana and Pil (2006), the structural, relational, and cognitive dimensions of social capital form together the internal social capital, which refers to the structure and the nature of the relationship among actors within a firm, while the external social capital focuses on the bonding between a firm and its key external resources providers. Considering the importance of social capital, the ties connecting a firm with its internal stakeholders such as employees and external stakeholders mainly as customers are critical assets for realizing the advantages of BI systems, as we will discuss later.

3.1.3. The 4I Model of Organizational Learning on Process Institutionalization

The 4I model of organizational learning (Crossan et al., 1999) consists of four recursive processes: intuiting, interpreting, integrating, and institutionalizing within individual, group, and organizational levels. Intuiting is a preconscious process allowing individuals to identify patterns and possibilities inherent in their personal experiences in order to spark of creative ideas (Crossan et al., 1999; Weick, 1995). Interpreting is a process for communicating ideas and insights in groups, resulting in common language and agreement (Crossan et al., 1999). Integrating is a process to actualize the ideas through coordination and shared practices, and eventually create recurring actions at the organizational level (Crossan et al., 1999). Institutionalizing refers to the process of embedding the learning experiences of individuals and groups into organizational systems, structures, policies, and routines. Process institutionalization enables a firm to stabilize its activities and to facilitate its knowledge assimilation and knowledge exploitation (Crossan et al., 1999; Simon, 1991; Simons, 1994). In this study, we consider ISO 9000 certifications as a process institutionalization of a firm. The ISO 9000 quality standard is based on the quality management principles that focus on leadership, employee participation, and a process approach. The ISO 9000 certifications require defining and planning the production processes. This is supported by documentations and internal and external audits to ensure that routines occur throughout the firm to pursue constantly improving quality (Naveh et al., 2004).

3.1.4. Business Intelligence Systems and Operational Efficiency

BI systems can be considered as an integral part of knowledge management (KM), with the intent to support decision-making by using a data warehouse, data mining, and online analytical procession (OLAP) technology. BI systems retrieve vast quantities of internal and external data that are extracted and transformed by the transactional systems from various sources. Then relevant data are transferred to the repository for multidimensional analysis, validation, and consolidation (Trkman et al., 2010). BI shortens the time needed for transforming data to information; hence, organizational members gain more timely access to operational data. It helps executives to make decisions based on a strong foundation of fact and to identify factors that critically affect their business. Through BI analysis, new knowledge is generated to fit the decision-making purpose, maximizing the value of information and knowledge assets (Curko et al., 2007; Rao and Kumar, 2011). Particularly, knowledge is a fundamental resource to develop a firm's operational efficiency to leverage organizational resources into operating outcomes and to sustain competitive advantage (Grant, 1996a; Miller and Roth, 1994; Roth and Jackson III, 1995; Tippins and Sohi, 2003). A firm with BI systems can help managers understand their business operations in many aspects and help identify factors to improve resource allocation so as to make decisions in a more reliable way, leading to improved effectiveness and stronger operational efficiency. Thus, we propose the first hypothesis.

H1. *The adoption of BI systems leads to higher operational efficiency.*

3.1.5. Business Intelligence Systems and Firm Risks

Risks are an essential aspect of management decision-making (Ruefli et al., 1999). Higher risks, as implied by increased volatility in profits, signal that a firm may undergo a weak and uncertain cash flow in the future (Luo and Bhattacharya, 2009). As such, a firm survives by means of its effective risk-management practice (Olson and Wu, 2010). Risk management involves identification, analysis, and uncertainty mitigation in decision-making (Wu et al., 2014). A firm adopts BI systems to its benefit by capturing tacit knowledge throughout all departments and employees, and also through the data mining and business analysis techniques of BI systems to detect an unfavorable condition, estimate operational risks, predict business performance, and manage the risk of internal frauds. BI systems are thus intended to aid risk alleviation and uncertainty prevention (Negash and Gray, 2008; Wu et al., 2014). Based on the updated and relevant knowledge, a firm can clearly understand its position in the competition and accurately take appropriate actions to alleviate risks, and executives make more data-driven and fact-based decisions rather than intuitive decisions, enhancing the quality of decisions and reducing associated risks. Accordingly, we propose the second hypothesis.

H2. *The adoption of BI systems leads to lower firm risks (i.e., lower volatility in returns).*

3.1.6. The Moderating Effect of Stakeholder Relationships

Mastering the integration of BI systems into business operations is challenging. Perhaps BI systems by themselves are also not enough to enhance operational efficiency and to alleviate risks unless a firm knows how to incorporate the data from social context into BI systems. A learning organization strives to create new knowledge by using BI systems, but this often involves problems in obtaining and combining internal and external information (Inkpen and Tsang, 2005). Accordingly, substantial numbers of reliable internal and external data sources are imperative for the successful adoption of BI systems at all organizational levels. Yet embarking on a BI initiative changes the way organizational members use and access information, and this requires a culture of open communication (Williams and Williams, 2010). Accordingly, the firm is required to engage in knowledge exchange activities between various parties and social communities (Boland and Tenkasi, 1995; Liebeskind et al., 1996). Thus, stakeholder relationships set the stage for a successful BI systems adoption (Williams and Williams, 2010).

Social capital resources are inherently embedded in social relations (Putnam, 1995; Wasko and Faraj, 2005) that have a strong effect on the extent to which interpersonal information sharing and knowledge exchange occur (Chiu et al., 2006; Nahapiet and

Ghoshal, 1998). Social capital also refers to the individual's ability to secure information and benefits through participation in community networks (Inkpen and Tsang, 2005; Portes, 1998). As such, an effective management of the stakeholder groups enables a firm to gain access to privileged information, to discover precious business opportunities, and to form prudent decisions with better information at hand (Inkpen and Tsang, 2005; Sinkula et al., 1997). Superior stakeholder relationships are more likely to elevate individual active sharing and to increase the depth, breadth, and quality of mutual information exchange (Chiu et al., 2006). Hence, we propose the following hypotheses.

H3a. *The positive impact of BI systems on operational efficiency is strengthened through superior stakeholder relationships.*

H3b. *The positive impact of BI systems on reducing firm risks is strengthened through superior stakeholder relationships.*

3.1.7. The Moderating Effect of Process Institutionalization

Successfully adopting BI systems requires rationalizing, coordinating, and stabilizing organizational routines to increase efficiency and to have better business information integration in daily operations and strategy (Grant, 1996b). Routines are supported by defined tasks, specified actions, and effective organizational mechanisms. Institutionalizing is the process of embedding organizational structures, systems, policies, and procedures and ensuring that routines are formed (e.g., Crossan et al., 1999; Lam, 2000). Routines and rules play vital roles in firm survival and prosperity (Crossan et al., 1999; Eisenhardt and Martin, 2000). A firm with formal processes and standard procedures is more likely to sift through the vast amounts of information and make them valuable when the relevant information is included in the formal documentation, providing operations guidelines to ensure objectives and quality goals are met (Daft and Lengel, 1983; Singh et al., 2011). Likewise, a rationalized firm is more likely to assimilate BI systems into its organizational fabrics to support the information flow (Feldman and March, 1981; Huber, 1990).

ISO 9000-certified firms are especially advantageous in integrating BI systems throughout the organization. First, the ISO 9000 series is based on the set of quality management principles that emphasize leadership, employee engagement, and a process approach for continuous improvement. The certification process is supported by a detailed review and documentation of the organizational routines, internal assessments, and accredited third-party audits (Guler et al., 2002; Naveh et al., 2004). Second, the implementation of ISO 9000 involves knowledge codification to enhance the transfer and accumulation of knowledge within a firm (Bénézech et al., 2001; Curkovic and Sroufe, 2007) and facilitates the management information system assimilation process (Yoo et al., 2006). Such a process institutionalization ensures the process of embedding BI systems in organizational structures and systems, thereby structuring the information flow and the use of knowledge. Over time, firms adapt to their routines embedded with BI systems for the creation of new knowledge through learning and knowledge sharing to steer and to improve organizational activities (Crossan et al., 1999). As a result, we propose the following hypotheses.

H4a. *The positive impact of BI systems on operational efficiency is strengthened in ISO 9000-certified firms.*

H4b. *The positive impact of BI systems on reducing firm risks is strengthened in ISO 9000-certified firms.*

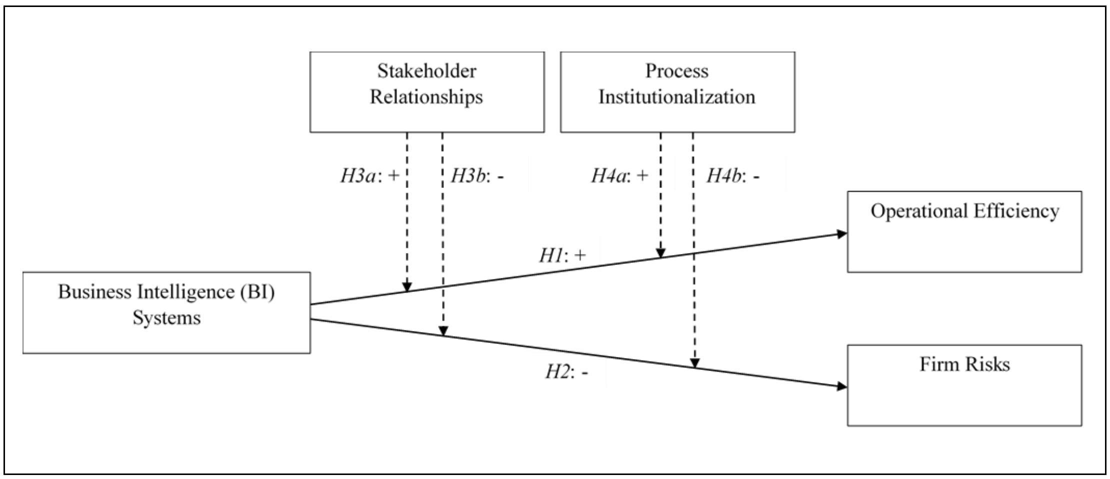


Figure 3.1. Conceptual Framework for Research Model of BI Systems

3.2. Methodology

3.2.1. Sample and Data Collection

In this study, we focused on manufacturing firms listed in the U.S. (SIC code: 2000-3999) as they are considered to be pioneers in the adoption of BI systems (Chen et al., 2012). We sampled a period of ten years from 2005-2014. The Internet technology became more matured in terms of its speed, functions, and contents since the early 2000s (Chen et al., 2012), making the development of BI systems more powerful. For example, with fast Internet access, many BI systems allow firms to carry out text and web analytics for both structured and unstructured contents (Chen et al., 2012). Through text and web-mining in BI systems, an immense amount of information related to industry, products, and customers from the Internet can be gathered, organized, and visualized by firms. In addition, with the rising importance of knowledge assets, BI systems were well-accepted in the market during our research period (Teo et al., 2016).

