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THE CONTEXTUAL IMPACT OF INNOVATION AND OPERATIONAL SPILLOVERS ON FIRM PERFORMANCE

by

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Submitted in Partial Fulfillment of the Requirements

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DEDICATION

To my mother Mrs. Amita Singhal and professor Dr. Manoj Malhotra. To all who have gotten second chances in life and valued them…

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ACKNOWLEDGEMENTS

Many thanks to my mother Amita Singhal and my grandmother Bimla Gupta for sharing my worries and doubling my happiness, because I owe it all to you. To my brother Saryou Singhal and my aunt Anita Mittal for always being my cheerleaders.

Besides my family, I would like to express my humble gratitude to my mentors Dr. Manoj Malhotra and Dr. Alan Mackleprang for their continuous support throughout my studies. I cannot say enough about the patience they have shown me. Dr. Malhotra has pulled me out from my darkest moments, and was like family in the absence of my actual family. Despite his extremely busy schedule, he would always check up on how I was proceeding. Dr. Mackleprang's never-ending optimism was another major driving force, and his one comment, "You are very close" is what got me through every time I hit a roadblock. It was his time and effort that enabled me to explore the depths of my dissertation topic. His belief that I am capable of doing good work is what inspires me to carry on.

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ABSTRACT

Extant literature across various research disciplines has investigated the influence of a firm's technological innovation on its performance. However, the findings on this relationship remain inconclusive as it is subject to many strategic and environmental factors. In this dissertation, the relationship between a firm's technological innovation and performance is evaluated. Additionally, this relationship is examined in the presence of various contextual factors.

In the first study, meta-analysis is utilized to quantitatively aggregate existing empirical research in this domain. Cultural and institutional aspects of the nation in which the firm operates are examined for their potential in explaining variability within the technology innovation-performance relationship. Results indicate that better performance outcomes are observed when innovation occurs in those nations that have lower inclination to avoid uncertainty and/or collectivistic attitudes. Counter-intuitively, performance suffers when innovation occurs in nations with stronger patent protection framework.

It has been increasingly demonstrated that research and development related innovation-knowledge spillovers can impact the performance of both the innovative firm as well as its competitor/s. In the second study, a contribution to the spillover literature is made by exploring spillovers of operational knowledge, referred to as *operational spillovers.* Specifically, spillovers related to inventory, sourcing lead time, and volume

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flexibility are examined. The results suggest that operational spillovers only help firms that need additional operational knowledge resources. A novel and counterintuitive finding is that the financial performance of all other firms is negatively impacted by learning via operational spillovers. These results suggest that operational spillovers should be sought only in specific circumstances, and otherwise avoided.

In the third and final study, the financial implications of operational spillovers from the industry leaders and laggards are examined within the context of the environment in which the firm operates. A firm's external operating environment largely determines the degree of uncertainty confronted in its day-to-day operations. Specifically, munificence, dynamism and complexity are examined as distinct components of environmental uncertainty. The final study answers how these dimensions of industry-level environmental uncertainty enable or prohibit the successful exploitation of operational spillovers.

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CHAPTER 1

Overview

1.1 Introduction

Technological innovation is a complex and multidimensional construct, that refers to innovations occurring on the operating side of an organization, for example, introduction of new/improved products and/or processes. The importance of technological innovation as a core capability of a firm to sustain competitive advantage is well documented in extant literature. However, the empirical findings on this relationship remain inconclusive, and consequently this dissertation focuses on examining ways in which innovation benefits firms that make those strategic investments, how the ability of a firm to enjoy these benefits is impacted by the action of other firms to which it is connected, and whether environmental effects tied to a given industry have a bearing on these relationships. Three inter-related, yet distinct studies, are structured to fulfill these objectives, and are described next.

1.2 Dissertation Organization

In Chapter 2 of the dissertation, an attempt is made to reconcile the mixed empirical results on the overarching relationship of technological innovation and firm performance. Thirteen major journals from the field of Operations Management (OM), Economics, Finance, Strategy, and Management were searched with the goal of collecting relevant studies that had empirically examined the said relationship. This inter-disciplinary literature review resulted in a sample of 28 published studies. By employing a multi-variate meta-analytic

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methodology, the findings on the focal relationship from each of the studies in the sample were quantitatively compiled and coded. Based on a meta-analysis of 132 effect sizes obtained from these 28 studies, the overall relationship between a firm's technological innovation and performance is shown to be significant and positive. Second, empirical support for the moderating influence of cross-cultural and institutional differences on the said relationship is also established. When innovation occurs in those nations that have lower propensity to avoid uncertainty and/or collectivistic attitudes, better performance outcomes are observed. In contrast, performance suffers when technological innovation occurs in nations that have stronger patent protection. The reasons for these expected as well as counter-intuitive results are discussed.

While Chapter 2 includes both the manufacturing and service sector firms, the subsequent chapters focus exclusively on the manufacturing sector where the notions of supply chains and inter-firm connections have been better established. In Chapter 3 of the dissertation, the context of spillovers is introduced into the evaluation of the focal relationship. There exists empirical evidence that firm's performance sensitivity to its internal innovation activities is also impacted by innovation carried out by its opponent firm (s) (Cohen et al., 2000; Heeley et al., 2007). Firms tend to exploit the innovation-knowledge resources that leak out from other innovative firms, and thereby imitate what its competitors are doing well. Such leakage of innovation-knowledge resources is referred to as *Spillovers* (Jaffe, 1998). Exploitation of spillovers brings down the innovation-related investment costs, as well as reduces the risk of failure because firms only use spillover knowledge from successful innovators. This expropriation can augment the rival firm's profitability, but would also tend to diminish the innovative firm's profitability. Several

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studies have empirically examined spillovers and their impact on firm performance using research and development (R&D) as the measure of innovation-knowledge spillovers. This dissertation for the first time introduces the notion of spillovers as they relate specifically to operational knowledge. These operational spillovers are characterized in terms of inventory, sourcing lead time, and volume flexibility. Using the resource-based view (RBV) of a firm, the impact of operational spillovers on firm performance is evaluated to empirically show that firms are heterogenous in nature when it comes to benefitting from operational spillovers. Even more interestingly, operational spillovers financially benefit only those firms which have undeveloped operational capabilities. All other firms are paradoxically hurt financially from operational spillovers.

In Chapter 4 of the dissertation, the focal relationship is evaluated in the context of three industry-level environmental factors. The environment of the industry in which a firm operates influences a firm's strategic decisions, as well as its performance, and is broadly categorized along three dimensions: munificence, dynamism, and complexity (Pagell and Krause, 2004). Together, these three factors reflect the degree of uncertainty the firm faces in their operating environment. Given that not all operational capabilities are equally relevant and valuable under all operating conditions, the aim of this chapter is to identify the external operating conditions that facilitate the reaping of financial benefits (penalties) from operational spillovers.

Finally, this dissertation concludes in Chapter 5 with a summary of overarching research findings, recommendations, potential limitations, and future research directions.

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CHAPTER 2

Relationship Between Technological Innovation and Firm Performance: A Meta-Analytic Investigation

2.1 Introduction

A firm's initiatives for innovation have been argued by many to be the driving force behind its success and growth (Greenhalgh and Rogers, 2010). Even during the 2008 financial crisis, many US companies, while cutting costs in other areas, continued to invest in research and development (R&D) (Scheck and Glader, 2009). In today's competitive market, start-ups can quickly replace incumbent firms if they do not strive to stay ahead of the innovation curve. In the presence of globalization and technological advancements, firms from emerging markets are steadily gaining dominance over their developed-country counterparts simply by innovating (Shaughnessy, 2017). In brief, firms need to continuously innovate to ensure competitive advantage and maintain their position in the market (Greenhalgh and Rogers, 2010). However, some scholars argue against the performance benefits of innovation primarily because of the inherent nature of innovation. Arguably, performance returns to innovation are diminished because of the (a) associated high investment costs to innovation, (b) uncertainty of returns to innovation (c) long delays in reaping those returns, (d) difficulty of effectively measuring those returns, and (e) perceived risk of failure by management, among others (Hall, 2010; Sood and Tellis, 2009).

On top of that, the inadequacy of the existing measures of innovation further complicates the credibility of the empirical findings of the innovation→ performance link

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(Zhang et al., 2012). To complicate the said relationship further, innovation does not occur in a vacuum, and is affected by a host of environmental conditions (both internal as well as external) (Zhang et al., 2012). Prior literature has attempted to evaluate how the implementation of innovation is influenced by various factors such as the country of operation and its culture (Power et al., 2010), environmental turbulence or uncertainty (Jean et al., 2012), type of structure (mechanistic or organic), industrial network of operation (Li and Atuahene-Gima, 2002), supplier involvement (Jean et al., 2012; Song et al., 2011), organizational size (Li and Atuahene-Gima, 2002; McDermott and Prajogo, 2012), and organizational structure and processes (Jansen et al., 2006). The evaluation of certain contextual factors (for example, cross-country differences) can get overwhelming for traditional-style studies; due to methodological and sample size limitations. On the other hand, a quantitative aggregation of all prior innovation-related studies using meta-analysis methodology affords one the possibility to examine the impact of such contextual factors that would be difficult to examine otherwise. Specifically, in this chapter the innovation→ performance link is examined under the lens of two such factors- the institutional and the cultural environment of a nation within which a firm operates.

As mentioned earlier, numerous studies have shown that a firm's working environment (both internal and external) can enable or inhibit the performance benefits from innovation activities (Heugens et al., 2009; Li et al., 2010; Oliver and Holzinger, 2008). First, the institution-based view suggests that firms enjoy greater performance benefits to innovation activities if they operate in nations with stronger institutional environments (Heugens et al., 2009). Two characteristics of a strong institutional environment relevant to the area of innovation are (a) the level of financial development

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and market regulation, and (b) the strength of intellectual property rights (Claessens and Tzioumis, 2006; Pisano, 2006; Varsakelis, 2001). Since innovation is a high-cost activity, firms that operate in financially well-developed and well-regulated nations can be expected to perform better. Additionally, firms that operate in nations with a strong legal framework for protection of intellectual property are better able to monopolize the financial returns on their innovative products. Second, both practicing managers and academic researchers have emphasized the importance of cultural elements in influencing innovation (Power et al., 2010; Steensma et al., 2000). In the context of innovation, the two most commonly studied cultural elements are degree of individualism and uncertainty avoidance (Shane, 1993) and empirical results have been shown to vary across these two dimensions (Rosenbusch et al., 2011). Consequently, using multivariate meta-analytical techniques that have been specifically designed to capture and assess such conflicting relationships, this chapter focuses on providing some resolution to this ongoing debate, as well as provide contextual insights about performance sensitivity to innovation efforts. Therefore, this chapter attempts to answer the following questions:

1. Do technological innovations enhance a firm's outcomes?
2. Does the relationship between technological innovation and firm performance differ across nations in terms of the extent of capital market regulatory-type institutional context and the strength of intellectual property rights in a nation?
3. Does the relationship between technological innovation and firm performance differ across nations in terms of uncertainty avoidance and degree of individualism?

The rest of the chapter is structured as follows. In section 2.2, the theoretical rationale for the hypothesized relationships is presented, while section 2.3, provides an

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overview of the meta-analytic methodology and the procedure to select and code studies. In sections 2.4 and 2.5, the results of this analysis and the implications of the findings are discussed. Potential limitations, and suggestions for future work are discussed in the concluding section of the chapter.

2.2 Literature Review and Hypothesis Development

2.2.1 Technological Innovation Construct

Prior research on innovation has categorized it in many ways. One of the most popular typologies to date has been the distinction between "*technological*" and "*administrative*" type of innovation (Damanpour et al., 2009). Administrative innovations are defined as "*those that occur in the administrative component and the social system of an organization*" while technological innovations, on the other hand, are defined as "*those that occur in the operating component and affect the technical system of an organization*" (Damanpour et al., 2009). Technological innovation is relevant in the context of Operations Management (OM), since it comprises product innovation and process innovation in both manufacturing as well as service industries. Product innovations are defined as those innovations that result in the introduction of a new or significantly improved product. Process innovations are defined as those innovations that result in the introduction of a new or significantly improved process. For example, introducing advanced manufacturing technologies or quality improvement programs can potentially enhance manufacturing systems (Boyer et al., 1997; McAfee, 2002). Prior literature has argued that different innovation types vary in their focus and outcomes (Damanpour et al., 2009). Most of the studies in this area examine technological-innovation construct as such, and very few of

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them distinguish between product and process innovations. Hence, given the limitations of the study sample, this chapter is restricted to the typology level of technological innovation.

The construct of technological innovation is multi-faceted in nature and to capture it appropriately and adequately, remains an open research area. Thus far, researchers have employed numerous measures, comprising both perceptual (Jansen et al., 2006) as well as objective type. The objective measures include, but are not limited to, R&D expenditures (Ettlie and Pavlou, 2006; Song et al., 2011), R&D intensity (Han et al., 2013), patent counts (Durand et al., 2008; Zhao, 2009), patent citations (Zhao, 2009), new product introductions (Girotra et al., 2007), product radicalness (Oke, 2007), innovation-related announcements (Hendricks and Singhal, 2008), and innovation awards (Zhang et al., 2012). All these existing measures of technological innovation offer their own set of contributions and drawbacks (Zhang et al., 2012). For example, the most frequently used measure of innovation in empirical research is R&D spending. As a financial measure, R&D spending can assist in the comparison of firms in terms of spending levels as a percentage of firm sales, and makes the argument that a firm that spends more also innovates more. However, R&D fails to capture a firm's internal capabilities to innovate. The R&D-spending measure incorrectly assumes that firms are homogenous in nature and that any two firms would perform identically at a given level of R&D. Recent research has shown that firms in fact differ in their abilities to innovate (Knott, 2008). In addition, innovation is not solely based on high amounts of R&D investment, but also on the working environment within a firm, for example, whether employees pursue risky ideas that have the potential of a breakthrough (Hall, 2010). In brief, innovation has multiple dimensions and no single measure can capture it in totality, at least not as yet (Zhang et al., 2012). Given such a

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setting, a meta-analysis of technological innovation can help to get an overall understanding of its relationship to firm performance.