To identify firms that have adopted BI systems, we focused on the major global BI solution providers. According to Gartner Inc., the world's leading information technology research and advisory body, the major providers of BI systems are SAP, Oracle, SAS, Cognos, QlikTech, MicroStrategy, Business Objects, Hyperion, Microsoft, IBM, Tableau, Information Builders, and Tibco Spotfire. These 13 firms are primary providers of comprehensive BI systems and occupy nearly two-thirds of the BI solutions and tools market (Sallam et al., 2011; Teo et al., 2016). Another one-third of the market is taken by over thousands of small BI solution providers (Forrester, 2014). These small players are very unlikely to be a major BI vendor of our sample firms, which are all large and stock-listed firms. In fact, almost 90% of our sample firms selected the top five BI solution providers out of the 13 vendors listed above, showing that the market is highly concentrated and they are very unlikely to select small BI solution providers.

Similar to the prior studies on BI systems (Elbashir et al., 2008; Rubin and Rubin, 2013; Teo et al., 2016), we identified the firms that have adopted BI systems through the names of major BI solution providers. Specifically, we searched for news announcements containing the names of major BI solution providers together with the names of the U.S.-listed manufacturing firms, and keywords such as "business intelligence systems" or "BI systems" in conjunction with "adoption", "introduce", or "implementation" through publicly available articles in the Factiva database. Factiva combines the *Dow Jones Interactive* and *Reuters Business Briefing* databases, providing an extensive coverage of the news from leading business resources such as the *Wall Street Journal* and *New York Times* (Gnyawali et al., 2010; Jiang et al., 2006). Through the articles, we identified the time of BI systems adoption.

We focused on the first announcement of BI systems adoption to avoid overlapping effects that could bias our statistical tests (e.g., Corbett et al., 2005; Hendricks and Singhal, 2008; Naveh and Marcus, 2005). Additionally, we eliminated announcements that are irrelevant to the adoption of BI systems within a firm such as product launches by the BI service providers and other confounding events such as mergers and the acquisition of another firm to develop in-house BI systems, and the executive appointments for initiating BI projects. To ensure data quality, each announcement was reviewed and verified independently by three members of our research team. We had 301 sample firms had at least one announcement about the adoption of BI systems from 2005-2014.

There are two stages of BI systems implementation. The first stage, *BI software installation*, is normally conducted right after a firm enters a contract with a BI solution provider. It involves the installation of BI software and components, the development of prototypes, and the merging of data from separate systems (Gangadharan and Swami, 2004; Zeng et al., 2006). In the second stage, *BI adoption*, the firm must provide extensive user training and adjust the system to facilitate users' acceptance (Gangadharan and Swami, 2004; Olexova, 2014; Zeng et al., 2006) to put the BI system in operations. Normally, firms make the related announcements on the second stage when they successfully adopted the BI system. On average, it takes about 6-18 months with an average of about a year for the full adoption of a BI system in daily operations (Horakova and Skalska, 2013; Olexova, 2014; Zeng et al., 2006). Previous studies suggested that a full adoption of information technology applications such as ERP, expert systems, and BI systems involves systems implementation and integration, information gathering, and user training (Agarwal and Prasad, 1997; Hunton, 2002; Sujitparapitaya et al., 2012). Accordingly, a full adoption of BI systems in this study refers to a firm that has completely implemented and integrated BI applications with its existing systems, as well as trained users in every functional business area who can access information through BI systems for decision-making to create a competitive advantage for the firms.

In this study, we take the time of full BI adoption (i.e., the second stage) as year *t*. One year immediately prior to the full adoption of a BI system (i.e., the software installation stage) is taken as year *t*-1. We consider two years preceding the adoption of a BI system (year *t*-2) as the base year to determine the control group as firms should be free from the impact of the BI system at *t*-2. Overall, we examined the abnormal operational efficiency and abnormal firm risks from years *t*-2 to *t*+1, which is the year after full BI adoption. Table 3.1. lists some examples of the announcements.

Announcement 1	
Company Name	Natus Medical Incorporated (NASDAQ: BABY)
Announced on	14 January 2013
Text extracted from Factiva	Working with NTT DATA, a Platinum level member in Oracle PartnerNetwork, and leverage out-of-box, industry-specific Oracle Business Accelerators, Natus implemented the Oracle E-Business Suite 12.1, including Oracle Advanced Supply Chain Planning, Oracle's Demantra, Oracle E-Business Suite Financials, … and Oracle Service Management. Natus also implemented Oracle Customer Relationship Management, … and Oracle Business Intelligence in aggressive 10-month implementation timeframe. With this integrated suite of Oracle Applications, Natus has been able to significantly reduce end of month reporting times, effectively meet increasing customer demand and establish a flexible and scalable platform to support future growth.
Announcement 2	
Company Name	Campbell Soup Company (NYSE: CPB)
Announced on	21 May 2007
Text extracted from Factiva	QlikTech, the world's leading provider of memory analysis and reporting solutions, announced today that Campbell Soup Company is using QlikView, its flagship business intelligence software solution to improve its supply chain management. "QlikView's analytical power and simplicity enable our employees to more easily access critical information from disparate sources at a moment notice," said Michael Mastroianni, vice president of North American planning, reliability and operations for Campbell's. In order to streamline operations and increase production efficiency, QlikTech and Terra Technology provide Campbell with the necessary tools to improve inventory analysis management and projections, sales and long-term forecasting analysis, demand planning, schedule compliance, transportation and warehouse scheduling. Today, members of the company's plant production, finance, and logistics departments use QlikView to make educated business decisions on a daily basis.
Announcement 3	
Company Name	Regal Beloit (NYSE: RBC)
Announced on	9 December 2008
Text extracted from Factiva	Regal Beloit Corporation, a leading manufacturer of electrical and mechanical motion control products serving markets throughout the world, has deployed Oracle Business Intelligence Applications to improve visibility into business operations and enhance decision-making enterprise wide. Oracle announced today.

Table 3.1. Examples of the Announcements about the Adoption of BI Systems

Table 3.2 presents the distribution of sample firms based on the 2-digit SIC codes. Most sample firms are from the chemicals, instruments, industrial machinery, and electronics industries. Table 3.3 presents the distribution of the sample firms based on the adoption year of a BI system. During this sample period, most firms adopted a BI system in early years between 2005 and 2007 and the figure remained stable after that. One plausible explanation could be referred to Gartner (Goasduff, 2015). Many recent BI projects involving more comprehensive, advanced BI software and components failed to go beyond the pilot test and experimentation, and eventually were abandoned to minimize the investment lost. Gartner further explained that firms select a right BI tool that is essential but not enough to achieve a successful adoption of BI systems. Firms need to change their cultures and enhance users' acceptance to accommodate a BI systems assimilation process into operations. Some studies also mentioned that many BI systems cannot be adopted throughout a firm after the implementation stage due to inadequate user training and internal communication (Olexova, 2014; Zeng et al., 2006).

2-Digit SIC codes	Industries	Number	Percentage of sample
28	Chemicals and allied products	56	18.60
38	Instruments and related products	50	16.61
35	Industrial machinery and equipment	47	15.61
36	Electronic and other electric equipment	46	15.28
20	Food and kindred products	18	5.98
37	Transportation equipment	17	5.65
23	Apparel and other textile products	8	2.66
25	Furniture and fixtures	8	2.66
30	Rubber and miscellaneous plastics products	8	2.66
33	Primary metal industries	7	2.33
27	Printing and publishing	6	1.99
34	Fabricated metal products	6	1.99
29	Petroleum and coal products	4	1.33
39	Miscellaneous manufacturing industries	3	1.00
Others	Other industries	17	5.65
Total		301	100

Table 3.2. The Distribution of Sample Firms Across Industries

Year	Number of BI Systems Adoption	Percentage
2005	59	19.60
2006	56	18.61
2007	45	14.95
2008	29	9.63
2009	27	8.97
2010	17	5.65
2011	17	5.65
2012	17	5.65
2013	19	6.31
2014	15	4.98
Total	301	100.00

Table 3.3. The Distribution of Sample Firms by the Adoption Year of BI systems

After we identified sample firms that had a BI adoption announcement, then we matched each sample firm with a portfolio of comparable control firms by performing the propensity score matching (PSM) method. (Please refer to 3.2.3. Propensity Scores Matching Method). Some observed factors i.e., pretreatment covariates in the PSM at 2-year prior to BI systems adoption were used in the matching. After eliminating the firms without sufficient information for the measures of covariates, the final sample consisted of 282 firms to match a control firm. We obtained data for operational efficiency and firm-risks measures from the Standard and Poor's COMPUSTAT for conducting the event study analysis (Please refer to 3.2.4. Event Study Methodology). We had a sample of 270 pairs for abnormal operational efficiency and 229 pairs for abnormal firm risks. We have fewer sample firms in analyzing firm risks as the measurement of firm risks involves the financial data over a continuous five-year period as stated in 3.2.2. Measurements.

Lastly, we collected ISO 9000 registration data through the *Quality Digest*, *Who's Registered*, and the *IAAR Directory of Registered Companies*, which are the most comprehensive databases on ISO 9000-certified firms (Anderson et al., 1999; Yeung et al., 2011). We used data from KLD, to construct the stakeholder relationships measure. The database covers approximately 1,100 publicly traded firms listed on the S&P 500, Domini 400 Social Index, Russell 1,000 Index, and KLD Large Cap Social Indexes (McPeak and Dai, 2011; Wong et al., 2011). To eliminate bias on particular interests, the KLD rating is based on multiple sources such as public documents SEC filings, annual reports of firms, press releases, reports from research partners, and information from the government (Entine, 2003; Wong et al., 2011). The KLD rating has been broadly applied, and its validity and reliability have been well established in prior research (e.g., Choi and Wang, 2009; Wong et al., 2011). Overall, the KLD rating is considered to be a comprehensive measure of stakeholder relationships (Agle et al., 1999; Choi and Wang, 2009). The final sample sizes were 141 and 123 for operational efficiency and firm risks, respectively.

3.2.2. Measurements

Operational efficiency. Operational efficiency is the relative efficiency of a firm regarding its ability to convert organizational resources into business outputs in comparison with its industry peers (Peng et al., 2008; Swink and Harvey Hegarty, 1998). We used the stochastic frontier estimation (SFE) methodology to measure the operational efficiency, which reflects the transformative efficiency of a firm's resources, such as a number of employees, capital expenditure, and cost of goods sold into its operating income, and measured the efficiency of each firm relative to competitors in the same industry (Carmel and Sawyer, 1998; Dutta et al., 2005; Li et al., 2010).

Although most previous studies measured the operational efficiency using subjective survey measurements with the focus such as on efficiency in the delivery process (Banker et al., 2006; Roth and Jackson III, 1995) and using accounting data including inventory turnover and labor productivity (Huson and Nanda, 1995), the SFE is a better approach from the traditional OM perspective to measure a firm's operational efficiency regarding the transformative framework from various operational inputs into operational output. The SFE methodology also enables us to compare a firm's operational efficiency with competitors in the same industry, whereas the measurements based on surveys and accounting figures lack of explanatory power on industry heterogeneity (Eroglu and Hofer, 2011). Additionally, the SFE methodology incorporates a composite error term composed of random effects and pure inefficiency (Aigner et al., 1977). It can isolate any influences from random factors other than inefficient behavior to prevent possible upward bias of inefficiency from the deterministic methods (Vandaie and Zaheer, 2014). Thus, we used the operations frontier function in equation (3.1) to model the output operating income by operational inputs, including a number of employees, capital expenditure, and cost of goods sold.

$$\begin{aligned}\ln(\text{Operating Income})_{ijt} = \beta_0 &+ \beta_1 \ln(\text{Number of Employees})_{ijt} \\ &+ \beta_2 \ln(\text{Capital Expenditure})_{ijt} \\ &+ \beta_3 \ln(\text{Cost of Goods Sold})_{ijt} + \varepsilon_{ijt} - \gamma_{ijt} \qquad (3.1)\end{aligned}$$

where ε_{ijt} is the purely stochastic random error term affecting operating income and γ_{ijt} captures the operational inefficiency of a firm i in industry j (2-digit SIC codes) in year t. γ_{ijt} ranges from 0 to 1, with 0 meaning no operational inefficiency relative to the industry. Thus, γ_{ijt} is a relative measure to indicate how inefficient a firm is in comparison with a corresponding frontier in the same industry and in the same year. The composite error term, $(\varepsilon_{ijt} - \gamma_{ijt})$, is estimated based on the difference between the maximum achieved operating income in an industry and the observed operating income so as to obtain a consistent estimate of firm-specific operational inefficiency, $\hat{\gamma}_{ijt}$. Hence, the operational efficiency of a firm i in industry j in year t is

$$\text{Operating Efficiency}_{ijt} = (1 - \hat{\gamma}_{ijt}) \times 100\%. \tag{3.2}$$

Firm risks. Firm risks refer to the unpredictable variability of the financial returns that is volatility in profits (Merriman and Nam, 2015; Ruefli et al., 1999). We used the standard deviation of ROA over a five-year period to measure firm risks (Kim et al., 2011; Li et al., 2013). ROA is measured as the ratio of operating income before interest, taxes, and depreciation and amortization to total assets (Guthrie and Datta, 2008). Large volatility in profits indicates that a firm is more likely to experience uncertain cash flow (Luo and Bhattacharya, 2009).

Stakeholder relationships. We used the data from KLD to construct the stakeholder relationships measure and considered firms that have an effective management of stakeholder relationships by primarily focusing on the employee relations and customer relations (Luo et al., 2014). Based on previous studies, we used items from employee relations and diversity dimensions of the KLD data to measure the firm-employee relationship (Hillman and Keim, 2001). We used items from product dimension of the

KLD data to measure the firm-customer relationship (Luo et al., 2014). Each dimension in the KLD is tabulated in terms of a number of strengths and concerns. By subtracting the total number of concerns from the total numbers of strengths, we obtained a net score for each individual dimension (Choi and Wang, 2009). Furthermore, we standardized the KLD indices of concerns and strengths for each dimension to ensure the resulting scores across dimensions were directly comparable (Choi and Wang, 2009; Mattingly and Berman, 2006). Finally, we computed an aggregate measure of stakeholder relationships by the average of the standardized scores on each dimension with equal weights (Choi and Wang, 2009; Hillman and Keim, 2001; Luo et al., 2014).

Process institutionalization. We used ISO 9000 certification as a proxy for process institutionalization. This is because firms pursuing the ISO 9000 quality standard need to define and plan their operational processes with supporting documentation and audits to achieve constant process improvement (Naveh et al., 2004; Singh et al., 2011). ISO 9000 enables the institutionalization of organizational routines for management practices, audits, and reviews. Firms with ISO 9000 certifications are considered to have a high level of process institutionalization. We assigned 1 to firms with ISO 9000 certifications and 0 to firms without ISO 9000 certifications.

3.2.3. Propensity Scores Matching Method

In this study, we compare the performance of BI-adopting firms versus non-BI-adopting firms from two years before full adoption to one year after full adoption. One challenge of this study is the potential self-selection bias and endogeneity issues when we compare sample firms with control firms (Li and Prabhala, 2007) as the adoption of a BI system might be related to some endogenous, firm-specific factors. Nevertheless, these issues can largely be solved by applying the PSM method (e.g., Nanda and Ross, 2012).

The PSM technique is a statistical matching method broadly applied in various disciplines including economics and statistics (e.g., Dehejia and Wahba, 2002; Heckman et al., 1998). The PSM matches each sample firm to one or more control firms based on the individual propensity score. In this study, the treatment is the adoption of a BI system. The propensity score is a conditional probability that a firm would adopt a BI system given some observed covariates regarding firm characteristics (e.g., Austin, 2011; Dehejia and Wahba, 2002). Firms in the sample and the control groups with approximately equal propensity scores are more likely to have similar distributions based on the covariates. Thus, by identifying a number of covariates that might influence the BI adoption decision, we can obtain a propensity score to control the self-selection bias and the endogeneity concern (Conniffe et al., 2000; D'Agostino, 1998). Besides, the PSM technique is less restrictive on the distribution of data. It allows non-parametric relations among all the covariates to determine a firm would adopt a BI system (Nanda and Ross, 2012).

We conducted the PSM using one-to-one nearest neighbor matching based on individual propensity scores. This matching method pairs a sample firm to a control firm with the closest distance. First, we chose some pre-treatment covariates in year *t*-2 that might influence a firm to adopt a BI system. Because having too many covariates would affect the matching quality (Dehejia and Wahba, 2002), we selected a few major firm characteristics that are likely to co-vary with the adoption of BI systems. We included firm size, organizational slack, sales growth, labor productivity, leverage, and firm age in our model. Larger firms are more likely to adopt BI systems (Damanpour, 1991; Low et al., 2011) due to their financial strengths and resources. According to previous studies (e.g., Lawson, 2001), organizational slack is a buffer resource that allows firms to adapt to technological changes in business activities more easily. A high sales growth environment might encourage the management to use BI systems to access quality information in the market and to support new product development (Chae et al., 2014). Firms with higher labor productivity might be more inclined to adopt any organizational innovation, including BI systems (Evans and Davis, 2005). A higher level of financial leverage might cause firms to be less flexible in response to unexpected changes in their cash flows, leading to more hesitation in investing in BI systems (Denis, 2011; Malshe and Agarwal, 2015). Older firms are likely to be more mature in their management skills and have more experience, which enhance organizational ability to identify and pursue further technological advancements (Sørensen and Stuart, 2000). After eliminating the firms without sufficient information on the measures of covariates, we obtained the final sample of 282 firms matched to their control firms.

We used both industry dummies (2-digit SIC codes) and year dummies. We measured firm size as the natural logarithm of total assets, organizational slack as the ratio of the difference between current assets and current liabilities to total assets, sales growth as the annual sales growth rate, labor productivity as a ratio of operating income to the number of employees, leverage as the ratio of total debts to total assets, and firm age as the natural logarithm of the number of years from the date of incorporation. Second, we assigned 1 to firms with BI systems adoption and 0 to firms without BI systems adoption. Then we performed the matching based on the influence of the pre-treatment covariates on the adoption of BI systems (Randolph and Falbe, 2014). Table 3.4 presents the results of the PSM.

The section on the summary of balance for all data in Table 3.4 shows the mean differences (Mean Diff) between the sample firms and control firms before matching. For example, the difference is 1.44 in firm size, 28.30 in labor productivity, and 0.19 in firm age. After matching, the Mean Diff reduced significantly, as shown in the section on the summary of balance for matched data. For example, the Mean Diff in firm size became -0.10, labor productivity became -3.71, and firm age became 0.04. Hence, the sample firms and control firms after the matching are similar in terms of firm size, organizational slack, sales growth, labor productivity, leverage, and firm age. Furthermore, smaller median (eQQ Med), mean (eQQ Mean), and maximum (eQQ Max) values of differences in empirical quantile functions for each covariate were obtained after matching, indicating a better matching (Randolph and Falbe, 2014). Specifically, the percentages of improvement for the covariates that are significantly different between the sample firms and control firms before matching (i.e., firm size, sales growth, labor productivity and firm age) ranges from 65.4% to 92.9%. All these covariates are insignificantly different after matching. Our PCM worked well in this study.