2.2.2 Technological Innovation and Firm Performance

The relationship between technological innovation and firm performance has been extensively investigated across disciplines, but the overall results are mixed and inconclusive (Han et al., 2013; Oke, 2007). Extant research has looked at various reasons to explain the inconclusive nature of the technological innovation → performance relationship. Examples of studies that demonstrate a negative relationship are Durand et al. (2008) that found a firm's financial performance (measured by return on sales) to be negatively affected by patent activity of that firm in the biotechnology sector; and Terwiesch and Loch (1998) that similarly concluded a negative to no impact of innovation intensity on a firm's profitability. The researchers on the dark side of this debate have argued in favor of a negative relationship between technological innovation and firm performance because of the associated sky-high investment costs, uncertainty of returns from those investments as well as long delays associated with those returns (Chandrasekaran and Tellis, 2008; Sood et al., 2009). Zhang et al. (2012) argues that the market only rewards 'commercially-successful' innovations and not just efforts in innovation like patenting. Then, an added challenge is accurately measuring firm's financial returns from innovation investments given the increasing speed of innovation diffusion across global markets and the existence of diverse patterns of consumer adoption across products and countries (Chandrasekaran and Tellis, 2008; Sood and Tellis, 2009).

Some scholars have attributed the contradictory nature of these findings to the lack of an all-encompassing and generalizable measure of technological innovation. For

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example, Heeley et al. (2007) studied the effect of R&D and patenting on firm's financial performance and found opposing results. They posit that R&D investment as an input to the innovation process is a marker of the level of a firm's innovation; while patenting reflects a firm's innovation output. They empirically showed that higher R&D intensity lead to an increase in stock returns, but patent count had no effect on stock returns. Given the drawbacks of the existing measures, Zhang et al. (2012) came up with a new measure of innovation-innovation awards. They argue that winning an innovation award measures the overall effectiveness of that innovation which goes beyond merely introducing an innovative product/process, thereby providing a more accurate picture of its effect on firm profitability. They do urge for more future research to better understand and resolve the ongoing debate.

Furthermore, researchers have argued that a firm's performance measures are subject to various contextual factors, and empirically investigated how they can influence the direction of the impact of innovation on firm performance. For example, Jansen et al. (2006) found that exploratory innovation had a positive impact on a firm's financial performance, while exploitative innovation had a negative impact if the operating environment was dynamic in nature. Thornhill (2006) concluded that innovation positively impacts performance under the effect of industry dynamism.

The review of innovation literature shows that the majority of the empirical research favors a positive relationship though. For example, the seminal meta-analysis paper by Capon et al. (1990) empirically concluded that R&D-intensive firms achieve higher financial performance. Chaney and Devinney (2006) similarly found positive market returns from innovation announcements. A survey-based study by Oke (2007), also

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concluded innovation to be positively related to firm performance. An event study by Zhang et al. (2012), that was based on a sample of 1141 firms, found innovation-award winning firms to be financially more successful.

To conclude, extant literature has explored various pathways to explain the conflicting nature of technological innovation → performance relationship, but given the associated complexity and richness of this debate, a generalizable conclusion is yet to be found. A meta-analytic investigation will help to validate and generalize the focal relationship over the varying empirical settings in different papers, something that can be overwhelming or out-of-scope for a single traditional-style empirical study. Accurately assessing the effects of technological innovation on firm-level outcomes may be critical to empirically proving that markets respond favorably to technological innovation, which in turn can motivate firms to invest in it. Given the above arguments, the first hypothesis to test the overall focal relationship is stated as follows, while recognizing that no distinction is made between the different stages of innovation process in this chapter (Wolfe 1994).

Hypothesis 1. *Technological innovations of a firm are positively related to its performance.*

2.2.3 Country-Level Moderating Effects

The country-level moderating effects relate to the influence of institutional environment and the influence of culture. The latter has multiple dimensions, two of which are specifically addressed in this study.

2.2.3.1 Influence of Institutional Environment

The institution-based view (IBV) says that a firm's strategies, practices, and outcomes are all influenced by the institutional environment of the nation in which the firm is based

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(Scott, 2013). The term ‘institutional environment’ of a nation represents the rules and regulations created by different institutional forces like political, legal, economic, and social systems. Ignoring the institutional environment prevents us from getting a deeper understanding of the drivers of firm performance in both developed (Oliver and Holzinger, 2008) as well as developing countries (Lau and Bruton, 2008). Heugens et al. (2009) in their meta-analytic study covering 11 Asian countries and 65 research papers, concluded a significant role of jurisdictional institutional factors on firm performance. IBV has re-emerged as a leading strategic perspective in recent research in explaining firm-level heterogeneity (Li et al., 2010; Mike et al., 2009; Van Essen et al., 2012; Wang et al., 2016). A study by Li et al. (2010) examined the role of offshore OEM cooperation on local Chinese suppliers under the influence of ill-developed formal institutions that are found in China. Another recent study by Wang et al. (2016) examined the role of institutional environment on buyer-supplier relationships in emerging markets.

In this chapter, it is posited that part of the heterogeneity in the strength of the focal relationship can be explained by the institutional environment of the nation in which the firm operates. In the case of innovation, UNESCO’s Institute of Statistics (UIS) in their (2009) report notes a weak institutional environment characterized by weakness of property rights and market regulation among others as an impediment to innovation. While the institutional environment has many dimensions, the focus here is specifically on the level of financial development and the level of intellectual-property protection of a nation.

Firms in general, and more specifically those that indulge in their own innovation activities, require funding. It has been empirically shown that firms perform better in nations that are more financially developed. One of the markers of financial development

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of a nation is *capital market regulation*. Firms use the capital market to raise those much-needed long-term funds. Availability of such long-term funds can feed a firm's research and development and/or patenting costs, in short, innovation activities. An innovation-related project is typically performed in multiple stages over a considerable amount of time. A firm's credit-worthiness is re-visited by the lending parties throughout the different stages of the project. The government monitors and regulates the capital market to ensure its efficient functioning. The primary purpose of these regulations is to protect investors from fraudulent transactions. Various studies have examined how these capital market regulations impact economic activity in a nation (Barbosa and Faria, 2011; Cressy, 1996). Well-established capital markets (characterized by the availability of financial credit) have been shown to positively impact a firm's innovation (Barbosa and Faria, 2011; Bottazzi and Da Rin, 2002). In line with Barbosa and Faria (2011), the availability of credit information (CII) is used as the proxy for capital market regulation. To conclude, well-regulated capital markets would allow a reliable and timely access to credit. One way to maintain/improve the access to credit is by increasing the accessibility and quality of information about a firm's credit-worthiness. Hence, it can be reasonably expected that the availability of credit information will moderate the focal relationship, which leads to the second hypothesis H2.

Hypothesis 2. *The stronger the capital market regulation in a nation, the stronger the relationship between technological innovation and firm performance.*

In addition to better access to finance, possessing rights of ownership (e.g. in the form of patents and trademarks) on the product/s of their innovative activities (referred to as the intellectual property) also enables firms to monopolize the returns on innovation

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(Ginarte and Park, 1997). The primary motivation for a firm behind investing in innovation is to augment profits and stay ahead of its competitors. The financial returns from an innovative product are deeply impacted by the ability of the firm to monopolize the sales of that product in the target market, as well as prevent any imitation of that product by its competitors (Jaffe, 1986; Nelson and Winter, 1982). Given the current level of globalization, innovating firms need to protect their inventions from both domestic as well as global competition (Chen and Puttitanun, 2005). The national governments have thus created a legal framework to provide protection to intellectual property of innovating firms with the objective of (a) incentivizing domestic firms to continue to innovate, and (b) attract multinational firms into investing in their country (Varsakelis, 2001). In order to draw comparison across nations in terms of the strength of patent protection offered, the *patent protection index (PPI)* created by Ginarte and Park (1997) is utilized. This index measures the level of patent protection in a nation across five dimensions: (1) extent of coverage of inventions that are considered patentable, (2) membership in international patent treaties, (3) duration of protection, (4) enforcement mechanisms, and (5) restrictions on patent rights (Park, 2008). To conclude, since the legal ownership of its intellectual property via patents enables the innovating firm to prevent imitation of their innovations, monopolize the market, and maintain their competitive edge, it is hypothesized that firms operating in nations with a stronger framework of patent protection would experience better performance-related outcomes from innovation.

Hypothesis 3. *The stronger the patent protection in a nation, the stronger the relationship between technological innovation and firm performance.*

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2.2.3.2 Influence of Culture

The influence of national culture on firm performance is well-established in both OM as well as other disciplines (Kirkman et al., 2006; Power et al., 2010). Cultural values and practices are engrained (in other words, institutionalized) within citizens of a nation. The management practices of a firm reflect the cultural mindsets of the country in which the firm is based. Majority of the work done on cross-cultural comparisons has adopted the framework of national culture created by Hofstede (Flynn and Saladin, 2006; Power et al., 2010). He identified six major dimensions of culture, namely power distance, uncertainty avoidance, individualism vs. collectivism, masculinity vs. femininity, long-term vs. short-term orientation, and indulgence vs. restraint (Hofstede et al., 2010). He proposed that national culture defines and influences how a firm's management and employees adapt to new practices and ideas, how they solve problems, how they make decision in uncertain business situations, whether they value team-work over individual accomplishment and more; and in turn effects firm outcomes. Innovation-related initiatives made by a firm are not foreign to this influence either. Becheikh et al. (2006) provide a comprehensive review of innovation-related empirical studies in the manufacturing sector from 1993-2003. They found that the overall results on the effects of culture on innovation-related firm outcomes are quite varied with some significant and some insignificant results. Hence, cross-cultural differences do play a role in whether firms succeed from the introduction of innovations.

Two of the six cultural dimensions proposed by Hofstede fit well in the context of innovation based on the inherent nature of innovation and the inclination of the extant empirical research. First, the dimension of Individualism vs. Collectivism (IDV) has been the most widely utilized in firm-level research (Kirkman et al., 2006). The IDV dimension

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captures the degree of individualism of a country's citizens, in other words, the degree to which people put their own interests over that of the community. Highly individualistic cultures, like the US, value individual merit and accomplishments. Individuals from these cultures tend to perform better in projects that ensure individual accountability and recognition compared to projects that require teamwork. People from collectivistic cultures, on the other hand, place more emphasis on relationship building (personal or firm-level or team-level) over a single individual's interests and achievements. Higher the value on this dimension, more individualistic is the nation's culture. Power and his colleagues (2010) assessed the influence of 'individualism vs. collectivism' on innovation-related investment outcomes in Western and Asian economies, and concluded that innovation-related investments led to better performance (cost, quality, delivery, and flexibility) in collectivistic (Asian) economies compared to that in individualistic (Western) economies. Another study by Rosenbusch et al. (2011), that focused on small and medium-sized manufacturing firms (SMEs), also concluded that firms based in collectivistic cultures benefitted more from innovation because work on innovation projects was done collaboratively between employees as well as with customers and suppliers. Moreover, they argue that firms in collectivistic cultures tend to imitate more than innovate. As fewer firms strive for innovation in collectivistic cultures, those few firms that do indulge in true innovative behavior can benefit more from their efforts than firms based in cultures where innovation is pursued by the bulk of them.

Innovation requires collective brainstorming of ideas and teamwork in facing the associated challenges. A collectivistic culture promotes communication and cooperation

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among team members. Building on the previous research, it is hypothesized in H4 that the focal relationship is stronger in more collectivistic cultures.

Hypothesis 4. *The lower the degree of individualism in a nation, the stronger the relationship between technological innovation and firm performance.*

Additionally, the Uncertainty Avoidance (UAI) dimension captures the overall degree of averseness of a country's citizens to uncertainty and ambiguity. The extent to which the citizens avoid unknown future situations can negatively influence the performance outcomes of innovation. Conversely, the extent of acceptance of new/different ideas, and innovative products/processes, can positively influence performance outcomes of technological innovation. Higher the value on this dimension, lower is the degree of discomfort of the nation's culture with uncertainty. Becheikh et al. (2006) found that cultures ranking low in UAI were overall more innovative. Given that innovation is the implementation of new and challenging ideas with uncertain outcomes, it is posited that firms would perform better if they are based in cultures that do not shy away from delving in innovative projects that don't have predictable outcomes. This leads to the final hypothesis H5.

Hypothesis 5. *The lower the degree of uncertainty avoidance in a nation, the stronger the relationship between technological innovation and firm performance.*

Figure 2.1 presents the proposed model, and its hypothesized relationships.

2.3 Data and Methodology

The methodology of Meta-Analysis (MA) is one of the many ways to summarize, interpret, and compare different empirical studies that examine the same construct(s) and

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relationship(s) (Lipsey and Wilson, 2001). MA can greatly aid in bringing one closer to the 'true' relationship between constructs of interest compared to a single primary study. and in turn promote theory building (Hunter and Schmidt, 2004; Lipsey and Wilson, 2001). It becomes a fitting technique for our research because our purpose is to integrate the mixed findings on technological innovation→ performance link while also testing for country-level moderating effects.

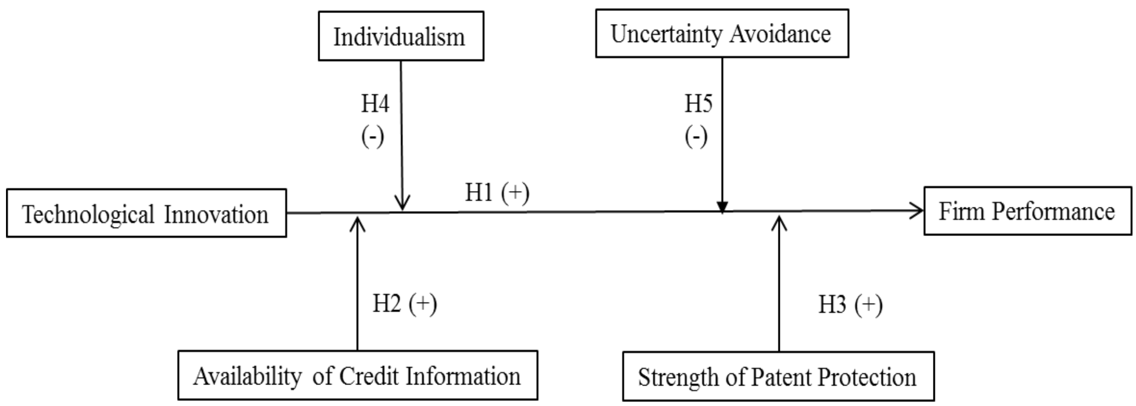

Figure 2.1. Proposed Technological Innovation and Firm Performance Model

Two different sets of meta-analytic techniques were utilized for the analysis. To test the first hypothesis H1, the Hedges and Olkin-type meta-analysis technique (commonly referred to as HOMA) (Hedges et al., 1985) was applied. HOMA computes the meta-analytic mean effect-size for the focal relationship, its standard deviation, and the corresponding confidence interval. The HOMA technique allows the use of both the fixed-effects model and the random-effects model. Since, the effect-size distribution for the focal relationship is assumed to be heterogeneous, the random-effects model was chosen instead of the fixed-effects model. The random-effects HOMA model corrects for both sampling error and other variability sources (denoted by a value) (Hedges et al., 1985). Also, the

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random-effects model is (a) more conservative than fixed-effects model, and (b) favored over a fixed-effects model in current MA practices (Heugens et al., 2009; Raudenbush et al., 2002; Van Essen et al., 2012). If the effect-size distributions are homogenous, both models produce comparable results.