Summary of balance for all the data:				
	Mean difference of the control firms from the sample firms (Mean Diff) (*t*-statistics)	Median of differences in empirical quantile functions (eQQ Med)	Mean of differences in empirical quantile functions (eQQ Mean)	Maximum value of differences in empirical quantile functions (eQQ Max)
distance	0.030	0.029	0.030	0.076
Firm Size	1.444 (10.358)***	1.550	1.445	2.112
Organizational Slack	-0.054 (-1.857)**	0.078	0.159	22.908
Sales Growth	-0.274 (-0.269)	0.048	5.432	1506.715
Labor Productivity	28.297 (2.307)**	12.188	77.512	12351.169
Leverage	0.011 (0.641)	0.035	0.068	6.768
Firm Age	0.192 (4.013)***	0.176	0.210	0.693
Summary of balance for matched data:				
	Mean Diff (*t*-statistics)	eQQ Med	eQQ Mean	eQQ Max
distance	0.000	0.000	0.000	0.009
Firm Size	-0.103 (-0.737)	0.281	0.316	1.335
Organizational Slack	0.019 (0.642)	0.024	0.036	0.669
Sales Growth	0.066 (0.065)	0.027	0.067	3.016
Labor Productivity	-3.711 (-0.303)	2.765	8.641	153.984
Leverage	-0.009 (-0.479)	0.010	0.016	0.151
Firm Age	0.038 (0.800)	0.057	0.065	0.406
Percent Balance Improvement:				
	Mean Diff	eQQ Med	eQQ Mean	eQQ Max
distance	99.899	99.978	99.716	88.131
Firm Size	92.889[#]	81.886	78.156	36.803
Organizational Slack	65.422[#]	69.587	77.530	97.080
Sales Growth	75.905	44.763	98.760	99.800
Labor Productivity	86.885[#]	77.314	88.852	98.753
Leverage	25.300	69.998	77.060	97.767
Firm Age	80.075[#]	67.657	69.012	41.504
Sample sizes (Total number of firms):				
	Control	Treated		
All	1098	282		
Matched	282	282		
Unmatched	816	0		
Discarded	0	0		

$^{*}p < 0.1$, $^{**}p < 0.05$ and $^{***}p < 0.01$ (two-tailed).

[#]Covariate that is significantly different between the sample firms and control firms before PSM.

Table 3.4. The Propensity Scores Matching of Sample and Control Firms

3.2.4. Event Study Methodology

Event study methodology measures the magnitude of an abnormal performance of firms associated with an event. This methodology has been widely employed in a variety of studies in finance, accounting, and management strategy to assess the stock price reaction to corporate announcements of a certain event (e.g., Brown and Warner, 1985). Later, this methodology are used to measure long-term abnormal performance (e.g., Barber and Lyon, 1996).

In this study, we applied the event study methodology to examine the impact of an event regarding the adoption of BI systems on the abnormal operational efficiency and abnormal risks of firms. Substantial costs and time are usually incurred in BI systems' adoption, which is a major event with potential implications for firms' competitiveness. As a result, such adoption is mostly announced by firms in public to acknowledge their stakeholders. Measuring the abnormal operational efficiency and abnormal risks of firms announcing their adoptions of BI systems enables us to assess the business value of BI systems.

Referring to Section 3.2.1, there are two stages of BI systems implementation. As stated above, it takes about 6-18 months with an average of about a year for the full adoption of a BI system in daily operations (Horakova and Skalska, 2013; Olexova, 2014; Zeng et al., 2006). In this study, we take the time of full BI adoption (i.e., the second stage) as year *t*. One year immediately prior to the full adoption of a BI system (i.e., the software installation stage) is taken as year *t*-1. We consider two years preceding the adoption of a BI system (year *t*-2) as the base year to determine the control group as firms should be free from the impact of the BI system at *t*-2. Overall, we examined the abnormal operational efficiency and abnormal firm risks over the event period from years *t*-2 to *t*+1, which is the year after full BI adoption.

This event study analysis included the tests concerning whether the abnormal performance of the sample firms is significantly different from 0 in the hypothesized direction. Equations (3.3) and (3.4) are used to calculate the abnormal performance (Barber and Lyon, 1996). Following Barber and Lyon and Corbett et al. (2005), we trimmed the data by removing outliers at each tail of the abnormal performance population.

$$AP_{i,t+k} = P_{i,t+k} - E[P_{i,t+k}] \tag{3.3}$$

$$E[P_{i,t+k}] = P_{i,t+\tau} + (PC_{i,t+k} - PC_{i,t+\tau}) \tag{3.4}$$

where $\mathrm{E}[P_{i,t+k}]$ is the expected performance of a sample firm *i* in any period $t+k$, using k as the ending year of comparison k = (-1, 0, 1) and τ as the base year (τ = -2). $PC_{i,t+k}$ is the performance of a control firm *i* in period $t+k$. $AP_{i,t+k}$ is the abnormal performance in terms of operational efficiency or risks of a sample firm *i* in period $t+k$.

We obtain data for operational efficiency and firm-risk measures from the Standard and Poor's COMPUSTAT for conducting the analysis. We have a sample of 270 pairs for abnormal operational efficiency and 229 pairs for abnormal firm risks. We have less sample firms in analyzing firm risks as the measurement of firm risks involves the financial data over a continuous five-year period as stated above.

3.2.5. Cross-sectional Regression Analysis

We examined the variables of stakeholder relationships (*H3a* and *H3b*) and process institutionalization (*H4a* and *H4b*) that could have moderating effects on the abnormal operational efficiency and abnormal firm risks. Following previous studies (Hendricks and Singhal, 2008), we conducted a cross-sectional regression analysis in which we estimated a multiple regression model as equation (3.5) to examine how stakeholder relationships and process institutionalization influence the abnormal operational efficiency and abnormal firm risks over a three-year period (years *t*-2 through *t*+1).

$$\begin{aligned}
\mathrm{CAR}_i = {} & \beta_0 + \beta_1(\text{Lagged Performance})_i + \beta_2(\text{Firm Size})_i \\
& +\beta_3(\text{Firm Labor Intensity})_i + \beta_4(\text{Firm Innovation})_i \\
& + \beta_5(\text{Industry Size})_i + \beta_6(\text{Industry Sales Growth})_i \\
& + \beta_7(\text{Industry Technonology Intensity})_i \\
& + \beta_8(\text{Stakeholder Relationships})_i + \beta_9(\text{Process Institutionalization})_i \\
& + \text{Year Dummies} + \text{Industry Dummies} + \varepsilon_i \qquad (3.5)
\end{aligned}$$

where *i* refers to the *i*th sample firm. CAR_i is either the abnormal operational efficiency of firm *i* or the abnormal risks of firm *i* over the period from years *t*-2 to *t*+1. Lagged performance is either the lagged operational efficiency or the lagged firm risks in year *t*-2 (the base year). All the control variables are in year *t*-2. Stakeholder relationships and process institutionalization are in year *t* (the event year).

We also considered both firm-specific and industry-specific factors that might potentially affect the benefits of BI adoption. So, a more rigorous model included firm size, labor intensity, firm innovation, and lagged operational efficiency or lagged firm risks. Larger firms might be able to obtain more benefits given they have more resources and wide-reaching organizational data (Dutta and Bose, 2015; Popovič et al., 2016). Labor intensive firms may also find BI systems more important as they often need have diversified organizational data by different members that need to be consolidated (Hendricks and Singhal, 2008). We measured labor intensity as the ratio of a number of employees to total assets (Dewenter and Malatesta, 2001). High-technology firms normally have greater R&D capability and in-house technical capacity to facilitate new technology assimilation (Rothaermel and Alexandre, 2009). Firm innovation was taken as the ratio of the R&D expenses to sales (Lo et al., 2013). Furthermore, our models included lagged operational efficiency and lagged firm risks to control for the persistent influence over time (e.g., Vandaie and Zaheer, 2014). All the firm-specific control variables are in year *t*-2.

Based on the 2-digit SIC codes, we also included several industry-specific factors such as industry size, industry growth, and industry technology intensity in the model. Larger industries are likely to be more complex in their supply chains and markets, requiring more industrial data and market intelligence (Brunnermeier and Cohen, 2003). The business environment of fast-growing and high-technology industries strongly prompts firms to implement management systems that facilitate information processing and enable firms to respond quickly, making BI systems more important (Mendelson, 2000). Industry size is measured as the natural logarithm of the firms' employee numbers in the corresponding industry in year *t*-2 (Lo et al., 2014), industry growth as the percentage change in the industry sales from year *t*-3 to year *t*-2 (Hendricks and Singhal, 2008), and industry technology intensity as the median R&D intensity of the industry in year *t*-2 (Liu et al., 2014). In addition, we considered the year dummies and industry dummies (2-digit SIC codes) as controls for unobserved effects.

3.3. Results

Table 3.5 reports the descriptive statistics of the operational efficiency and firm risks for the sample and control firms before the adoption of BI systems. We conduct the paired-sample *t*-test, and the statistical results show that the mean difference of operational efficiency and firm risks between the sample and control firms at the base year (i.e., year *t*-2) are insignificantly different from zero ($p > 0.1$).

	N	Mean	Median	Std. dev.	Min.	Max.
			Sample firms			
Operational Efficiency[a]	270	62.704	62.005	18.639	1.901	99.967
Firm Risks	229	0.044	0.025	0.104	0.004	1.488
			Control firms			
Operational Efficiency[a]	270	64.856	66.598	19.431	0.053	99.961
Firm Risks	229	0.048	0.028	0.101	0.004	1.378

[a] In percent

Table 3.5. Descriptive Statistics of Pre-Event Data for Sample and Control Firms (Year *t*-2)

3.3.1. Results of the Event Study Analysis

We test the hypotheses and examine whether the operational efficiency significantly increases, or if the firm risks significantly alleviate through the adoption of BI systems. Table 3.6 and Table 3.7 present the corresponding statistical results, which provide insights into the patterns of the abnormal operational efficiency and the abnormal firm risks over time. The whole event period consists of three phases, year *t*-2 (the base year) to year *t*-1, year *t*-1 to year *t*, and year *t* to year *t*+1, where *t* is the year that the sample firms have adopted BI systems. *N* is the sample size in each time phase. The sample size progressively decreases due to the unavailability of longitudinal data.

Barber and Lyon (1996) pointed out that nonparametric statistical methods such as the Wilcoxon signed-rank (WSR) test and the Sign test have to be used rather than the parametric *t*-test when the abnormal values are not normally distributed. The WSR test is preferred for symmetric distribution, and the Sign test is used if the distribution is highly skewed (Corbett et al., 2005). Following the study of Corbett et al. (2005), we conduct both the Kolmogorov-Smirnov and Shapiro-Wilk tests for normality and the skewness test on the abnormal values of operational efficiency and firm risks to determine which test that we should focus on in our analysis. For completeness, we present all three statistical tests in our results.

As shown in Table 3.6, there is no abnormal increase in the operational efficiency in the implementation period of BI systems (i.e., year t-2 to year t-1, $p > 0.1$). However, the abnormal value of the operational efficiency significantly increases just after the firms have adopted BI systems in the year t (i.e., year t-1 to year t, $p < 0.05$) as well as the year immediately after the adoption of BI systems (i.e., year t to year t+1, $p < 0.05$). Thus, Hypothesis 1 is supported. The cumulative results indicate that from the base year leading up to the year to the adoption of BI systems (i.e., year t-2 to year t), the abnormal increase in the operational efficiency is insignificant ($p > 0.1$). While comparing the base year with the year after the adoption of BI systems (i.e., year t-2 to year t+1, $p < 0.05$), we detect a significant increase in the abnormal operational efficiency. Together with the yearly figures, this suggests that firms achieve significant abnormal improvements in operational efficiency with the adoption of BI systems.

Table 3.7 shows the abnormal changes in the values of firm risks. We find a significant decrease in the abnormal value of the firm risks just after the firms have adopted BI systems at year t (i.e., year t-1 to year t, $p < 0.05$) whereas the abnormal firm risks in the subsequent year are weakly significant (i.e., year t to year t+1, $p < 0.1$). The cumulative abnormal decrease in firm risks appears to be significant from the base year to the year of the adoption of BI systems (i.e., year t-2 to year t, $p < 0.05$), and in the period between the base year and 1 year immediately after the adoption of BI systems (i.e., year t-2 to year t+1, $p < 0.05$). These support a significant abnormal decrease in firm risks with the adoption of BI systems. Thus, Hypothesis 2 is supported.

Time period	*N*	sk	Median (Statistics)	% Positive (Statistics)	Mean (Statistics)
			Yearly abnormal change in operational efficiency[a]		
t-2 to *t*-1	270		0.851	52.59	0.395
			(0.616)	(0.853)	(0.273)
t-1 to *t*	234		3.203	55.13	3.932
			(2.090)**	(1.577)*	(2.294)**
t to *t*+1	206		2.937	53.88	3.801
			(1.733)**	(1.118)	(1.938)**
			Cumulative abnormal change in operational efficiency		
t-2 to *t*	234		2.808	52.14	4.121
			(1.131)	(0.654)	(1.415)*
t-2 to *t*+1	206		7.029	55.34	8.365
			(1.676)**	(1.542)*	(1.740)**

Notes:

1. *p<0.1, **p<0.05 and ***p<0.01. The p-values shown are those for the one-tailed test of the null hypothesis that there is no abnormal operational efficiency, using the Wilcoxon signed-rank test, sign test, and t-test, respectively.
2. Wilcoxon signed-rank test Z-statistic for the median, binomial sign test Z-statistic for the percentage, and t-statistics for the mean.
3. An "s" in column "sk" indicates that the absolute value of the skewness is greater than one.
4. In all the cases, the hypothesis of normally distributed abnormal performance was rejected by both the Kolmogorov-Smirnov and Shapiro-Wilk test with p-values less than 0.05. The t-test is therefore never appropriate, but still reported due to completeness. Sign test should only be considered if the skewness is substantial, otherwise one can use the Wilcoxon signed-rank test.
5. % Positive indicates the percentage of firms achieving positive abnormal changes in operational efficiency.
6. [a]In percent.

Table 3.6. Abnormal Changes in Operational Efficiency

Time period	N	sk	Median (Statistics)	% Negative (Statistics)	Mean (Statistics)
			Yearly abnormal change in firm risks		
t-2 to t-1	229	s	0.000	50.66	0.007
			(0.234)	(-0.198)	(0.921)
t-1 to t	193	s	-0.005	56.99	-0.008
			(-2.263)**	(-1.963)**	(-2.743)***
t to t+1	176		-0.003	57.39	-0.004
			(-1.364)*	(-1.982)**	(-1.134)
			Cumulative abnormal change in firm risks		
t-2 to t	193	s	-0.005	55.96	-0.009
			(-1.679)**	(-1.667)**	(-1.949)**
t-2 to t+1	176		-0.009	54.55	-0.011
			(-1.770)**	(-1.211)	(-1.730)**

Notes:

1. *$p<0.1$, **$p<0.05$ and ***$p<0.01$. The p-values shown are those for the one-tailed test of the null hypothesis that there is no abnormal firm risks, using the Wilcoxon signed-rank test, sign test, and t-test, respectively.
2. Wilcoxon signed-rank test Z-statistic for the median, binomial sign test Z-statistic for the percentage, and t-statistics for the mean.
3. An “s” in column “sk” indicates that the absolute value of the skewness is greater than one.
4. In all the cases, the hypothesis of normally distributed abnormal performance was rejected by both the Kolmogorov-Smirnov and Shapiro-Wilk test with p-values less than 0.01. The t-test is therefore never appropriate, but still reported due to completeness. Sign test should only be considered if the skewness is substantial, otherwise one can use the Wilcoxon signed-rank test.
5. % Negative indicates the percentage of firms achieving negative abnormal changes in firm risks.

Table 3.7. Abnormal Changes in Firm Risks

3.3.2. Self-selection Bias and Endogeneity Concern

We employ the PSM in 3.2.4 by considering several pre-treatment covariates that are likely to influence the adoption of BI systems to control for the self-selection bias and endogeneity problems. As shown in Table 3.4, the PSM performs effectively to match the sample and control firms. Additionally, we conduct the paired-sample tests for changes from year t-3 to year t-2 to show any systematic bias in the operational efficiency and the firm risks prior to the implementation of BI systems in year t-2. We use the Kolmogorov-Smirnov and Shapiro-Wilk tests to show that the abnormal operational efficiency from t-3 to year t-2 ($p < 0.05$ in the Kolmogorov-Smirnov test; $p < 0.01$ in the Shapiro-Wilk test) and the abnormal firm risks from t-3 to year t-2 ($p < 0.01$ in both Kolmogorov-Smirnov test and Shapiro-Wilk test) are not normally distributed. The absolute skewness values for the abnormal operational efficiency (0.254 < 1) and abnormal firm risks (0.425 < 1) are less than 1, meaning that the data distributions of both abnormal values from t-3 to year t-2 are likely to be symmetrical. Thus, WSR is the most appropriate statistical test to determine our results for the systematic bias tests. Based on the WSR tests, there are no significant change in the abnormal values of the operational efficiency and firm risks from year t-3 to year t-2 ($p > 0.1$); thus, the abnormal changes in the operational efficiency and firm risks mostly appear after implementing BI systems. Thus, our sample selection is robust and free from endogeneity problems.

3.3.3. Results of the Cross-sectional Regression Analysis

We further examine the moderating effects of stakeholder relationships and process institutionalization on the abnormal operational efficiency and abnormal firm risks, which we take from year t-2 to year t+1. We collect ISO 9000 registration data for each sample and assign a binary variable of 1 for firms with ISO 9000 certifications and 0 for firms without ISO 9000 certifications. Because KLD only covers around 1,100 publicly traded firms listed on the S&P 500, Domini 400 Social Index, Russell 1,000 Index, or KLD Large Cap Social Indexes (McPeak and Dai, 2011; Wong et al., 2011), our final samples with sufficient information about the stakeholder relationships contain 141 firms for the abnormal operational efficiency and 123 firms for the abnormal firm risks.

Table 3.8 reports the descriptive statistics and correlations of the study variables, and Table 3.9 and Table 3.10 present the cross-sectional regression analysis results. Model 1 reports the estimation with only the intercept and control variables. Models 2 and 3 consider the moderating roles of stakeholder relationships and process institutionalization, respectively. Model 4 reports the full model. All models are significant according to the F-statistics in Table 3.9 and Table 3.10 ($p < 0.01$).

The moderating effect of stakeholder relationships is significantly positive for abnormal operational efficiency in Models 2 and 4 ($p < 0.05$) in Table 3.9, suggesting that the impact of BI systems adoption for abnormal operational efficiency is more positive when firms have superior stakeholder relationships. Thus, Hypothesis 3a is supported. Furthermore, the impact of stakeholder relationships is significantly negative for abnormal firm risks in Model 2 (p < 0.01) and Model 4 (p < 0.05), as shown in Table 3.10, indicating that firms with superior stakeholder relationships alleviate firm risks further with the adoption of BI systems. Thus, Hypothesis 4a is supported. Including the stakeholder relationships in the model improves the explanatory power of the regression models with the increase of the adjusted R-squared from 0.264-0.283 for abnormal operational efficiency and from 0.306-0.334 for abnormal firm risks.

As Models 3 and 4 of Tables 3.9 and 3.10 show, process institutionalization of firms having BI systems adoption is significantly related to abnormal operational efficiency (p < 0.01) and abnormal firm risks (p < 0.01). This suggests that firms are able to obtain higher operational efficiency and lower firm risks in a more process-institutionalized environment. Therefore, Hypothesis 3b and Hypothesis 4b are supported. Having the process institutionalization in the model improves the explanatory power of the regression models because of the increase of the adjusted R-squared from 0.264-0.314 for abnormal operational efficiency and from 0.306-0.350 for abnormal firm risks.

The control variables regarding lagged operational efficiency and lagged firm risks are significantly negative (p < 0.01) to the corresponding abnormal operational efficiency and abnormal firm risks, indicating that firms with low operational efficiency before

BI systems adoption are able to benefit from higher operational efficiency after BI systems adoption than firms with high operational efficiency before BI systems adoption. Also, firms with high firm risks before BI systems adoption gain further reduction in firm risks after BI systems adoption than firms with low firm risks before BI systems adoption. As Table 3.9 shows, firm innovation is significantly positive for abnormal operational efficiency ($p < 0.05$ in Model 3; $p < 0.1$ in Models 1, 2, and 4). This suggests that more innovative firms enjoy higher operational efficiency after adopting BI systems. Industry size is significant and positive for abnormal operational efficiency ($p < 0.05$ in Model 4; $p < 0.1$ in Models 1-3) and marginally significantly positive for abnormal firm risks ($p < 0.1$ in Model 4). Firms in big industries improve operational efficiency more after BI systems adoption. Yet most big industries are more complex, and firm risks are less likely to reduce significantly than for small industries after BI systems adoption. Industry technology intensity is slightly positive to abnormal operational efficiency ($p < 0.1$ in Models 2 and 4), suggesting that firms in a more technology-intensive industry obtain higher operational efficiency after the adoption of BI systems.