To test for hypotheses H2-H5, Meta-Analytic Regression Analysis, (referred to as MARA) (Lipsey and Wilson, 2001) was applied. MARA uses a weighted least-squares (WLS) regression model in which the dependent variable is the observed effect size for the focal relationship. MARA helps to fill in the gap on the causes of heterogeneity in the effect-size distribution by testing for two types of moderating effects: (a) methodological artifacts that cause the observed effect size to differ from the actual effect size, and/or (b) new/external moderating variables that were not part of any of the studies comprising the study sample. Both the methodological artifacts and external moderators (CII, PPI, IDV and UAI) were included to conduct MARA.

Like HOMA, one can choose between a fixed-effects model and a mixed-effects model to run MARA. A fixed-effects model assumes that all between-study differences can wholly be attributed to systematic variance (captured by the newly-included moderators) and subject-level sampling error. A mixed-effects model assumes the same, but also considers a third random component that is either unmeasured or even immeasurable. A mixed-effects model has a lower Type-1 error rate, and offers more conservative results (Geyskens et al., 2009). Again, the mixed-effects model was used for the same reasons as those stated for HOMA.

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To conduct the entire meta-analysis, starting from study selection to analyzing coded data, the instructions laid out by Lipsey and Wilson in their book (Lipsey and Wilson, 2001) were followed, and referred to as the LW procedure for the rest of the paper.

2.3.1 Study Selection

To assess the research model, a sample frame was established by collecting empirical studies that theorize and measure the focal relationship. This effort included carefully examining Google scholar, web of science, EBSCO, and JSTOR databases, and filtering studies using search terms including but not limited to "performance", "innovation", "R&D expenditure", "patent", "new product introduction", "technological innovation", "product innovation", "process innovation", "innovation award", "innovation survey." Thirteen journals were screened for relevant papers. In addition to Management Science (MS), Academy of Management Journal (AMJ), Strategic Management Journal (SMJ), Research Policy (RP), and Journal of Product Innovation Management (JPIM) that comprise the top five most-cited journals to publish innovation-related research (Crossan, 2010), this journal list included Journal of Operations Management (JOM), Productions and Operations Management (POM), Decision Sciences (DS), International Journal of Operations and Production Management (IJOPM), International Journal of Production Economics (IJPE), Journal of Business Venturing (JBV), International Journal of Business (IJB), and Journal of Management Studies (JMS). In addition, Zhang et al. (2012) provide an excellent review of innovation literature, and we were able to add two more papers to the sample from those reviewed in their study.

Once the first set of research studies was accumulated, each paper was manually studied in detail to ensure that only papers that analyzed the focal relationship were

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included. Papers that were empirical in nature, and which provided all the information needed to conduct meta-analysis, were shortlisted. Accordingly, conceptual papers, qualitative papers, case studies and analytical-modeling papers were not considered. The reference lists of papers were also screened to look for any other potentially relevant papers that had not come up in the web search. This process resulted in a final sample of 28 studies. This sample size is consistent with other published meta-analysis studies in operations management and other fields (Gerwin and Barrowman, 2002; Mackelprang and Nair, 2010; Nair, 2006). Appendix A.1 provides a summary of the list of studies.

2.3.2 Coding Procedure

Sufficient time and care was taken in evaluating each study. Both focal variables i.e. technological innovation, and firm performance, have been conceptualized and operationalized differently across research disciplines. Measures of performance gathered from the collected sample comprised of both objective measures (for e.g., market measures like Tobin's Q and market share; and accounting measures like ROA and ROS), and subjective measures (gathered from single-item or multi-item Likert-based survey data). Similarly, measures of technological innovation also comprised of both objective measures (secondary sources and/or economic data) and subjective measures (single-item or multi-item Likert-based). All the different measures of performance and technological innovation were included regardless of their type. This is in line with the current conventional practices in meta-analytic studies (Carney et al., 2011; Gerwin and Barrowman, 2002; Hülsheger et al., 2009; Van Essen et al., 2012). The type of operationalization of all variables (performance, innovation, and control variables, if any) examined in each of the 28 studies was coded, along with any transformation applied on those variables. Apart from the type

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of operationalization used, collected studies also differed in other characteristics. For example, majority of the studies have examined the focal relationship in the manufacturing sector and collected cross-sectional data. Only two studies in the sample inspected panel data. The descriptive statistics of the final sample are shown in Table 2.1.

Table 2.1. Descriptive Statistics of the Study Sample (N = 28)

Methodological Characteristics	**Number of Studies**
Data from Manufacturing Sector	14
Data from Service Sector	4
Data from Both Sectors	10
Cross-Sectional Design	26
Panel Design	2
Controlled for Firm Size	18
Controlled for Industry Effects	11
Technological Innovation Operationalization	**Number of Studies** [a]
Subjective Measures	16
Objective Measures	17

Note. [a] Some researchers have used more than one type of measure in their study. Hence, the total number of studies adds up to a number greater than the study sample of 28 papers.

To test for H1, effect sizes between all variables (dependent, independent and control variables, if any); their significance test values (these can be t-statistics, z-value, and/or p-value); and sample sizes from each of the 28 studies were coded. The LW procedure uses a statistically standardized 'effect size'. In other words, the effect-size statistic standardizes findings across studies such that they can be directly compared (Lipsey and Wilson, 2001). If a study contained multiple measurements of the focal relationship, for e.g. Heeley et al. (2007), all measurements from that study were included because it ensures higher estimation accuracy (Bijmolt and Pieters, 2001). Correlation was

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used as the effect-size statistic (Carney et al., 2011; Heugens et al., 2009; Van Essen et al., 2012). Since meta-analysis focuses on both the direction and magnitude of the effects across studies, and not on statistical significance, both significant and insignificant effect sizes from each paper in the study sample were included to reduce bias in outcomes (Lipsey and Wilson, 2001). This approach is also consistent with previous meta-analytic studies (Carney et al., 2011; Gerwin and Barrowman, 2002; Heugens and Lander, 2009; Mackelprang and Nair, 2010). The words 'effect size' and 'correlation' are used interchangeably hereafter.

Both bivariate (Pearson Product-Moment) correlations and partial correlations were included as effect sizes (Geyskens et al., 2009; Lipsey and Wilson, 2001; Van Essen et al., 2012). It must be noted that partial correlation is an unbiased, scale-free, linear estimate of association that also renders the capability to detect model misspecification and is the more commonly used effect size. Using partial correlations makes it possible to include studies with missing effect-size data since it can be directly computed from the regression output. Not all studies embodied both types of correlations in the study sample. Therefore, to ensure that each study was represented in the analysis, the data from both types of correlations was aggregated (Mor Barak et al., 2009). In total, 132 effect sizes were obtained from the 28 studies in the sample, out of which 87 were partial correlations, and 45 were bivariate correlations.

To control for skewness in the effect-size distribution, all effect sizes were transformed to a Fisher Z-transform (Hedges et al., 1985) before being used in the analysis. This transformation ensured that all effect-size values were now relatively closer to a normal distribution. Additionally, the effect sizes are weighted using an inverse variance

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weight, denoted by w (Hedges et al., 1985). The sample size (N) of each study was used to weight the effect size obtained from that study, so that studies using a larger dataset carry more weight than those using a smaller dataset.

To test H2-H5, four new moderating variables were proposed in this study, and the data for them was extracted from independent sources. The first moderator called '*Credit Information Index (CII)*' is used as a proxy for capital-market regulation to test H2. The second moderator called '*Patent Protection Index (PPI)*' is used as a proxy for strength of patent protection in a nation and is used to test H3. The third moderator variable, called '*Individualism vs. Collectivism (IDV)*' measures the degree of individualism in a nation and is used to test H4. The fourth moderator variable, called '*Uncertainty Avoidance (UAI)*' measures the degree of discomfort with uncertain situations of a national culture and is used to test H5. To control for multi-collinearity, all four moderators were orthogonalized before conducting MARA.

Next, it also needs to be determined if the heterogeneity in the effect-size distribution is influenced by the design and methodology employed by the studies (Lipsey and Wilson, 2001). Based on the varying methodological characteristics of the 28 studies, five methodological moderating variables were created. Two dummy variables were created to capture if study used only manufacturing-industry data or only service-industry data, or data from both industries (10=manufacturing industry data, 01=service industry data). The following characteristics were also included as dummy variables: (1) use of cross-sectional data or panel data, (2) controlled for firm size or not, and (3) controlled for industry effects or not. Table 2.2 provides a description of all the moderating variables that were included in the analysis.

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Table 2.2. Description of the Moderating Variables

Moderators	Description
Credit Information Index (CII)	CII measures rules affecting the scope, accessibility, and quality of credit information available through either public or private credit registries. The index ranges from 0 to 6, with higher values indicating the availability of more credit information. CII scores were obtained from World Bank's Doing Business database-http://www.doingbusiness.org.
Patent Protection Index (PPI)	PPI measures the strength of patent protection in a nation. It is an unweighted sum of scores along five dimensions: (1) extent of coverage of inventions that are considered patentable, (2) membership in international patent treaties, (3) duration of protection, (4) enforcement mechanisms, and (5) restrictions on patent rights. The index ranges from 0 to 5, with higher values indicating stronger protection. PPI scores were obtained from Ginarte and Park (1997) and Park (2008).
Individualism (IDV)	IDV measures the degree of individualism of a nation. IDV dimension scores were obtained from http://geert-hofstede.com/
Uncertainty Avoidance (UAI)	UAI measures the degree of discomfort with uncertainty and ambiguity. UAI dimension scores were obtained from http://geert-hofstede.com/
Methodological Variables	**Description**
Manufacturing Industry Data	Dummy variable coded as 1 if study examined only manufacturing industries.
Service Industry Data	Dummy variable coded as 1 if study examined only service industries.
Study Design	Dummy variable coded as 1 if study used cross-sectional design.
Firm Size	Dummy variable coded as 1 if study controlled for firm size.
Industry Effects	Dummy variable coded as 1 if study controlled for industry effects.

2.4 Analysis and Results

The STATA macros provided by Lipsey and Wilson were used for the analysis (Wilson, 2001). In section 2.4.1, the big picture of how firm performance is affected by

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technological innovation (H1 results) is evaluated, followed by a discussion of the moderation effects on the focal relationship (H2-H5 results).

2.4.1 Results for Hypothesis 1

HOMA is run to test H1, and the corresponding results shown in Table 2.3 indicate a positive and significant relationship between technological innovation and firm performance. So H1 is supported. The mean of the relationship is 0.1 and is statistically significant with a p-value < 0.001, also the 95% confidence interval does not include zero. The effect size is in the small-to-medium range (Cohen, 1992), thus implying that technological innovation tends to positively but moderately influence firm performance. These findings need to be investigated further to evaluate if the strength of the focal link is heterogenous. To do so, the Cochran's (1954) Q test of homogeneity was performed, along with calculating the I^2 index. The Q-test value is 2985.1 and is statistically significant with a p-value <0.001. The I^2 index measures the degree of homogeneity, and a value > 0.75 indicates a high level of heterogeneity. The value of I^2 implies that the effect-size distribution is substantially heterogeneous. Therefore, it is worthwhile to examine next how much of this observed heterogeneity is accounted for by the moderators.

Table 2.3. Results of HOMA (Hypothesis 1)

Focal Relationship	N	k	Mean ρ	S.E.	Q test	I^2
Technological Innovation to Firm Performance	102,519	132	0.099****	0.016	2985.1***	95%

Note. N= total sample size; k= no. of effect sizes; mean ρ=estimate of population correlation; S.E.= standard error of mean ρ; Q= Cochran's homogeneity test statistic; I^2= scale-free index of heterogeneity; * p-value<0.1, ** p-value<0.05, *** p-value<0.01, **** p-value<0.001

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2.4.2 Results for Hypotheses 2-5

MARA was run to test H2-H5 with two different regression models as shown in Table 2.4. Model 1 includes only the methodological variables. Model 2 represents the full model that includes both sets of variables described in Table 2.2. Three statistics indicate the model fit: (1) the R^2 value, (2) the Q_{model} value, which represents the variance explained by the regression model, and (3) the $Q_{residual}$ value, which represents the variance left unexplained by the model.

Table 2.4. Results of MARA (Hypothesis 2-5)

Variables	Model 1		Model 2	
	Coefficient [a]	**S.E.**	**Coefficient [a]**	**S.E.**
Constant	.037	0.089	0.161	0.099
Methodological Variables				
Manufacturing Industry Data	0.036	0.037	0.036	0.041
Service Industry Data	0.126**	0.058	0.036	0.065
Study Design	0.07	0.078	-0.058	0.085
Firm Size	-0.027	0.039	-0.011	0.040
Industry Effects	-0.023	0.034	-0.024	0.039
Moderators				
Credit Information Index (CII)			-0.006	0.017
Patent Protection Index (PPI)			-0.039*	0.020
Individualism (IDV)			-0.064****	0.019
Uncertainty Avoidance (UAI)			-0.033*	0.017
R^2	0.05		0.14	
k	132		132	
Q_{model}	10.75**		29.32****	
$Q_{residual}$	193.66****		174.31***	

Note. [a] Unstandardized regression coefficients; k= no. of effect sizes; Q= Cochran's homogeneity test statistic; * p-value<0.1, ** p-value<0.05, *** p-value<0.01, **** p-value<0.001

As per Table 2.4, the R^2 value increased from Model 1 (0.05) to Model 2 (0.14). Both models fit the data reasonably well, and the fit improves when moving from one model to the next. The Q_{model} value increased from Model 1 (Q=10.75; p-value<0.05) to Model 2 (Q=29.32; p-value<0.001). This implies that the full model (Model 2) captures

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the heterogeneity well. The $Q_{residual}$ value decreased from Model 1 ($Q=193.66$; p-value<0.001) to Model 2 ($Q=174.31$; p-value<0.01) but remains significant. This implies that even though Model 2 fits reasonably well, the included moderators do not 'fully' capture the heterogeneity in the effect-size distribution. Hence, additional moderators need to be tested to account for the leftover heterogeneity.