Variables	1	2	3	4	5	6	7	8	9	10
1. Operational Efficiency	1									
2. Firm Risks	-.071	1								
3. Stakeholder Relationships	-.029	.059	1							
4. Process Institutionalization	.041	-.143	.086	1						
5. Firm Size[i]	.074	-.409**	.037	.340**	1					
6. Firm Labor Intensity[ii]	-.321**	-.102	-.066	.174	.214*	1				
7. Firm Innovation	-.041	.325**	.113	-.131	-.436**	-.158	1			
8. Industry Size[i]	.059	.017	.189*	.019	-.048	.062	.065	1		
9. Industry Growth	-.010	.149	.062	-.063	.067	.014	.109	.325**	1	
10. Industry Technology Intensity	.094	.159	.066	.000	-.184*	.059	.219*	.436**	.289**	1
Mean	.629	.036	.342	.472	1.858	.004	.000	22.924	.106	.035
Standard deviation	.198	.036	1.665	.501	1.478	.003	.001	12.915	.114	.024
Minimum	.006	.006	-5.144	.000	-1.487	.000	.000	-.538	-.341	.000
Maximum	.999	.180	6.045	1.000	5.142	.014	.009	43.754	.332	.128

Note:
*$p<0.05$ and **$p<0.01$ (two-tailed).
[i]In thousands of employees.
[ii]In thousands of employees/millions of U.S. dollars.

Table 3.8. Correlations and Descriptive Statistics

Variables	Model 1	Model 2	Model 3	Model 4
Intercept	-50.684	-65.223	-44.739	-56.895
	(-0.911)	(-1.179)	(-0.833)	(-1.058)
Lagged Operational Efficiency	-1.140***	-1.225***	-0.970***	-1.052***
	(-3.804)	(-4.103)	(-3.298)	(-3.554)
Firm Size	0.053	0.037	0.008	-0.001
	(1.360)	(0.938)	(0.211)	(-0.026)
Firm Labor Intensity	-0.949	-1.695	-1.168	-1.750
	(-0.471)	(-0.838)	(-0.599)	(-0.891)
Firm Innovation	0.358*	0.314*	0.379**	0.342*
	(1.953)	(1.724)	(2.143)	(1.933)
Industry Size	0.010*	0.011*	0.011*	0.011**
	(1.731)	(1.835)	(1.921)	(1.992)
Industry Growth	0.137	0.352	0.187	0.356
	(0.215)	(0.550)	(0.302)	(0.573)
Industry Technology Intensity	4.842	5.507*	5.293	5.793*
	(1.449)	(1.662)	(1.640)	(1.801)
Stakeholder Relationships		0.066**		0.053**
		(2.048)		(1.680)
Process Institutionalization			0.344***	0.318***
			(3.108)	(2.860)
Year Dummies	Included	Included	Included	Included
Industry Dummies	Included	Included	Included	Included
R^2	0.385	0.406	0.432	0.445
Adjusted R^2	0.264	0.283	0.314	0.325
F-statistics	3.178***	3.303***	3.673***	3.695***

Notes:

1. * $p<0.1$, ** $p<0.05$ and *** $p<0.01$ (two-tailed tests for control variables and one-tailed test for moderating variables; $N=141$).
2. t-statistics in parentheses.

Table 3.9. The Impact of Stakeholder Relationships and Process Institutionalization on Abnormal Operational Efficiency (Year *t*-2 to Year *t*+1)

Variables	Model 1	Model 2	Model 3	Model 4
Intercept	-5.747	-4.446	-7.018	-5.792
	(-0.769)	(-0.606)	(-0.969)	(-0.808)
Lagged Firm Risks	-1.288***	-1.234***	-1.204***	-1.168***
	(-6.034)	(-5.867)	(-5.771)	(-5.652)
Firm Size	-0.000	0.001	0.005	0.006
	(-0.068)	(0.199)	(0.956)	(1.078)
Firm Labor Intensity	0.353	-0.632	1.025	0.127
	(0.130)	(-0.234)	(0.388)	(0.048)
Firm Innovation	0.077	0.078	0.067	0.069
	(1.435)	(1.479)	(1.280)	(1.330)
Industry Size	0.001	0.001	0.001	0.001*
	(1.121)	(1.425)	(1.466)	(1.694)
Industry Growth	0.052	0.081	0.056	0.080
	(0.831)	(1.277)	(0.924)	(1.298)
Industry Technology Intensity	0.184	0.107	0.291	0.215
	(0.340)	(0.201)	(0.555)	(0.415)
Stakeholder Relationships		-0.009***		-0.008**
		(-2.267)		(-1.938)
Process Institutionalization			-0.038***	-0.034***
			(-2.754)	(-2.478)
Year Dummies	Included	Included	Included	Included
Industry Dummies	Included	Included	Included	Included
R^2	0.454	0.482	0.494	0.513
Adjusted R^2	0.306	0.334	0.350	0.368
F-statistics	3.064***	3.268***	3.434***	3.541***

Notes:

1. *p<0.1, **p<0.05 and ***p<0.01 (two-tailed tests for control variables and one-tailed test for moderating variables; N = 123).
2. t-statistics in parentheses.

Table 3.10. The Impact of Stakeholder Relationships and Process Institutionalization on Abnormal Firm Risks (Year *t*-2 to Year *t*+1)

3.4. Discussions and Conclusions

Our results show that when a firm adopts a BI system, its operational efficiency is increased and firm risks are alleviated. Compared with control firms, sample firms obtain significantly higher operational efficiency just after the firms have adopted BI systems and in the year immediately after adoption of BI systems. As shown in Table 3.6, the median (mean) increase in operational efficiency is 3.2% (3.9%), with nearly 55% of firms experience improvements in their operational efficiency in the year of BI adoption. However, the median (mean) of changes in operational efficiency slightly drops to 2.9% (3.8%), with nearly 54% of firms experience positive change in operational efficiency in the year after the adoption of BI systems. The median (mean) increase in the operational efficiency is 7% (8.4%), with nearly 55% of firms experience improvement in their operational efficiency from the base year to the year after the adoption of BI systems.

Similarly, as shown in Table 3.7, sample firms significantly reduce risks in profit returns in the year of adoption of BI systems and the subsequent year. In the year of BI systems adoption, the median (mean) abnormal decrease in the firm risks is 0.005 (0.008), with nearly 57% of sample firms experience reduction in their financial risks. In the year after adoption of BI systems, the median (mean) abnormal decrease in firm risks shrinks to 0.003 (0.004). Nearly 57% of sample firms experience reduction in their financial risks from the adoption of BI systems. From the base year to the year after the adoption of BI systems, the median (mean) abnormal decrease in firm risks is 0.009 (0.011), with nearly 55% of sample firms experience less volatility in profits.

More important, sample firms further enhance operational efficiency and lower firm risks through better stakeholder relationships and higher process institutionalization. Our results show that superior stakeholder relationships increase operational efficiency and alleviate firm risks to a greater extent with the adoption of BI systems. This might indicate that superior stakeholder relationships help a firm to cultivate an open communication environment to acquire more reliable internal and external data to generate more insightful analyses through BI systems. Using ISO 9000 certifications as the proxy of process institutionalization, we find that a firm's adopting BI systems with institutionalized process leads to stronger improvements in the operational efficiency and lowers the volatility in profits. Process institutionalization provides a stable work environment with established procedures, streamlining the information collection process and facilitating BI systems assimilation. Superior stakeholder relationships and higher process institutionalization might be helpful in integrating BI systems into business operations, making firms more likely to gain benefits from BI adoptions. We discuss the theoretical and practical implications below.

3.4.1. Theoretical Implications

Consistent with the growing attention on managing knowledge, researchers in information systems have explored various types of KM systems to support knowledge use, transfer, and creation in organizations. Most of these are IT tools and provide a systematic process to capture, organize, and codify data, and then disseminate knowledge. However, previous studies on KM have shown that KM systems by themselves are not enough for organizational capacity improvements (Alavi and Leidner, 2001; Swan et al., 2000). In addition to KM systems, firms can implement BI systems, broad sets of technologies, to retrieve and analyze data. More important, BI systems differ from KM systems by having intelligence techniques to discover and multidimensionally analyze hidden patterns in large amounts of data. While knowledge is useful in general, having relevant and impactful knowledge provides higher value to firms (Liu et al., 2014). Through BI applications, valuable knowledge is created to support decision-making, increasing the information value of data resided in the database (Curko et al., 2007; Herschel and Jones, 2005). The KBV of the firm emphasizes knowledge as the most valuable strategic resource that confers firm competitiveness (e.g., Craighead et al., 2009; Nonaka and Takeuchi, 1995; Ranft and Lord, 2002). Knowledge is a fundamental resource to develop organizational capabilities (Grant, 1996b; Tippins and Sohi, 2003). Scholars in OM have long realized that activity residing in organizational capabilities and routines leads to competitive advantages. Yet effects of BI systems on organizational outcomes as operational efficiency and associated risks in profits volatility have not been examined in literature. Very little has been known about whether the two outcomes are both improved.

Taking the KBV for competitive outcomes of BI systems, we postulate and demonstrate that BI systems help improve operational efficiency and mitigate risks of volatility in profits. More important, it is necessary to explore the circumstances in which such competitive outcomes from the adoption of BI systems are more likely to be realized. Firms' simply having the BI systems in place are unlikely to take full advantage in KM (López-Nicolás and Meroño-Cerdán, 2011). Previous studies have suggested that tacit knowledge is a critical source of competitive advantages (López-Nicolás and Meroño-Cerdán, 2011; Mårtensson, 2000). Firms can enhance their competitiveness through building effective social relations and knowledge-sharing communities (e.g., Yli-Renko et al., 2001). A quality certification process such as ISO 9000 enhances knowledge codification, and in preparation for ISO 9000 audits, firms create a shared value and mutual understanding (e.g., Bénézech et al., 2001). Process documentation might be helpful in building organizational memory that facilitates knowledge retrieval and access (Lin and Wu, 2005; Naveh et al., 2004). Accordingly, we extend the understanding of the realization of BI systems' business value from a social capital perspective. Also, we demonstrate that the benefits of adopting BI systems are significantly better for firms with more effective stakeholder relationships and greater process institutionalization, which simultaneously lead to higher operational efficiency and lower risks. Our study sheds light on whether BI systems can improve organizational capacity while mitigating firm risks. More important, we enhance the understanding of how BI technologies, social relations, and process institutionalization interact to achieve effective KM development strategies, further improving competitive outcomes. We contribute to theory by exploring the possible synergy among social capitals, process institutionalization, and knowledge-based advantage.