Further examination of the MARA results in Table 2.4 reveals that only three out of four moderators: PPI, IDV, and UAI are statistically significant. First, in looking into the moderating role of a capital market regulatory-type institutional context, results show that CII does not drive the focal relationship ($p>0.1$). Furthermore, CII has a negative moderating effect, contrary to what was hypothesized. Hence, H2 is not supported. This was a surprising result. Numerous studies have shown a correlation between financial development (characterized by well-developed capital market) of a nation and firm performance for the simple reason that firms need 'access to finance' (Claessens and Tzioumis, 2006). This correlation is even more pertinent to innovative firms since innovation necessitates high investment costs. A possible explanation for the counter-intuitive result is that, availability of credit information is not the only factor behind ensuring that firms in fact do get timely access to finance. So even in the presence of transparency and availability of information about borrower firms (as reflected by a high value of CII), a lender might still deny the loan for the following reasons. First, studies have shown that innovation-related investments are treated differently than regular investments because of the associated risks and unpredictable returns (Hall, 2010). Furthermore, most of the innovation investment is spent on intellectual capital (which is considered tacit) and intangible assets. This exacerbates the perceived riskiness and

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uncertainty of returns from the innovation-related investment (Hall, 2010). Recent literature has shown that access to credit is different for innovative firms vs. that of non-innovative firms (Bellucci et al., 2014; Hall, 2010). This is further complicated by whether the firm is a start-up or an incumbent (Bellucci et al., 2014; Hain and Christensen, 2013). Another possible explanation as to why the results here do not reconcile with extant research is omitted-variable bias. It is possible that the results reflect the omission of firm-level characteristics from the model like firm growth over time and/or firm assets, both of which can influence a lender's decision in giving out credit. In brief, the intrinsic nature of innovation coupled with past firm innovation-related outcomes might take precedence over the availability of credit information when it comes to lending decisions. And the direction of the relationship is potentially being influenced by these omitted variables.

Second, results indicate that the strength of patent protection (PPI) does significantly moderate (p-value=0.054) the focal relationship however not as hypothesized. Hence, H3 is only partially supported. This result runs contrary to the basic assumption that incentives drive firm actions as well as what numerous previous studies have shown, that PPI has a positive impact on innovation (Chen and Puttitanun, 2005; Lerner, 2009; Varsakelis, 2001). A possible explanation for this is that even though patenting provides a firm ownership over its inventions, it also publicizes a firm's internal intellectual capital. A study by Cohen et. al (2000) discussed how competitors can work around the patent until its expiry, after which they can go ahead and use the patent. This behavior discourages the innovating firm to patent their inventions. Second, Pisano (2006) has argued that the impact of patent protection on the '*rate and direction*' of innovation and its outcomes is more complicated than what has been hypothesized thus far. Additionally, the choice to patent

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is dependent on the '*appropriability regime*' in which the firm operates. The appropriability regime in a nation is a combination of the strength of patent protection as well as the ease of imitability. Firms may not choose to patent their inventions it they don't deem imitation to be a concern. Also, given that the primary motivation of a firm is to maximize its financial returns from an innovative product, firms today are following an alternate strategy of intentionally sharing their proprietary knowledge as long as the receiver does not appropriate it. Additionally, Lerner (2009), also found strengthening of the patent protection framework to negatively impact innovation. Hence, in the current age of technological advancements, the legal framework of patent protection is perhaps becoming more of a deterrent when firms are moving away from patenting their inventions.

In terms of the moderating role of national culture, both IDV and UAI negatively moderate the influence of technological innovation on firm performance. Hence, both H4 and H5 are fully supported. Result for H4 implies that firms based in highly individualistic cultures (or higher value of IDV) tend to experience lower performance outcomes from technological innovation. This result indicates that fostering collaboration and communication among employee groups as well as giving precedence to the team-level success instead of to individual freedom and accomplishment can promote better innovation-related outcomes. Similarly, firms based in nations having a higher value of UAI also tend to experience lower performance outcomes with technological innovations. In other words, firms whose employees do not pull back from uncertain and ambiguous circumstances can gain better innovation-related outcomes.

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2.4.3 Results for Methodological Variables

Results for the effect of methodological variables on the focal relationship is presented in Table 2.4. Overall, none of the methodological variables were significant. In Model 1, only ‘Service Industry Data’ was positive and statistically significant with a p-value <0.05. However, it turned insignificant after inclusion of the four main moderating variables. Finally, the temporal design of the study, controlling for firm size, and controlling for industry-level effects, also did not impact the focal relationship.

2.4.4 Robustness Test

The objective measures of technological innovation were separated from the subjective measures, and HOMA was run separately for both categories. This was done to assess if the overall results were independent of the way technological innovation was operationalized. Table 2.5 shows the breakdown of these results, which indicate that even though the direction of the focal relationship remains unaffected by the type of measure used for technological innovation, the strength of the focal relationship does get affected.

Table 2.5. Robustness Test

Technological Innovation Operationalization	N	k	Mean ρ	S.E.	Q test	I^2
Subjective Measures	16,508	46	0.195****	0.008	628.77***	93%
Objective Measures	86,011	86	0.056****	0.018	2337.85***	96%

Note. N= total sample size; k= no. of effect sizes; mean ρ=estimate of population correlation; S.E.= standard error of mean ρ; Q= Cochran’s homogeneity test statistic; I^2= scale-free index of heterogeneity; * p-value<0.1, ** p-value<0.05, *** p-value<0.01, **** p-value<0.001

The focal relationship is positive and statistically significant (p-value <0.001) for both types of innovation measures. However, the mean for the subjective-measure category

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is 0.195, while for the objective-measure category is 0.056. This implies that one would observe a relatively stronger influence of technological innovation on firm performance when subjective measures were employed, relative to when objective measures were employed. Summarizing, even though a modestly positive relationship is indicated between the focal variables, its magnitude clearly varies and is driven by the type of measure (subjective vs. objective) used for technological innovation.

2.5 Discussion

Zhang et al. in their 2012 study noted that the link between innovation and performance outcomes was "weak and inconsistent". They attributed the inconclusive nature of this relationship to (a) inadequacy of the existing innovation measures, and (b) lack of knowledge and understanding of the factors on which the innovation-performance link might be contingent. Use of meta-analysis as a research methodology afforded high statistical power in quantitatively compiling these mixed research findings. First, the relationship between technological innovation and firm performance is statistically significant and modestly positive. Second, these results further indicate that the sources of variability in the strength of the focal relationship stem not only from the different ways of measuring technological innovation, but also from the contextual factors at play.

Four new moderating variables (CII, PPI, IDV, and UAI) were introduced to account for the said variability. Evidence was found that the focal relationship is conditional on the institutional effect of the strength of patent protection in a nation (represented by PPI). The direction of the result was however, contrary to what was hypothesized. Increasing the strength of patent protection tends to dampen the performance outcomes of technological innovation. This counter-intuitive result indicates that strong

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patent protection frameworks might in fact prove to be a deterrent to the firm in maximizing its profits especially in situations where the innovative product is either not vulnerable to imitation and/or intentional sharing of intellectual property holds the potential to enhance financial returns.

Both IDV and UAI significantly influence the focal relationship when examining the impact of cross-cultural differences on the performance sensitivity to technological innovation. The ideal cultural environment for the focal relationship is low levels of individualism and low levels of uncertainty avoidance. Consider the example of United States (US) that ranks low on UAI dimension and is number one in the Global Entrepreneurship Rankings Index (2017). US is also a highly individualistic nation. Individual freedom, creativity and merit is given considerable importance. This is reflected in the work-culture of firms. For example, employees prefer to work from home instead of going to the office every day. They can communicate with other employees via email/mobile if required. This affords them flexible schedules which is argued to be necessary for coming up with new innovative ideas. However, many firms are starting to realize what our results also indicate: a "*tight correlation between personal interactions, performance and innovation*" and are implementing changes accordingly (Waber et al., 2014). For example, Yahoo revoked mobile work privileges and Facebook got rid of individual cubicles in their office building (Miller and Rampell, 2013). Overall, the interaction of the institution-based view and the culture-based view helps us to get a deeper understanding of the technological innovation-performance relationship.

This research also makes some methodological contributions. It introduces the meta-analytic methodology of Lipsey and Wilson (LW) to the operations management

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(OM) discipline. To the best of our knowledge, the Hunter and Schmidt (2004) approach of artifact-corrected meta-analysis has been the conventional standard thus far. OM researchers are increasingly utilizing secondary data over survey data. The introduction of the LW approach is timely because it facilitates a more quantitative aggregation of empirical research findings across such studies that do not need correction for measurement error. It has already become the popular choice in other disciplines (management, finance, economics, and international business) (Carney et al., 2011; Van Essen et al., 2012). The LW approach allows one to find relationships across different types of effect sizes. Both partial correlations as well as bivariate correlations were used. Using partial correlations made it possible to include studies with missing effect-size data since it can be directly computed from the regression result. Using the LW procedure allowed us to test for potential moderators.

2.6 Conclusion

To conclude, the research in this chapter has attempted to shed more light on the issues recently raised in the OM literature by empirically resolving some of the inconsistency in the focal relationship and attributing it to institutional and cultural factors at play. Nevertheless, it suffers from several limitations. Primarily, the three moderators included in the analysis did not sufficiently account for the heterogeneity in the effect-size distribution of the focal relationship. There is still considerable variability that is unaccounted for. Future research can benefit from further exploration of the underlying mechanisms to account for some of that variability. Specifically, in terms of the institutional context of credit availability, contradictory results were found. Further research is needed to get a more nuanced view of what other variables might in fact be

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influencing the relationship between credit availability and innovation-related firm performance.

In terms of methodological limitations, the study sample is not exhaustive because it includes only 28 studies. Also, all included studies were published in the public domain. Future research can extend the study sample to include more international journals; as well as different types of research studies like working/unpublished work (thesis, articles), and books (if available) etc. First, this would decrease confirmatory-bias and selection bias (Pfeffer, 2007). It should be noted that meta-analytic studies do suffer from selection bias because outcomes with negative or null findings mostly go unreported and hence are difficult to find (Lipsey and Wilson, 2001). Second, given that enough studies are available, the technological-innovation construct can be further segregated into product and process innovation, and a meta-analysis can be done on each separately. Current research has focused on elucidating the effects of innovation on firm performance as being quadratic in nature (Story et al., 2015). Therefore, another interesting direction for future research would be to model the focal relationship as quadratic instead of linear. Future meta-analysis researchers are also encouraged to employ the LW procedure when their study sample includes studies that examine secondary data, as well as to use partial correlations as a complement to bivariate correlations.

Furthermore, outside the framework of meta-analysis, the literature review done in this chapter strongly suggests that most of the innovation research has assumed firms to be homogenous in nature. It would be interesting to investigate if firms in fact vary in how much they can benefit from innovation, and if they do, which factors can potential account for that variability. One recommendation for an influencing factor to the said relationship

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is the innovation being done by competitors. A firm can imitate the innovations being carried out by its competitors by using the innovation knowledge that leaks out of those firm/s. Existing research has established both innovation as well as imitation as strategies adopted by firms to transform their financial performance (Jaffe, 1986). This innovation knowledge that leaks out from one firm and is exploited by another is referred to as *Spillovers (Adams and Jaffe, 1996)*. Spillovers, in terms of R&D knowledge, have been shown to increase the financial performance of imitating firms but decrease the financial performance of innovative firm (Cohen et al., 2000). Future OM research can benefit from extending this area of research to an operations context. Hence, the next chapter of this dissertation (a) narrows down on the technological-innovation typology to target operational innovation specifically, (b) investigates if spillovers in terms of operational knowledge exist, and if they do, (c) examines the moderating role of operational-knowledge spillovers on the performance outcomes of firms from operational capabilities in the form of inventory, sourcing lead time, and flexibility.

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CHAPTER 3

Assessing the Implications of Inventory, Sourcing Lead Time, and Volume Flexibility Spillovers on the Financial Performance of Manufacturing Firms

3.1. Introduction

Responding to ever-growing competition, manufacturing firms continually seek ideas to improve their operational performance (Hammer, 2005). Such innovative ideas however, need not be developed in-house, but rather could be learned from another firm. For example, the highly successful Kanban system which was pioneered by Japanese manufacturing firms was subsequently adopted widely by American manufacturing firms.

Research on benchmarking (Sarkis, 2000; Shah and Ward, 2003) suggests that firms can compare their own operational competencies to industry standards or other high-performing firms, and set targets to improve themselves by imitating and/or emulating these firms. Walmart in an attempt to boost its online retailing operations, and "*catch-up*" to Amazon.com, its immediate competitor, recently made some changes to its operational policies (Yohn, 2017). It introduced free two-day shipping on online purchases and offered discounts to customers willing to pick-up their online orders from a Wal-Mart store. However, despite imitating a similar shipping policy as Amazon.com, Walmart has yet to realize the desired benefits. In its desire to "*catch-up*" to Amazon.com, Walmart has not fully exploited its internal operational capability (that it gained after acquiring Jet.com, the

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other e-commerce giant) of holding less inventory, which would then allow it to offer items at significantly lower prices. Does this mean that imitation as a strategy is necessarily a wrong move for all firms? Of course not. What works for one company might or might not work for another (potentially reflected by varying operational performance between firms), which raises the question about what factors must a firm consider before making the choice of imitating rival firms.

The innovating firm, on the other hand, may try to prevent imitation of their innovations to monopolize the market and maintain their competitive edge. For example, one way of discouraging imitation is for firms to not patent their most priced innovations. This strategy may sound counterintuitive, since patenting affords the firms legal right of ownership. However, it also turns the in-house idea into public knowledge, and competitors can work around the patent until the time limit expires, after which they can move ahead and use the patented idea (Cohen et al., 2000). Apple's lawsuit against Samsung for patent infringement (Mullin, 2016) is a classic example of an industry giant being protective about its innovations to maintain its position in the industry. Nevertheless, 100% protection is impossible due to a variety of reasons (Harhoff, 1996; Knott, 2008), and other firms do eventually gather the by-products that leak outside the innovating firm. Samsung has been Apple's long-standing supplier of processors. Through this relationship, an unintended transfer of knowledge of Apple's operations, technological processes and market size forecasts to Samsung occurred (Seifert and Isaksson, 2013), and today Samsung is Apple's biggest competitor. Such leakage of information from one firm (that generates new knowledge) to another (that accumulates new knowledge) is referred to as *Knowledge Spillovers* (Jaffe, 1986). These spillovers can be exploited by the firm that accumulated it.

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A firm can then combine this external spillover knowledge with its own internal capabilities, which is exemplified by Apple's Ipod in a somewhat reversed context than the situation with Samsung. Apple gained from the R&D and market penetration of Sony's Walkman, but then added its own capability, a digital music division, to that external knowledge and launched the "21st century Walkman", something Sony failed to accomplish (Yastrow, 2011).