3.4.2. Managerial Implications

Our research contributes some important practical implications for firms. Firms are uncertain about the business value of BI systems. The implementation of BI systems requires large investments in infrastructure and resources over a long period of time, and there are many challenges in this process that have caused more than half of BI projects to fail during implementation (Goasduff, 2015; Yeoh and Koronios, 2010). Our results show that the adoption of BI systems leads to higher operational efficiency while mitigating firm risks (in terms of lower volatility in profits). In particular, we further demonstrate how such benefits from the adoption of BI systems are likely to be strengthened. The benefits of BI systems depend on firms' social relationships and process formalization, not on the BI systems alone. For example, if firms actively manage their social capitals, it might help to develop strong relationships with their employees and customers for knowledge sharing (Yli-Renko et al., 2001). Using the timely and reliable data provided from stakeholders might enable firms to obtain more meaningful analysis from BI systems. In addition, if firms effectively adopt ISO 9000 principles, they probably have developed a structure with systematic routines to promote information flows and therefore facilitate BI assimilations throughout their organizations (Shin et al., 2001). In the fast development of "big data" and under knowledge-intensive competition, firms need to consider how the competitive outcomes from the adoption of BI systems can be strengthened and sustained.

Firms today need to manage vast amounts of business data available in various internal and external sources (i.e., big data). Firms need to enhance their KM capability by deploying BI systems to support wider organizational activities. For example, BI systems enable operations managers to track and collect more data more easily from a supply chain. By increasing the visibility and transparency of the process from order and material procurement to production and delivery, operations managers might gain more comprehensive insights from asset utilization to productivity and equipment deployment, while also tracking resources' availability, detecting quality problems, and ensuring an efficient manufacturing process (Elbashir et al., 2008). Accessing relevant and timely reports for decision-making, firms achieve higher returns with lower risks in operations and supply chain management.

3.4.3. Conclusions

Successful adoption of BI systems is vital for firms to derive values from their data, particularly in the era of big data where valuable insights can be derived from properly analyzing and sharing huge amounts of data. However, the extant literature is limited in understanding the business value of BI systems, particularly their impact on operational efficiency and firm risks. Also, little is known regarding the favorable organizational environments in the adoption of BI systems. Based on the event study analysis on the adoption of BI systems in the U.S., we find that the adoption of BI systems leads to higher operational efficiency while lowering firm risks. Furthermore, we find that the impacts of BI systems adoption on the operational efficiency and firm risks are significantly improved more for firms with better stakeholder relationships or higher process institutionalization.

CHAPTER FOUR

CONCLUSIONS AND FUTURE WORK

4.1. General Conclusions and Research Contributions

In a dynamic and competitive business environment, firms have to constantly improve their products and processes through various organizational initiatives. In knowledge-based competition, firms often make substantial investments in research and development (R&D) projects and seek to improve their organizational efficiency through information technology such as business intelligence (BI) systems. In this thesis, we provide empirical evidence regarding the impact of R&D investments on firms' financial risks and explore the possibility of risk reduction through operational improvements and quality management initiatives.

Based on our analyses, we find that R&D investments significantly lead to financial risks for firms, whereas these risks can be alleviated with high operational efficiency or by embarking on quality management initiatives. Additionally, a firm adopting BI systems gains higher operational efficiency and lower volatility in profits after the adoption. We find that superior stakeholder relationships and higher process institutionalization positively moderate the impact of firms' operational efficiency and risk reduction from the adoption of BI systems. Overall, this thesis documents important and timely issues on the returns and risks of some organizational initiatives, including R&D and BI systems adoption. Our empirical evidence highlights organizational initiatives that could generate returns for firms but emphasizes the potential risks behind these initiatives. More important, we contribute to OM practice by proposing possible factors that could mitigate these risks. Firms will have to invest in operational improvements and quality management practices alongside R&D initiatives. Likewise, operations managers should take the development of stakeholder relationships and process institutionalization into account when they embark on a BI project.

Using the Zollo and Winter's (2002) learning mechanisms, including experience accumulation, knowledge articulation, and knowledge codification, we consider operations and quality management practices as an organizational learning process. Through operational and quality improvements, firms can accumulate experience and knowledge for more stable and predictable performance. We regard process improvements as organizational proactive efforts toward deliberate learning, in which firms explore opportunities for articulating a tacit knowledge of individuals. Process improvements facilitate incremental improvements and create firms' dynamic capabilities. Thus, we argue that the financial risks associated with R&D activity can be reduced if firms simultaneously invest in R&D and operational improvements or quality management practices. Our empirical evidence shows that investments in R&D and operational improvements and quality management are not competing or mutually exclusive. Instead, they reinforce each other to mitigate firm risks.

Second, we take the KBV on the competitive outcomes of BI systems. Regarding the availability of big data nowadays, firms can acquire and analyze huge amounts of data by adopting BI systems in support of their decision-making, which leads to a higher operational efficiency and a lower risk to profit returns. We contribute to theory by linking social capital and process institutionalization to the KBV. The social capital theory highlights the positive influence of social relations on firms' competitiveness, and the process institutionalization emphasizes the documented, standardized organizational routines that facilitate information flow, thus supporting the assimilation of technological systems throughout the firms. Through the theoretical lens of the social capital theory and the process institutionalization, we advance our understanding of the moderating effects of stakeholder relationships and process institutionalization on the adoption of BI systems, which leads to additional enhanced operational efficiency and lower volatility in profit returns. More important, our study provides empirical evidence that firms can achieve a higher return and lower risk from the adoption of BI systems.

This thesis provides important implications for future studies. In particular, from the perspective of organizational learning, operational and quality improvements can be the driver that enhances operating routines and shapes firms' dynamic capabilities. This perspective differs from the dominant view that operational improvements and quality management are static exploitative routines that impede R&D activities. We argue that operational efficiency and quality management practices can be considered as organizational practices that lead to higher dynamic capabilities for firms.

Overall, we argue that while R&D investments improve a firm's explorative capacity, investments in operational improvements and quality management enhance a firm's dynamic capability. Instead of considering R&D investment as an exploratory organizational activity and process and quality management as an exploitative organizational activity are conflicting and mutually exclusive, we argue that they reinforce each other to mitigate financial uncertainties in regard to R&D investments and enhance a firm's dynamic capability.

4.2. Limitations and Recommendations for Future Research

There are some limitations in this thesis that might provide a useful direction for additional research. First, R&D investment in my study is measured as a financial ratio of R&D investments to net sales of firms. As such, this measurement of R&D is limited to classify the types of R&D into radical innovations or incremental innovations. For future studies, the impacts of radical and incremental innovations on firm risks are recommended to explore. Second, like any other research using secondary data, the measurement of our constructs cannot be perfect. For example, we use ISO 9000 as a proxy of process institutionalization. Firms with ISO 9000 is considered to have higher process institutionalization than firms without it. Although the adoption of ISO 9000 is iconic for instituting process-based management systems (Guler et al., 2002; Iden, 2012), it cannot be a perfect indicator. In particular, the construct of process institutionalization is multi-dimensional and there is no perfect proxy from any secondary dataset. Third, we focus on the customers of several leading vendors in the BI solutions and tools market and neglect firms that might adopt other lesser-known vendors. Nevertheless, the selected vendors held nearly two-thirds of the market share in the research period (e.g., Dresner et al., 2004; Sallam et al., 2011; Schlegel et al., 2007; Teo et al., 2016). For future studies, researchers can compare the benefits of BI systems in analyzing structured versus unstructured data. BI systems mainly revolve around the analysis of structured and unstructured data (Baars and Kemper, 2008). Structured data are usually classified by their natures such as financial, production, and logistics data. For example, operations managers can get an instantaneous analysis through BI systems on whether their inventories are aligned with market demand patterns by capturing data from the inventory and orders records. Unstructured data are more complex and include the data found in e-mails, social media platforms, and business interactions. For example, marketing managers can understand more about customer experience using a BI system. They can analyze data from their customer service platform on Twitter to get potential product trends and support their marketing strategy decisions. BI systems that are used to capture and analyze the hidden patterns in unstructured data might allow a firm to gain a better position and generate competitive outcomes because unstructured data can provide profound insights that are difficult to imitate.

Additionally, future studies might consider the impacts of contextual factors on the relation between R&D investments and firm risks, as well as explore whether the risks of R&D would differ under various contextual factors in the operating environments. For example, the rate of product obsolescence is relatively high in fast clockspeed industries (Fine, 1998). To keep pace with the rapid development of business, firms in fast clockspeed industries might make more frequent, huge investments in product development than firms in slow clockspeed industries. This might lead to higher operational and financial risks to firms in the fast clockspeed industries.

Appendix A

A Six Sigma Implementation Announcement

Extracted from Factiva

Q4 2007 Polyone Corporation Earnings Conference Call - Final

9589 words
7 February 2008
Voxant FD (FAIR DISCLOSURE) WIRE
FNDW
English

OPERATOR: Good day, ladies and gentlemen, and welcome to the fourth quarter 2007 **PolyOne** Corporation's earnings conference call. My name is [Latasha] and I will be your coordinator for today. At this time, all participants are in a listen-only mode. We will be facilitating a question-and-answer session towards the end of this conversation. If at any time during the call you require assistance, please press star 0 and a coordinator will be happy to assist you.

I would like to turn the call over to Mr. Dave Wilson, Chief Financial Officer. Please proceed, sir.

DAVE WILSON, CFO, **POLYONE** CORPORATION: Thank you, Latasha. And thank everyone for joining us this morning. As Latasha said I'm Dave Wilson, **PolyOne** CFO, joining me today is Steve Newlin, **PolyOne**'s Chairman, President, and Chief Executive Officer, who will open the discussion with remarks pertaining to our fourth quarter operating performance. I will then follow with a more...

Last night, as I think you all know, we released our fourth quarter earnings report and also posted it within the Investor Relations section of the **PolyOne** web site. If you did not receive our release, and would like to be added to our mailing list, please call or e-mail me and I will...

... the release, and in attachment seven through ten, we provide reconciliations of non-GAAP financial measures to the most directly comparable GAAP financial measures and an explanation of how **PolyOne**'s management uses these non-GAAP measures.

... Private Securities Litigation Reform Act of 1995. Forward-looking statements give current expectations or forecasts of future events and are not guarantees of future performance. They are based on **PolyOne**'s management expectations that involve a number of business risks and uncertainties, any of which could cause actual results to differ materially from those expressed in or implied by...

...

STEVE NEWLIN, CHAIRMAN, PRESIDENT, CEO, **POLYONE** CORPORATION: Well, thank you, Dave. And welcome to all of you participating in **PolyOne**'s fourth quarter and full-year 2007 earnings call. I'm going to begin with a brief summary of our quarter followed by a review of the accomplishments that...

...

PolyOne distribution enjoyed another strong quarter. They have 10% sales growth being leveraged into 5.7 million of operating income, up over $2 million compared to a year ago...

...

...yield notes. It really pleases me to point out that as a result, our debt is now at an all time low. Clearly the Oxy Vinyl divestiture materially reduced **PolyOne**'s historic earnings volatility and played a leading role in the incremental deleveraging of our balance sheet, allowing us to accelerate our global specialization strategy. Recall that within three...

... TPE's. The deal was closed on January 2nd, and we expect GLS to be slightly accretive to earnings in 2008. With this addition to our business portfolio, **PolyOne** immediately vaults into a leading position in the TPE marketplace, a $3.5 billion global segment of the industry, possessing above-average sales growth and profit margin characteristics....

...

... As part of this deal, we acquired a vinyl compound manufacturing plant in [Dong Wong, a city in the [Phong Dong] province of southern China. This is **PolyOne**'s fourth manufacturing site in China. The other three make a broad array of specialty products for the business equipment, electrical, packaging, and textile printing markets. Importantly,...

...

PolyOne distribution delivered record sales and operating income in 2007. Since national LTL thermo plastics distributors serves more than 5,000 plastics processors across North America, with a value proposition...

...

... capital that generates economic value and exceeds our 15% pre-tax threshold. We are confident that achieving these targets will drive higher quality, more sustainable earnings, resulting in **PolyOne** being benchmarked and re-evaluated against the higher multiple specialty peer group.

...execution and cultural change, which is never easy. With their influence, we're becoming more disciplined in our business processes, more accountable to results, more urgent in our **implementation**, and I would like to add more confident about our future.

... environment, but understand that we are aggressively pursuing a number of strategic growth initiatives that are not solely reliant on the health of the economy. We believe this places **PolyOne** in a very desirable position relative to our peers. As evidenced by our preliminary expectations for year-over-year earnings growth in 2008 and 2009. Our 2007 performance demonstrated...

...mindful of the economic uncertainty plaguing corporate America near-term, uncertainty that could eventually impact the global economy. Nonetheless we're encouraged and excited about our future. Never in **PolyOne**'s history have so many opportunities been present to effect change and drive incremental cash flow and earnings. I say this because our strategy is working. Our innovation pipeline... ... or insensitive. But we have the business discipline to walk away from unprofitable business that doesn't make sense for us and our customers. Through operational excellence initiatives and **implementation** of our lean **six sigma** programs we are generating internal cost savings, with the opportunity to deliver a $50 million improvement in the next three years. And we continue to accelerate global expansion...

...

...% from a year ago. This was our first quarter in 2007 with a meaningful positive year-over-year comp. The improvement was driven by a 15% improvement in **PolyOne** distribution sales, reflecting the market gains in the face of softening economic conditions, and a 10% increase in international sales, largely reflecting FX benefits, coupled with the...

...

...Excluding these FX benefit, however, the operating income improvement remained a meaningful 33%, reflecting greater penetration of new specialty niches and mix improvements in both Europe and Asia. **PolyOne** distribution finished the year with strong performance to drive full-year earnings to a record level. For the quarter, operating income was $5.7 million, up 2.1...

...

... imbedded in this increases was a $9 million turn-around in our North American color profitability. Our international operating income grew 25%, to nearly $27 million, and **PolyOne** distribution, as we've mentioned, set a record of over $22 million, up 16%, compared to 2006 performance. Looking at our financial profile, we ended the...

...

... a year ago. And, therefore, the fact that we've grown in this space, the delta is really the incremental business gains in market share that the team **PolyOne** has been able to achieve. I will tell you that we see it soft. We see housing, in particular, which everyone sees, but just generally we see...

...

...you talked more about some of your initiatives and some of the benefits you're going to see. Can you give some more color as revolving around your lean and **six sigma** initiatives in your plants and some of the throughput benefits you expect to see out of those?

STEVE NEWLIN: Yes, I think I captured that question. Were you asking about lean **six sigma** and benefits that we're seeing and where we're going with that, is that correct?

...

... a great time, he is working hard, he's getting a lot of data, making an impact right away in our business, and he is steeped in lean **six sigma**. And here is what we know. We're behind where we should be and where a lot of faster-moving firms on this front have already – they'...

...

...to be closed. So that optimization study is under way as we speak. And that is a result of leaning out the business, and I would say that the **six sigma** end of your question is, we're very, very early in **six sigma**, and we have lots of work to do to gain insight, knowledge, to get the kind of black belt population and green belt population and cultural change we need to get to the **six sigma** side of the equation. So we measure all of these things, we have targets that are established by business, and we track very closely how we're doing....

...

Voxant, Inc.

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Appendix B

A Business Intelligence Systems Adoption Announcement

Extracted from Factiva

Campbell Soup Company Heats Up Customer Satisfaction With QlikTech

839 words
21 May 2007
08:30
Business Wire
BWR
English

RADNOR, Pa. - (BUSINESS WIRE) - QlikTech, the world's leading provider of memory analysis and reporting solutions, announced today that **Campbell Soup** Company (**NYSE**: **CPB**) is using QlikView, its flagship **business intelligence** software solution to improve its supply chain management. QlikView is enabling Campbell's employees to analyze corporate data in innovative ways to improve inventory control and ensure the right product mix is available to customers at the right time.

"QlikView's analytical power and simplicity enable our employees to more easily access critical information from disparate sources at a moments notice," said Michael Mastroianni, vice president of North American planning, reliability and operations for Campbell's. "Thanks to QlikView we now have a level of organizational visibility that was not previously achievable. This allows us to better leverage data in our management systems and understand the financial implications of supply chain decisions."

In order to streamline operations and increase production efficiency, Campbell's supply chain team enlisted Terra Technology, a provider of Demand Sensing solutions for consumer goods companies to **deploy** QlikView at the company's Camden, New Jersey headquarters. QlikTech and Terra Technology provide Campbell with the necessary tools to improve inventory analysis management and projections, sales and long-term forecasting analysis, demand planning, schedule compliance, transportation and warehouse scheduling. Today, members of the company's plant production, finance, and logistics departments use QlikView to make educated business decisions on a daily basis.

"It is essential for leading companies like Campbell to have access to tools that allow the highest possible level of supply-chain optimization," said Robert F. Byrne, president and CEO of Terra Technology. "With QlikView, we can offer Campbell and our other clients, a simple, yet exceptionally powerful tool that enables their employees to quickly and deeply delve into data and make on-demand business decisions."

"Campbell recognizes the need to identify and address the changing dynamics of its market to stay one step ahead of the competition, and it is meeting these challenges by investing in their business analysis process and systems," said Rick Pitts, CEO of US Operations for QlikTech. "By implementing QlikView, Campbell has provided its employees the tools they need to make on-the-fly decisions and improve customer satisfaction."

QlikTech is leading a new class of easy-to-use, fast and flexible business analysis solutions that empower individuals to improve corporate performance and drive innovation. QlikTech's flagship product, QlikView, extends the company's vision of simplifying business analysis, offering solutions that can be deployed in days, where users can be trained in minutes, and where end users have the freedom to be more creative in their analyses.

About **Campbell Soup** Company

Campbell Soup Company is a global manufacturer and marketer of high quality simple meals, including soup, baked snacks, vegetable-based beverages, and premium chocolate products, with annual revenues in excess of $7.5 billion. Founded in 1869, the company has a portfolio of more than 20 market-leading brands, including "Campbell's," " Pepperidge Farm," "Arnott's," "V8," and "Godiva." For more information on the company, visit Campbell's website at www.campbellsoupcompany.com [http://www.campbellsoupcompany.com].

About Terra Technology

Terra Technology is the leading provider of demand sensing and inventory optimization solutions for consumer goods companies. Terra's pattern recognition technology works in conjunction with traditional demand planning systems to monitor daily demand signals and reduce near-term forecast error by 50%. More accurate forecasts stabilize the supply chain, improving customer service, lowering inventory requirements, decreasing unplanned changeovers and reducing costs. Headquartered in Norwalk, Connecticut; Terra's customers include **Campbell Soup**, Georgia-Pacific, McCain Foods and Ventura Foods. For more information, please visit us at www.terratechnology.com [http://www.terratechnology.com] or call us at 203-847-4007 x108.

About QlikTech

QlikTech, the global leader in next-generation **business intelligence** solutions, offers sophisticated in-memory analysis and reporting solutions for enterprise and individual customers. QlikTech supports an open information architecture, where business information is broadly, affordably and quickly available to those who need it. QlikTech's flagship product, QlikView, uses next-generation patented in-memory association technology to make sophisticated analysis dramatically easier to **deploy**, use and maintain. QlikView's click driven, visually interactive interface is simple for end users to learn and use.

QlikTech is the world's fastest growing **business intelligence** software company with more than 5,880 customers in 73 countries and is adding more than 10 new customers each working day. In addition to thousands of small and midsized companies, QlikTech's customers include large corporations such as Tetra Pak, Deutsche Telekom, Reuters, 3M, Colonial Supplemental Insurance, and BMW. QlikTech is privately held and venture backed by Accel Partners, Jerusalem Venture Partners, and Industrifonden. Founded in Sweden, QlikTech is headquartered in Radnor, Pennsylvania, has subsidiaries in the United Kingdom, Germany, Netherlands, and Scandinavia. More than 500 companies around the world partner with QlikTech. For more information on QlikView, please call 1-888-828-9768 or visit www.QlikTech.com [http://www.QlikTech.com].

Racepoint Group Dan Ring, 781-487-4656 dring@racepointgroup.com

Business Wire

Document BWR0000020070521e35l004ia

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