Knowledge spillovers related to R&D knowledge have been widely shown to impact firm performance (Griliches, 1991; Knott, 2008). However, knowledge spillovers are not limited to just R&D-related spillovers, but potentially could encompass any type of knowledge, including operational knowledge. While the concept of operational-knowledge spillovers has traditionally been viewed anecdotally as simply imitating operational practices, those relationships are formalized by extending knowledge spillovers to include spillovers of operational knowledge (Cheng and Nault, 2007; Koufteros et al., 2007). Formally, in this dissertation the following two questions are addressed (1) the extent to which operational-knowledge spillovers (referred to as *Operational Spillovers or OM Spillovers* interchangeably*)* exist within the context of manufacturing firms, and (2) the extent to which a relationship exists, if any, between operational spillovers and financial performance of manufacturing firms. Operational spillovers related to inventory (INV), sourcing lead time (SLT) and volume flexibility (VF) in particular are evaluated.

While it may be assumed that accumulated knowledge must have a positive impact on financial performance, it is not necessarily true that all firms make use of the spillovers that they accumulate. They may lack the capability to do so (Cohen and Levinthal, 1990), as in the case of Walmart introducing two day shipping policy. Alternately, firms may not

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have sufficient funds to invest, or they may decide that the potential performance benefits from new knowledge thus acquired do not justify the additional investment costs (Knott, 2008). Monetary investment required to exploit external spillovers can be substantially high for firms employing traditional operational practices (Bessen, 2005; Mansfield et al., 1981). However, technological advancements can alter how firms respond to external spillovers, and can afford firms the ability to benefit from them at a fraction of the original costs. The most recent example for a technological advancement is 3D printing and additive manufacturing practices (D'Aveni, 2015). Such technological advancements can drive imitation, which while being beneficial to the imitating firm, can be detrimental to the innovating firm that spent significantly on manufacturing R&D to produce a high-quality product (Schubert and Jost, 2015). Technological changes have been taking place from the 1990s to the present. However, any empirical examination related to operational spillovers and firm performance is absent.

The remainder of the chapter is structured as follows. The next section provides an overview of the relevant literature in OM and other disciplines. Section 3.3 builds upon this literature to create the resulting hypotheses. Subsequent sections present the data, the methodology, and the results. The implications of operational spillovers for future OM research are discussed in the concluding section of the chapter.

3.2. Related Literature

A growing body of literature has examined the existence and impact of spillovers as a phenomenon across disciplines (Cheng and Nault, 2007; Jaffe, 1998; Zhang et al., 2010). Prior work in this area has traditionally focused on R&D-knowledge spillovers, and is currently in the process of identifying newer mechanisms that result in various other types

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of spillovers (Zhang et al., 2010). R&D-knowledge spillovers are typically defined as the leakage of knowledge that has been created by another firm through its R&D endeavors, which are then used by another firm/s for its own advancement (Jaffe, 1998).

Some of the major characteristics of spillovers are highlighted next. First, spillovers can occur via numerous mechanisms like outsourcing, merger and alliances, employee mobility between firms etc. (Song et al., 2003). Second, spillovers can result from both voluntary and involuntary sharing between firms (Harhoff, 1996). For instance, Harhoff (1996) modeled a scenario where a supplier firm can intentionally share knowledge with its buyers and these knowledge spillovers can replace the buyers' own R&D efforts. Third, spillovers can arise from both new and existing processes. Fourth, spillovers can occur both within firms (across departments) as well as between firms. They can occur across industries, and/or across technological/geographic boundaries as well (Adams and Jaffe, 1996). Fifth, the firm(s) benefitting from spillovers may or may not be direct competitors of the knowledge-generating firm. These firms may operate in a different industry or target a different market. Last but not the least, spillovers have been shown to have both positive and negative performance effects for a firm.

Scholars have examined spillover types other than R&D as well. For instance, Cheng and Nault (2007, 2012) have shown how IT spillovers affect the variation in returns to IT investments. Mayer (2006) examined two spillovers--knowledge and reputation on contracting in IT firms. Knott (2008) empirically demonstrated that contrary to past recommendations, investing more in R&D does not affect a firm's ability to derive more R&D spillover benefits. Spillover effects have been studied in cross-country settings as well (Zhang et al., 2010). For example, Mayer (2006) uses transaction cost theory to

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demonstrate how poor performance of a supplier can damage its reputation, and that reputational spillover can in turn have a negative effect on that supplier's revenue. On the other hand, a show of superior performance from the supplier can also lead to a positive reputational spillover. FDI spillovers have been shown to have both positive and negative effects on the productivity of domestic firms in emerging markets (Zhang et al., 2010).

In operations management (OM) research, both empirical and analytical studies have directly and indirectly examined spillovers, but mostly in the context of supply chains. These studies provide limited evidence that firms benefit from spillovers. Koufteros et al. (2007) and Perols et al. (2013) studied knowledge spillover effects in operations, and concluded that building embedded ties with suppliers can potentially open doors for incoming spillover effects (via both direct and indirect ties) for the firm. Perols et al. (2013) extended the work of Mayer (2006) by studying the effect of supplier integration on spillover of new technology innovations, as well as the effect of technology spillover on time-to-market. Xue et al. (2013) found that spillovers from supplier-side electronic integration affects customer service performance. When suppliers are shared between rival firms, any investments in the improvement of supplier capabilities by a buyer firm creates opportunities for benefits to *spill over* into other buyer firms. Given such a setup, a buyer firm's investment decisions may be influenced by potential quality spillovers (Agrawal et al., 2015) and/or capacity spillovers (Qi et al., 2015) and/or reliability spillovers (Wang et al., 2014), and/or knowledge and reputational spillovers (Kang et al., 2009).

On the other side of the supply chain, spillovers can also occur when a supplier invests in downstream buyers (Harhoff, 1996). The focal firm might choose to share the previously owned knowledge/resources in order to increase coordination between supply

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chain partners (Yao et al., 2013). Yao et al. (2013), who investigated organizational-learning spillover effects for a manufacturing supplier firm, found that learning spillovers do exist between product releases and posit that the learning spillovers from previous product releases may lead to reduction in inventory levels of the newer releases. Learning spillovers can also benefit firms in supply chain dyads (Yao et al., 2012). Andritsos and Tang (2014) provided some indirect evidence of spillovers resulting from improved TQM processes in a health care environment.

3.3. Theoretical Framework

Based on Jaffe's work, a spillover framework as it pertains to different types of operational spillovers and their impact on performance is shown in Figure 3.1.

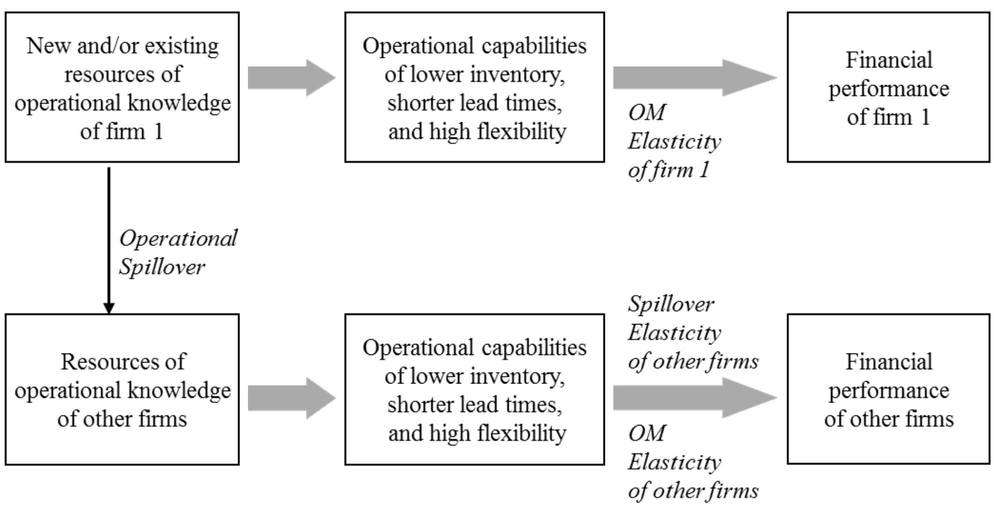

Figure 3.1. Framework for Operational Spillovers in Manufacturing Firms (Adapted from Jaffe 1998)

Firm 1 in the figure is the firm that generates operational spillovers and is referred to as the leader firm in the rest of the paper. The rest of the firms operating in the industry in which Firm 1 operates, accumulate these operational spillovers. Section 3.3 further elaborates on the Figure 3.1 and provides an explanation behind the flows of operational

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knowledge between Firm 1 and other firms. Section 3.4.4 explains how to measure the amount of operational spillovers leaking from the leader firm to other firm/s in that industry.

3.4. Hypotheses Development

The resource-based view (RBV) of the firm asserts that firms realize varying financial performance outcomes because firms differ in terms of their (a) operational resources and (b) internal capabilities to exploit those available resources. Resources can be both tangible (e.g. Property, Plant and Equipment) and intangible (e.g. knowledge) in nature.

In the field of operations management, firms employ their internal resource of operational knowledge to better manage inventory (INV), sourcing lead time (SLT), and volume flexibility (VF) and turn them into profit-generating capabilities. This operational-knowledge resource and the resulting operational capabilities can be applied by the firm to a wide variety of processes in numerous industries. In line with RBV, firms possess varying operational capabilities due to varying resource configurations, including operational-knowledge resource. It is further posited that firms also vary in their ability to generate operating profits through these operational capabilities. While some highly capable firms may be able to generate significant advantage in operating profits through their operational capabilities, other firms are likely to be not as proficient at generating operating profit via operational capabilities. Given this, the following is hypothesized:

Hypothesis 1a: *Manufacturing firms differ in their ability to impact their operating profit via operational capabilities of inventory (INV), sourcing lead time (SLT), volume flexibility (VF).*

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Furthermore, operational-knowledge as a resource cannot be fully protected by the more capable firm from leakage, in that other firms are continuously attempting to imitate the more-capable firms in an effort to bring their own capabilities to a comparable level (Barratt and Oke, 2007). Imitating firms capitalize on the operational knowledge that leaks out from the more capable firm (also called operational-knowledge spillovers) to complement their own internal resource of operational-knowledge for financial gains. As such, operational-knowledge spillovers can be viewed as a potential source of intangible resources to manufacturing firms. Given that there is significant evidence of R&D-knowledge spillovers (Knott, 2008; López-Pueyo et al., 2008); and strong indication from industry examples and recent changes in manufacturing practices, as discussed in the introduction section, operational-knowledge spillovers are expected to occur. Whereas some firms will be able to exploit these spillovers, others will be unable to effectively utilize such resources. In this chapter, it is contended that not all firms will have the necessary level of skill required to successfully imitate these operational capabilities that were built upon the more sophisticated bundle of operational-knowledge resource of the leading firm (s). Given this, the following is hypothesized:

Hypothesis 1b: *Manufacturing firms differ in their ability to impact their operating profit via operational spillovers.*

When evaluating the level of operational capabilities required by firms, extant research has consistently suggested that there is an optimal level for these capabilities such that exceeding this level or falling short of this level leads to sub-optimal performance (De Treville et al., 2004; Eroglu and Hofer, 2011; Jack and Raturi, 2002). Firms with capabilities near their optimal point also possess an optimal level of resources, as they

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pertain to RBV. Firms with too few resources can be viewed as being resource constrained, while firms with too many resources are subject to resource underutilization (Grewal and Slotegraaf, 2007; Paeleman and Vanacker, 2015; Sirmon and Hitt, 2009; Sirmon et al., 2010). Within the framework of the current research, the concept of *operational elasticity* or *OM elasticity* is developed here for the first time in literature. OM elasticity gauges the extent to which an additional unit of operational capability impacts operating profit. By calculating a firm's OM elasticity, it is possible to understand where the firm falls in relation to its optimal level of a given operational capability.

A negative value of OM elasticity indicates that operating profit increases (decreases) as the operational-capability level decreases (increases). Such a condition is indicative of a firm with an 'under-developed' potential to profit from operational capabilities. Taking the example of INV, firms with a negative INV elasticity possess excess levels of inventory, such that any further increase in the inventory held results in decreased operating profit. Conversely, a positive OM elasticity indicates that operating profit increases (decreases) as operational-capability level increases (decreases). This condition is indicative of a firm with an 'over-developed' potential to profit from operational capabilities. In the case of INV, these firms have the potential to profit from an increase in inventory, but they remain inventory-constrained, and hence potentially end up losing sales due to inventory shortages. Their operating profit would increase if they held additional units of inventory. Taken together, as a firm's OM elasticity nears zero, the firm's operating profit becomes increasingly more insensitive to changes in the levels of INV, SLT, and VF. It is contended that firms near optimal levels of operational capabilities are less sensitive to small changes in those levels, since the resulting level is still very near

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optimal. However, firms that are very far from optimal levels are much more sensitive to changes. Within RBV parlance, firms near their optimal OM elasticity have an optimal level of capabilities such that they are able to optimally utilize their resources. Resource levels diverging from this level results in constrained resource or excess resource conditions, resulting in sub-optimal resource utilization. This logic leads us to the following hypothesis:

Hypothesis 2: *There is an inverted-U relationship between the extent (as measured by OM elasticity) to which manufacturing firms derive operating profits from operational capabilities and their financial performance.*

The ever-growing literature on determinants of firm performance have recognized both in-house innovation and imitation of competitors as strategies to enhance financial outcomes (Jenkins, 2014; Lavie, 2006; Schubert and Jost, 2015). Maintaining this in terms of resources, an interaction of development of internal resources as well as imitation of external resources from competitors has been shown to augment firm profitability (Lavie, 2006). Hence, it is expected that manufacturing firms would be able to financially benefit from external operational-knowledge resources from its competitors more so when complemented by their internal capabilities. For this research, this relationship is slightly complicated by the fundamental anchoring of the operational capability in question. In terms of INV capability, *lower* amounts of inventory are considered ‘better’ for a firm. Hence, the goal of the firm is to increase its INV capability by lowering the amounts of inventory held. Similarly, in terms of SLT capability, *shorter* lead times are considered ‘better’ for a firm. However, VF, is oriented in the opposite direction wherein *higher* the VF, the better for the firm because the goal of a firm is to increase its VF capability by

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becoming increasingly flexible. This holds true for all firms regardless of their level of OM elasticity, or in which direction the firm is away from zero.

Hence, drawing upon RBV, it is expected that firms regardless of where they lie on the curve (i.e. regardless of the level of OM elasticity) will benefit positively from external resources of operational-knowledge that *spills over* from its competitors. Such spillovers can aid the firm in transforming their own operational capabilities towards more optimal levels. Considering again the example of INV, external INV spillovers are expected to benefit the firms in further lowering their inventory investments. A positive spillover elasticity indicates that operating profit increases (decreases) as the pool of operational-knowledge spillovers increases(decreases). A firm with a positive spillover elasticity possesses an enhanced ability to exploit the external-operational-knowledge spillovers compared to a firm with a negative spillover elasticity. To conclude, it is posited that exploiting external spillover resources can move the firm towards increased financial outcomes when complemented by its existing capabilities. Taken together, the following hypothesis is proposed:

Hypothesis 3: *The relationship between operational capabilities (in terms of INV, SLT, and VF) and financial performance of manufacturing firms is positively moderated by an increased ability to exploit the corresponding operational-spillovers (as measured by OM spillover elasticity).*

3.5. Data and Measures

The target sample for this research is US manufacturing firms (SIC codes in the range of 2000 and 3999). Firm-level annual data was collected over the period 1990-2016 from COMPUSTAT. Firms included in the sample came from the domestic population that

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traded in USD currency only, and comprised both active and inactive firms. Firms are considered active if they are currently carrying out trading activities like selling goods/services and so their accounting transaction are ongoing. Inactive firms comprise previously active firms that are not trading goods/services at present. From this sample, firm-year observations were deleted if they contained zero (=4300 observations approximately) and/or negative (=29 observations) values for key variables. For example, a negative value of sales is considered as erroneous, and the corresponding observation was deleted. Next, all missing R&D values were converted to zero as per (Chauvin and Hirschey, 1993; Hirschey et al., 2012). Next, firms that generated less than $30 million revenue in total over the 27 year period (=887 firms) were dropped (Rumyantsev and Netessine, 2007). This process resulted in an unbalanced panel data set consisting of 220 industries and 5668 firms, with a grand total of 66,569 firm-year observations. The final sample was partially complete i.e. both the dependent and independent variables contained missing values. Stata commands used for the analyses are already equipped to handle such data as they have built-in list-wise deletion. Actual sample varies across the different models estimated as the list of variables used varies across models. Actual sample used is presented in the Analysis and Results section 3.5 below each model's results. The creation of measures is discussed next.

3.5.1 Inventory (INV)

Inventory investments by firm i in year t is calculated as ½ (total inventory_t + total inventory_{t-1}) (Jain et al., 2013). It is then normalized by firm size (measured by total assets), and winsorized (95 5 percentile) to remove outliers. Firms with smaller inventory investments are better in terms of inventory management.

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3.5.2 Sourcing Lead Time (SLT)

In this chapter, the type of lead time considered is sourcing lead time, defined as the time it takes for a firm to receive materials from its suppliers. In line with Rumyantsev and Netessine (2007), SLT is operationalized as the average number of days of accounts payable outstanding. Although days of accounts payable cannot exactly replace the actual lead time data which is not available from public data sources, it has been shown to follow the same relationships with inventory and firm performance (Rumyantsev and Netessine, 2007). Hence, Sourcing Lead Time_{it} = 365/[($COGS_{it)}$ / AP_{it}], for firm i in year t, where AP_{it} refers to accounts payable and $COGS_{it}$ refers to the cost of goods sold. It is then normalized by firm size (measured by total assets), and winsorized (95 5 percentile) to remove outliers. In line with their work, the distribution of SLT was cross-checked to confirm that it did not show any questionable spikes and had an almost normal distribution verifying that majority of the data for the SLT proxy did not comprise of any contractually set payment schedules between firms. Firms with shorter lead times are considered better.

3.5.3 Volume flexibility (VF)

Manufacturing flexibility is multi-dimensional construct and is well-established as a competitive priority for firms used in responding to changes in demand by changing capacity, or in other words, production levels (Koste and Malhotra, 1999; Zhang et al., 2003). Pagell and Krause (2004) emphasize a re-evaluation of the flexibility-related findings given today's socio-economic conditions. One of its dimensions, volume flexibility, defined as "*the ability to effectively increase or decrease aggregate production in response to customers*" (Pagell and Krause, 2004) has gained renewed importance in the

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last decade given the ongoing advancements in digitization and 3D printing (D'Aveni, 2015). Volume flexibility permits a firm to increase or decrease production levels (da Silveira, 2006; Upton, 1994) without experiencing *"large changes in performance outcomes"* (Koste and Malhotra, 1999).

Volume flexibility (VF) is operationalized as the average percentage change in production calculated over a five-year period. First, production for firm i in year t is calculated as (cost of goods sold$_t$ + inventory$_t$ – inventory$_{t-1}$) (Bray and Mendelson, 2012). 140 observations had a negative production value and were dropped from the sample. Production is then normalized by firm size (measured by total assets). Next, the rate of change of production is calculated, taken as an absolute value to capture both upward and downward VF. It is then averaged out over a five-year period (t to t-4) and winsorized (95 5 percentile) to get the final measure. Firms with a higher value are considered more flexible. It must also be noted that other than taking average of production rate change over five years, using the maximum value also led to consistent results.

3.5.4 Operational Spillovers

The pool of external spillovers available to a firm was calculated using the 'leader distance' functional form (Eeckhout and Jovanovic, 2002; Nelson and Winter, 1982). Leader distance for a firm i within an industry y (at the 4-digit SIC level) in year t is the difference between the focal firm i and the industry leader in terms of the operational variable of interest. Leader distance form was chosen because it takes into account heterogeneity of the firms (Klepper, 1996; Knott, 2008). The term 'industry leader' does not necessarily imply a firm that has the highest financial performance. In fact, industry leader is characterized in terms of its standing with respect to INV, SLT, and VF. In terms of INV,

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the industry leader is the firm that has the lowest inventory investments relative to all other firms in that industry in a given year. In terms of SLT, the industry leader is the firm that has the shortest lead times relative to all other firms in that industry in a given year. In terms of VF, a higher value is considered to be better, thus the industry leader is the firm that has the highest VF relative to all other firms in that industry in a given year. Given the calculation of leader distance measure of operational spillovers, the leader firm itself would have a spillover pool value of zero. That is, the financial profits (or losses) accrued by the leader firm are purely from its own operational capabilities (refer to Figure 3.1). On the other hand, the financial profits (or losses) accrued by the rest of the firms are a result of their existing operational capabilities as well as the accumulated operational spillovers (Jaffe, 1998). Since the focus of this research is on the impact of operational spillovers on financial performance, consequently, the subsequent data analysis does not include the leader firms.

3.5.5 Dependent Variables and Control Variables

To test H1 and calculate firm-specific elasticities, the dependent variable used is firm operational performance, which is operationalized as *Operating Profit (OP)*. Operating profit is calculated as the difference between a firm's revenues and its cost of goods sold (COGS). To test H2 and H3, the dependent variable used is firm financial performance, which is measured in two ways (a) *Return on Sales (ROS)*, and (b) *Return on Assets (ROA)*. ROS is calculated as net income divided by total sales, and ROA is calculated as net income divided by total assets. All three measures were winsorized (95 5 percentile) to remove outliers. Finally, the following variables are used as firm-level controls. Net property, plant, and equipment is used as a proxy for firm capital, and number of employees is used as a

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proxy for labor. A one-year lagged value of R&D expenditure is included to account for the potential lag between innovation initiatives (as reflected by R&D investment) and realization of financial profits (Knott, 2008). Leverage, which is calculated as total liabilities divided by total assets of a firm i in year t, is used as a control for H2 and H3. Table 3.1 shows the descriptive statistics. Table 3.2 presents the correlation matrix calculated using list wise deletion. Hence, the sample size (N=25,664) is smaller than the size of the actual dataset.

Table 3.1. Descriptive Statistics

Variable	Obs	Mean	Median	SD	Min	Max
ln(Capital)	53,032	3.359	3.294	2.632	-6.908	12.517
ln(Labor)	53,032	-0.169	-0.234	2.020	-6.908	6.414
ln(R&D)	53,032	-1.193	0.831	5.418	-9.210	9.549
ln(OP)	53,032	3.982	3.963	2.169	-0.794	9.175
ROS	53,031	-0.064	0.027	0.296	-1.605	0.235
ROA	53,031	-0.026	0.031	0.184	-0.790	0.201

3.6. Analysis and Results

To better understand the effects of operational spillovers, the analysis begins by first verify the heterogeneity of firms (H1 results) and then calculating OM elasticity and spillover elasticity measures. Then, the effect of OM elasticity on firm's financial performance in the presence of operational spillovers is discussed (H2 & H3 results). For each dependent variable, three models are estimated-one for each of the three operational measures.

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Table 3.2. Correlations Table

	Variables	1	2	3	4	5	6	7	8	9	10	11	12	13
1	Ln(OP)	1												
2	Ln(Capital)	0.88	1											
3	Ln(Labor)	0.90	0.93	1										
4	Ln(Lagged R&D)	0.31	0.22	0.23	1									
5	Leverage	-0.01[b]	0.01	0.04	-0.05	1								
6	Ln(INV)	-0.33	-0.33	-0.23	-0.28	0.08	1							
7	Ln(INV Spillover)	-0.33	-0.34	-0.27	-0.14	0.05	0.83	1						
8	Ln(SLT)	-0.91	-0.93	-0.91	-0.24	0.01[b]	0.34	0.35	1					
9	Ln(SLT Spillover)	-0.89	-0.92	-0.91	-0.24	0.03	0.33	0.35	0.98	1				
10	Ln(VF)	-0.33	-0.34	-0.40	0.10	0.03	-0.18	-0.03	0.33	0.34	1			
11	Ln(VF Spillover)	-0.04	-0.10	-0.11	0.27	-0.06	-0.21	0.01	0.10	0.10	0.19	1		
12	ROS	0.41	0.29	0.32	-0.03	-0.22	0.00[b]	-0.04	-0.33	-0.33	-0.36	-0.09	1	
13	ROA	0.42	0.32	0.33	-0.01[b]	-0.26	-0.09	-0.13	-0.36	-0.36	-0.35	-0.08	0.88	1
14	INV Elasticity	-0.12	0.01[b]	-0.04	-0.06	0.05	-0.01[b]	-0.01[b]	0.06	0.06	0.07	-0.02	-0.15	-0.12
15	INV-Spillover Elasticity	-0.06	-0.01[b]	-0.03	-0.03	0.02	-0.04	0.00[b]	0.05	0.05	0.07	0.02	-0.11	-0.08
16	SLT Elasticity	-0.24	-0.20	-0.22	-0.03	-0.02	0.00[b]	0.03	0.20	0.21	0.15	0.07	-0.19	-0.16
17	SLT-Spillover Elasticity	-0.04	0.00[b]	-0.01[b]	0.05	0.00[b]	-0.03	-0.02	0.00[b]	0.01[b]	0.04	0.02	-0.10	-0.07
18	VF Elasticity	0.01[b]	0.08	0.10	-0.01[b]	0.05	0.07	0.03	-0.06	-0.07	-0.11	-0.05	0.01	0.00[b]
19	VF Spillover Elasticity	-0.06	-0.05	-0.04	0.04	-0.01[b]	0.02	0.04	0.05	0.05	0.04	0.03	-0.02	-0.02

N=25,664; All correlations are significant at $p<0.05$ unless indicated with [b].

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Table 3.2. Continued

		14	15	16	17	18
14	INV Elasticity	1				
15	INV-Spillover Elasticity	0.52	1			
16	SLT Elasticity	0.15	0.17	1		
17	SLT-Spillover Elasticity	0.12	0.14	0.65	1	
18	VF Elasticity	-0.04	-0.04	-0.07	-0.01	1
19	VF Spillover Elasticity	0.05	0.08	0.04	0.03	-0.15

3.6.1 Calculation of Firm-Specific Elasticities

To generate firm-specific elasticities, Random Coefficient Modeling (RCM) was used. RCM is an extension of linear regression models, used to handle clustered panel data. The intercept as well as the slopes can vary across clusters in RCM. For a panel data set, the RCM equation (with one explanatory variable) is represented by $Y_{it} = (\beta_0 + u_{0i}) + (\beta_1 + u_{1i}) X_{it} + \varepsilon_{it}$ for firm i and time t. Each coefficient (for intercept and explanatory variables) has two parts- a mean (or fixed) component (denoted by β_i), and a random component (denoted by u_i). The mean component (β_i) is the same for each firm. The random component is unique to each firm. The random component (unlike the mean component) is not directly estimated, but a Best Linear Unbiased Prediction is calculated instead. RCM allows for the study of individual firms' responses, both those included in the sample and those outside the sample, and are referred as "firm-specific effects" (Alcácer et al., 2013). RCM is an appropriate technique for the purposes of this research, where the purpose is to estimate marginal effects of operational inputs and spillovers in the presence of firm heterogeneity. Equation 1 represents the RCM model for firm i and time t used to generate the elasticities.

$$\ln(Y)_{it} = (\beta_0 + u_{0i}) + (\beta_1 + u_{1i}) \ln(K)_{it} + (\beta_2 + u_{2i}) \ln(L)_{it} + (\beta_3 + u_{3i}) \ln(R)_{it-1} + (\beta_4 + u_{4i}) \ln(O)_{it} + (\beta_5 + u_{5i}) \ln(S)_{it} + \varepsilon_{it} \quad (1)$$

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where Y is firm's operating profit, K denotes capital, L denotes labor, R is R&D, O refers to one of the three operational measures, and S denotes the corresponding operational spillover. Any zero values for explanatory variables were converted to a 0.0001 before taking natural log to avoid the problem with log-transformation of zero.

Stata's linear-mixed-model command was used to estimate the model. A separate model was run for each operational measure. Analysis was done in line with the mixed-model estimation process, running a null model first and then testing for significance of each added effect (using the likelihood ratio test) eventually building up to a full model including all fixed and random effects. Table 3.3 shows the RCM results for INV, SLT, and VF.

Table 3.3. RCM Results

DV=Ln(OP)	**(1)**	**(2)**	**(3)**
Variables	**OM = INV**	**OM = SLT**	**OM= VF**
Ln(Capital)	0.191^{***}	0.079^{***}	0.189^{***}
	(0.007)	(0.007)	(0.008)
Ln(Labor)	0.667^{***}	0.564^{***}	0.674^{***}
	(0.010)	(0.010)	(0.013)
Ln(Lagged R&D)	0.051^{***}	0.033^{***}	0.061^{***}
	(0.003)	(0.002)	(0.003)
Ln(OM)	-0.160^{***}	-0.304^{***}	-0.033^{***}
	(0.012)	(0.011)	(0.009)
Ln(Spillover)	0.014^{*}	0.042^{***}	0.003
	(0.007)	(0.008)	(0.003)
Constant	3.077^{***}	3.395^{***}	3.456^{***}
	(0.027)	(0.024)	(0.035)
N	52921	53032	29778

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Standard errors are in parentheses and are two-way cluster robust.

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The coefficients for capital, labor and R&D are all positive and comparable across the three operational measures (OM) (INV, SLT, and VF), which is as expected because any investment by a firm is done only to increase its profits. Table 3.3 only provides information about the direct/average component of OM elasticity and spillover elasticity. In all three models (#1-3), the *average* effect of the operational measure is negative on a firm's profit and the *average* effect of the corresponding OM spillover is positive on firm's profit for the entire sample after accounting for firm heterogeneity. To verify that these effects differ across firms with respect to OM and OM-spillover pool, the variance of the direct component was checked for statistical significance. Stata reports these statistics post estimations. For each of the three measures, the variance for the direct component of the operational measure was found to be statistically significant with a p-value<0.001 (t-statistic for INV = -41.4, for SLT = -51.6, for VF = -39.5). Similarly, the variance for the direct component of the corresponding OM spillover was also found to be statistically significant with a p-value<0.001 (t-statistic for INV = -44.0, for SLT = -27.2, for VF = -51.1).

For each of the three operational measures (INV, SLT, and VF), *firm-specific* elasticities were then calculated by adding both the mean and random components. In other words, OM elasticity is calculated as ($\beta_4 + u_{4i}$) and OM-spillover elasticity calculated as ($\beta_5 + u_{5i}$). The descriptive statistics for the two elasticity measures for all three operational measures are shown in Table 3.4. For example, in the case of INV (Model 1 in Table 3.4), the INV elasticity of a firm is its ability to generate profit from its own inventory investments and it ranges from -1.024 (lowest) to 1.36 (highest) in this sample. The INV spillover elasticity ranges from -0.566 (lowest) to 0.68 (highest) in this sample.

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Table 3.4. Descriptive Statistics for Firm-Specific Elasticities

Elasticities	Obs	Mean	SD	Min	Max
Model 1- Inventory (INV)					
OM Elasticity	52,921	-0.167	0.177	-1.024	1.360
Spillover Elasticity	52,921	0.013	0.071	-0.566	0.680
Model 2- Lead Time (SLT)					
OM Elasticity	53,032	-0.318	0.196	-1.431	1.498
Spillover Elasticity	53,032	0.041	0.045	-0.284	0.727
Model 3- Volume Flexibility (VF)					
OM Elasticity	29,778	-0.031	0.144	-1.157	0.787
Spillover Elasticity	29,778	0.002	0.058	-0.526	0.508

Figures 3.2-3.4 present the histograms for firm-specific OM elasticities for INV, SLT, and VF respectively.

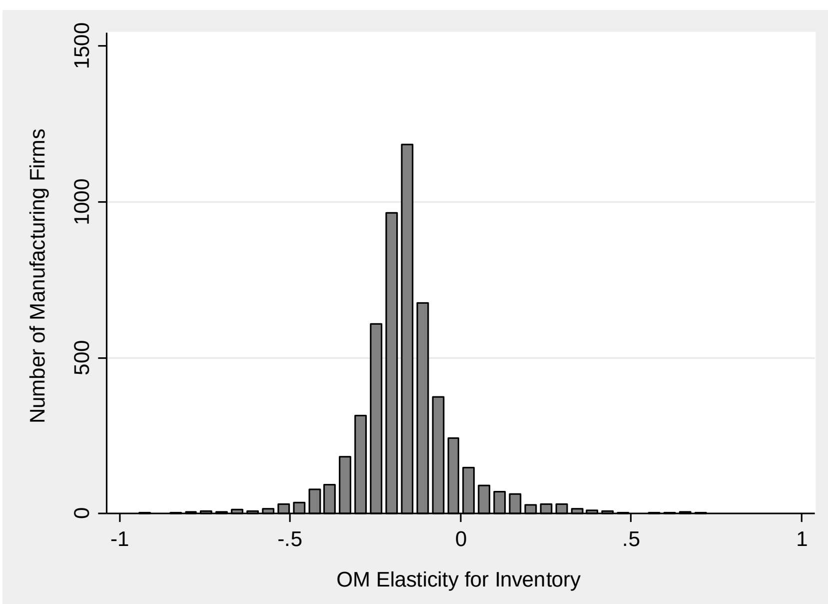

Figure 3.2. Histogram of Firm-Specific OM Elasticities for INV

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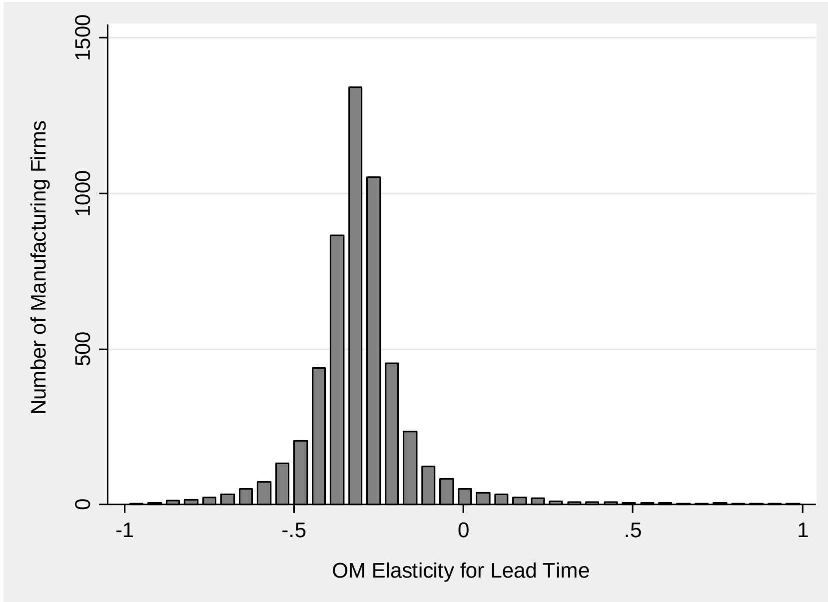

Figure 3.3. Histogram of Firm-Specific OM Elasticities for SLT

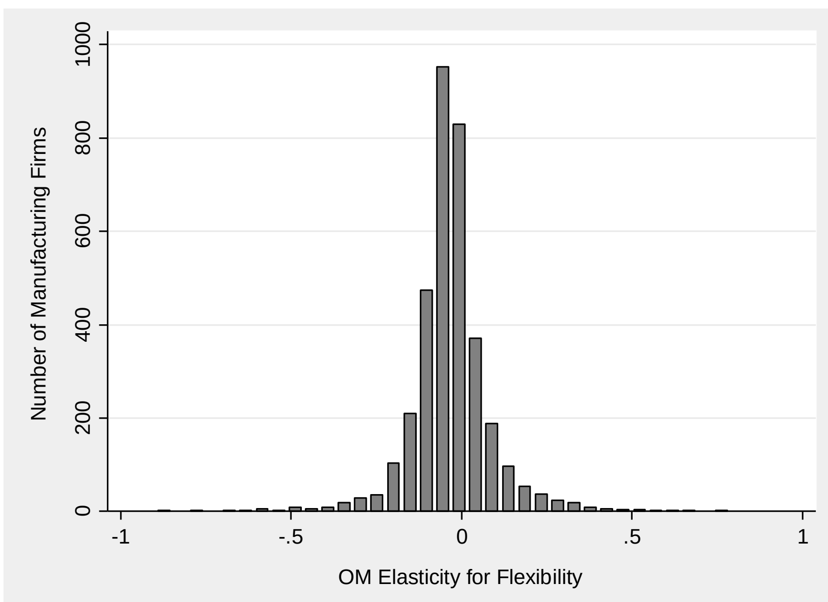

Figure 3.4. Histogram of Firm-Specific OM Elasticities for VF

Figures 3.5-3.7 present the histograms for firm-specific spillover elasticities for INV, SLT, and VF respectively.

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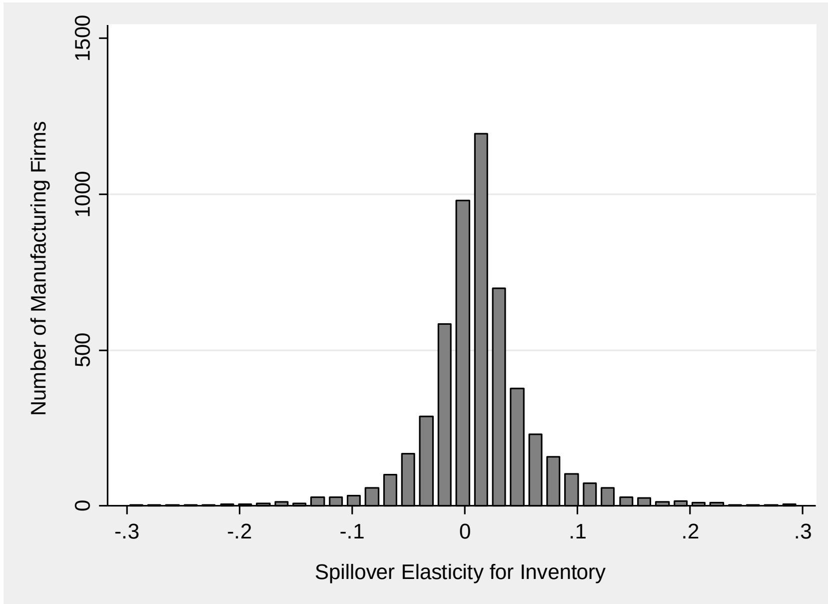

Figure 3.5. Histogram of Firm-Specific Spillover Elasticities for INV

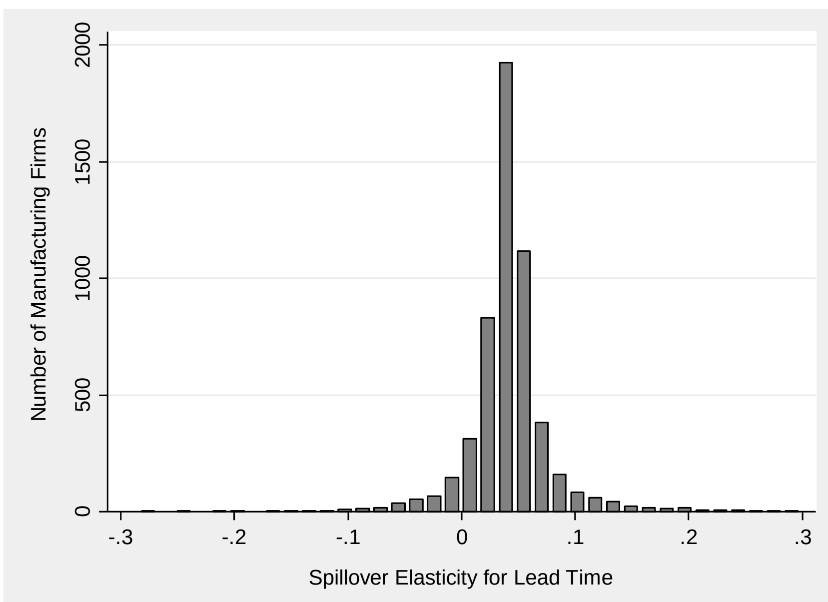

Figure 3.6. Histogram of Firm-Specific Spillover Elasticities for SLT

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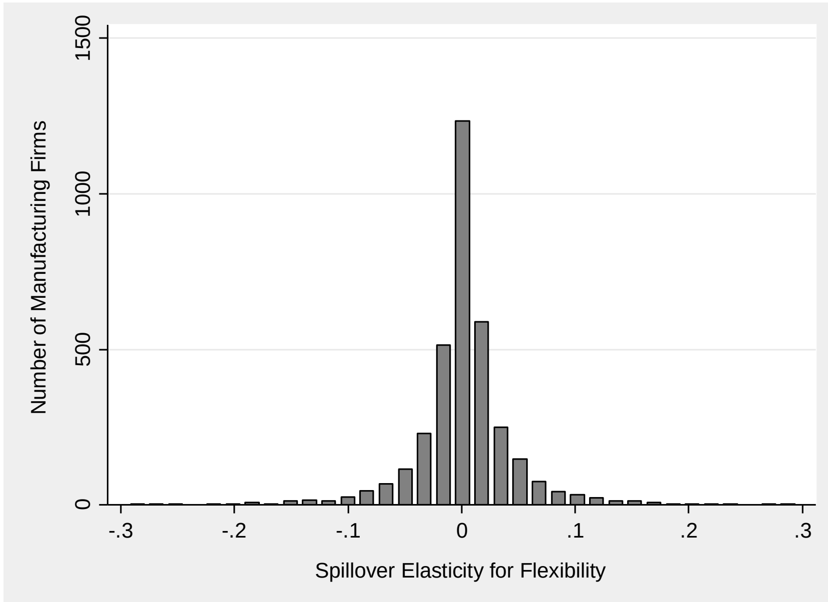

Figure 3.7. Histogram of Firm-Specific Spillover Elasticities for VF

The histograms together with the reported t-test results collectively lend support to the first hypothesis H1. Thus, there is considerable variance across firms in terms of the extent to which a firm's operational measure (OM) influences its profit, and the extent to which the corresponding OM spillover influences its profit.

As expected, OM elasticity and OM-spillover elasticity is negative for a subset of firms in the sample, and positive for the rest. This implies that for a 1% increase in, say, inventory investments, the OP would decrease for a firm with a low INV elasticity while the OP would increase for a firm with a high INV elasticity. A firm i's elasticity is generally regarded as being low or high relative to another firm. <u>However, to aide ease of understanding, a negative elasticity value is referred to as low elasticity and a positive elasticity value is referred to as high elasticity from here onwards.</u>

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3.6.2 Quadratic Nature of OM Elasticity

To test the second hypothesis H2, an OLS regression was run as shown in equation 2, with a double-clustered robust error structure (Cameron et al., 2011; Mackelprang and Malhotra, 2015). Firm size (proxy used is ln(#employees)), R&D, leverage, time, and industry (4-digit level) effects were included as control variables.

$$Y_{it} = \beta_1 \ln(X1)_{it} + \beta_2 X2_{it} + \beta_3 (X2*X2)_{it} + \beta_4 \ln(L)_{it} + \beta_5 \ln(R)_{it-1} + \beta_6 \ln(Z)_{it} + \beta_7 (\text{no. of years}) + \text{industry dummies} + \varepsilon_{it} \qquad (2)$$

where Y is firm's financial performance (ROA/ROS), X1 is one of the three operational measures, X2 is the corresponding OM elasticity of that operational measure, ln(L) is firm size, R is the one-year lagged R&D value, and Z denotes leverage for firm i and time t. Results for hypothesis H2 are summarized in Table 3.5.

Table 3.5. OLS Regression Results for Hypothesis 2

	(4)	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
	OM = INV		**OM = SLT**		**OM = VF**	
Variables	**ROA**	**ROS**	**ROA**	**ROS**	**ROA**	**ROS**
Ln(Lagged R&D)	-0.004***	-0.007***	-0.005***	-0.008***	-0.002***	-0.004***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
No. of Years	-0.002***	-0.001	-0.003***	-0.004***	-0.000	0.001
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Ln(Labor)	0.032***	0.053***	0.001	0.022***	0.021***	0.030***
	(0.002)	(0.004)	(0.002)	(0.005)	(0.001)	(0.002)
Leverage	-0.022	-0.030*	-0.022*	-0.028*	-0.078***	-0.094***
	(0.012)	(0.015)	(0.011)	(0.013)	(0.017)	(0.018)
Ln(OM)	-0.008*	0.044***	-0.038***	-0.038***	-0.058***	-0.091***
	(0.003)	(0.008)	(0.002)	(0.004)	(0.004)	(0.008)
OM Elasticity	-0.110***	-0.216***	-0.037**	-0.085***	-0.056***	-0.078***
	(0.011)	(0.024)	(0.011)	(0.022)	(0.014)	(0.023)

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OM Elasticity^2	-0.136***	-0.288***	-0.097***	-0.222***	-0.092*	-0.233**
	(0.037)	(0.066)	(0.024)	(0.047)	(0.038)	(0.072)
N	52838	52838	52944	52944	29729	29729

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Standard errors (SE) are in parentheses and are two-way cluster robust

Results of industry dummies are not shown in the interest of brevity. The Variance Inflation Factor (VIF) for all models was less than 4, implying that multicollinearity was not an issue. The interpretation of these results for each operational measure is discussed next.

3.6.2.1 Inventory (INV)

Models 4 and 5 (ROA & ROS respectively) present the results of regressing firm financial performance on the INV elasticity. Both the linear and quadratic term for INV are significant and negative with a p-value< 0.001. The results indicate a concave or an inverted-U relationship between INV elasticity, and ROA and ROS lending support to H2. The concave curve is such that the maximum predicted value of ROA and ROS occurs at an elasticity value close to zero (-0.5). This implies that firms whose INV elasticity is closer to zero, are expected to reap the maximum financial gains (in terms of ROA and ROS) from INV. The inverted-U relationship also indicates that as you move farther away to the left of the curve, i.e. the INV elasticity goes increasingly negative, and the financial benefits steadily decrease. Firms that fall on the farther left side of the curve, while being less capable in converting inventory investments into operating profits, arguably compensate by holding excess inventory which ultimately results in the firm suffering financial losses.

Similarly, as you move farther away to the right of the curve, i.e. the INV elasticity goes increasingly positive, but the financial benefits again steadily decrease. This is in line

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with what is hypothesized. Firms lying on the farther right side, are exceedingly capable in converting inventory investments into operating profits, but contrary to intuition, they are not the ones that are financially more profitable. The understanding is that these firms are straddling the point of being overly lean (Eroglu and Hofer, 2011), i.e. they are holding the least possible amounts of inventory resulting in inventory shortages and eventual loss of sales. Perhaps their strategy is to stay as close to the leader (defined as the firm with lowest inventory investments) as possible. They are considering only the absolute inventory investments when implementing their operational policies and not their INV elasticity, which if included in the decision-making analysis, can completely change the picture. If these firms were to in fact increase their inventory investments, they could derive improved firm profitability by capturing lost sales.

3.6.2.2 Sourcing Lead Time (SLT)

Models 6 and 7 (ROA & ROS respectively) present the results of regressing firm profitability on OM elasticity in terms of SLT. Both the linear and quadratic term for SLT are significant and negative with a p-value< 0.01. The results indicate a concave relationship or an inverted-U between SLT elasticity, and ROA and ROS lending support to H2. The concave curve is such that the maximum predicted value of ROA and ROS occurs at an elasticity value close to zero (-0.2). This implies that firms whose SLT elasticity is closer to zero, are expected to reap the maximum financial gains (in terms of ROA and ROS) from SLT capability. These firms are in fact, almost financially immune to small changes in SLT. It is the firms that lie to the farther left and farther right of these firms that are highly sensitive to any changes in SLT. Like INV, firms that lie to the left are operationally 'less capable' in terms of SLT while those on the right are operationally

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‘exceedingly capable’. In general, longer SLTs imply longer intervals between deliveries from suppliers, and in turn indicates more inventory in holding. Shorter SLTs, on the other hand, imply less inventory in holding which in turn echoes leaner operations. Shorter SLT is a marker of leaner operations, however *too much* lean can turn into a riskier proposition (Eroglu and Hofer, 2011). Any unplanned changes in production or unexpected errors, or unpredictable spikes in demand can throw-off the entire production system, thus resulting in financial distress. The exceedingly-capable firms are arguably trying to stay as close as possible to the leader firm (defined as the firm with the shortest lead-time) in terms of SLT; however, they are not able to adequately address changes in demand because of inventory shortages resulting from shorter SLTs. The less-capable firms, on the other hand, are holding excess inventory as reflected from longer SLTs, and hence suffering financially. It is possible that these are the firms that sell products associated with higher margins and want to avoid stock-outs at any cost (Rumyantsev and Netessine, 2007).

3.6.2.3 Volume flexibility (VF)

Models 8 and 9 (ROA & ROS respectively) present the results of regressing firm profitability on VF elasticity. Both the linear and quadratic term for VF are significant and negative with a p-value< 0.01. The results indicate a concave relationship or an inverted-U between VF elasticity, and ROA and ROS lending support to H2. The concave curve is such that the maximum predicted value of ROA and ROS occurs at an elasticity value close to zero (-0.2). This implies that firms whose VF elasticity is closer to zero, are expected to reap the maximum financial gains (in terms of ROA and ROS) from VF. In a similar vein as INV and SLT, firms that are closer to zero are almost financially immune to small changes in VF. Additionally, both, firms to the farther left as well as to the farther right of

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the curve, are financially inferior to firms that have almost zero VF elasticity. It should be recalled that, unlike SLT and INV, a higher level of VF is considered better for a firm. The left side of the curve comprises of firms with a low VF elasticity, indicative of firms that have too much VF. For these firms, an increase in volume flexible capabilities would simply provide additional capabilities when the current level is adequate, resulting in decreased ROS and ROA. Firms on the right side of the curve have an insufficient level of VF, such that they are unable to meet demand effectively resulting in diminished financial performance.

However, it is possible that these firms are compensating for the lack of capabilities by exploiting external spillovers from the leader firm. Hence, the potential moderating role of spillover elasticity on OM elasticity→ financial performance link is discussed next.

3.6.3 Moderating Effect of Spillover Elasticity

To test the third hypothesis H3, the model presented in equation 2 was extended to include spillover elasticity as a moderator. Results for hypothesis H3 are summarized in Table 3.6.

Table 3.6. OLS Regression Results for Hypothesis 3

	(10)	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**
	OM=INV		**OM=SLT**		**OM= VF**	
Variables	**ROA**	**ROS**	**ROA**	**ROS**	**ROA**	**ROS**
Ln(Lagged R&D)	-0.004***	-0.006***	-0.004***	-0.008***	-0.002***	-0.004***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
No. of Years	-0.002***	-0.001	-0.003***	-0.004***	-0.000	0.001
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Ln(Labor)	0.032***	0.053***	0.000	0.020***	0.021***	0.030***
	(0.002)	(0.004)	(0.002)	(0.004)	(0.001)	(0.002)
Leverage	-0.022	-0.029*	-0.022*	-0.028*	-0.078***	-0.094***

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	(0.012)	(0.015)	(0.011)	(0.013)	(0.017)	(0.018)
Ln(OM)	-0.009*	0.043***	-0.038***	-0.039***	-0.058***	-0.091***
	(0.003)	(0.008)	(0.002)	(0.004)	(0.004)	(0.008)
OM Elasticity	-0.111***	-0.210***	-0.054**	-0.115***	-0.052***	-0.070**
	(0.014)	(0.028)	(0.018)	(0.031)	(0.013)	(0.024)
OM Elasticity^2	-0.232***	-0.433***	-0.194***	-0.468***	-0.076	-0.210*
	(0.043)	(0.074)	(0.036)	(0.069)	(0.045)	(0.090)
Spillover Elasticity	-0.106**	-0.200**	-0.073	-0.277*	0.043	0.090
	(0.038)	(0.074)	(0.071)	(0.133)	(0.042)	(0.077)
OM Elasticity*	0.049	0.049	-0.205	-0.115	0.374***	0.644**
Spillover Elasticity	(0.069)	(0.130)	(0.201)	(0.375)	(0.102)	(0.229)
OM Elasticity^2*	0.543***	0.852***	0.761***	1.575***	0.318	0.564
Spillover Elasticity	(0.097)	(0.167)	(0.165)	(0.331)	(0.166)	(0.318)
N	52838	52838	52944	52944	29729	29729

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Standard errors in parentheses and are two-way cluster robust

Similar to testing for H2, a double-clustered robust error structure (Cameron et al., 2011; Mackelprang and Malhotra, 2015) was used in the estimation of the OLS regression. R&D, firm size (proxy used is ln(#employees)), leverage, time, and industry (4-digit level) effects were included as control variables. The Variance Inflation Factor (VIF) for all models was less than 4, implying that multicollinearity was not an issue. The interpretation of these results for each operational measure is discussed next.

3.6.3.1 Inventory (INV)

Models 10 and 11 (ROA & ROS respectively) in Table 3.6 present the results for the moderating effect of INV spillover elasticity. The interaction of spillover elasticity with the quadratic term of INV elasticity is significant with a p-value less than 0.001. The results show that, spillover elasticity moderates the quadratic association between INV elasticity

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and financial performance. Graphically the interaction is presented in Figures 3.8 and 3.9 for ROA and ROS respectively. These graphical results further indicate that the impact of INV spillovers varies depending on the position of the firm on the inverted-U curve of INV elasticity. Not all firms benefit from an increased ability to learn from INV spillovers.

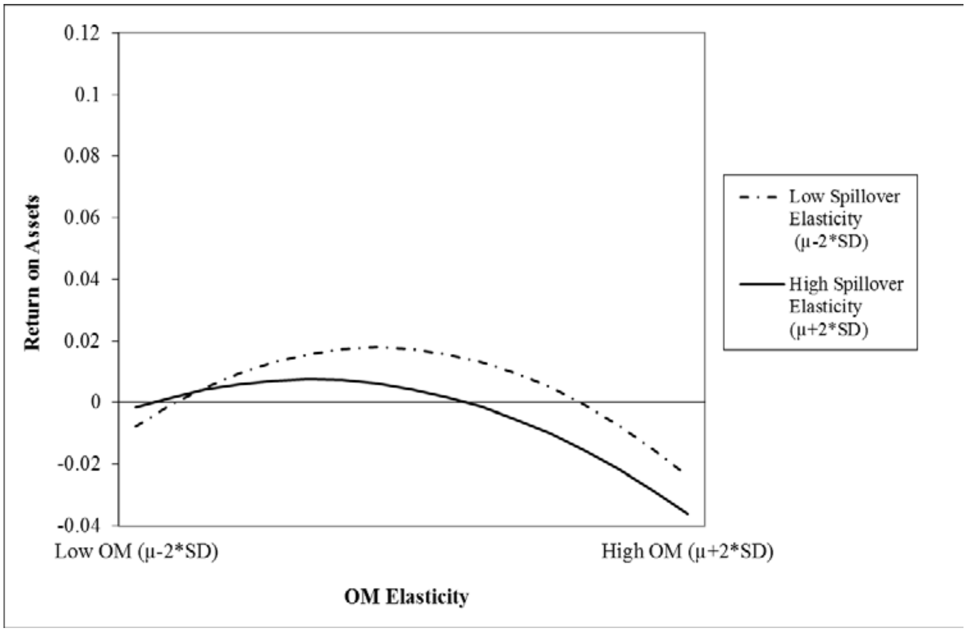

Figure 3.8. Interaction Plot: DV=ROA and OM = INV

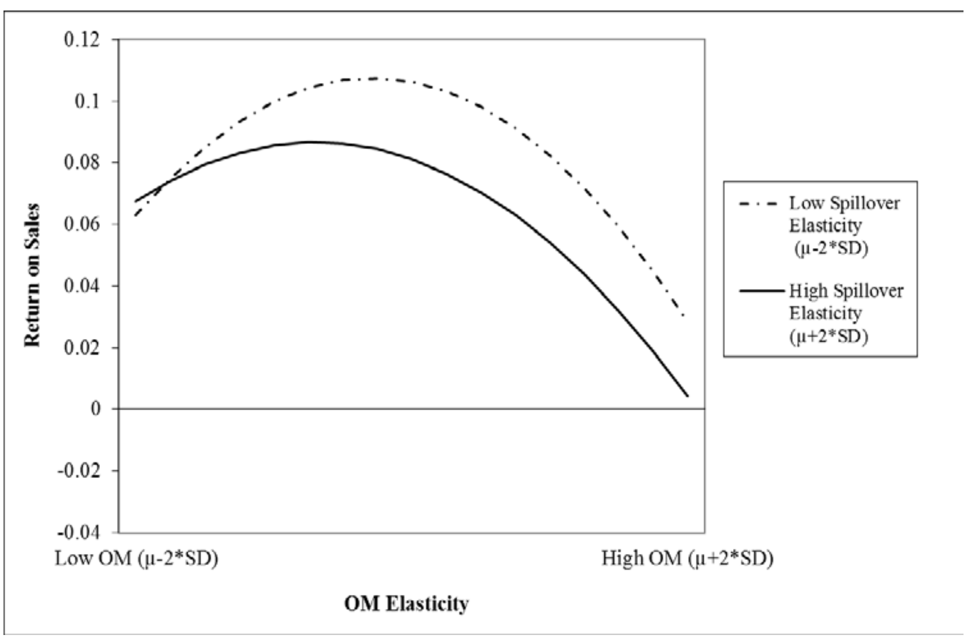

Figure 3.9. Interaction Plot: DV=ROS and OM = INV

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Firms that are near optimal (INV elasticity near zero) have the highest performance and do not learn from spillovers—in this case any learning from INV spillovers would result in less optimal inventory practices. The firms lying on the left side of the quadratic curve of INV elasticity hold inventory in excess, while the firms on the right side of the curve are inventory constrained. Firms on the left have inadequate INV capabilities, and can benefit from learning. They can successfully compensate and improve their inventory practices through learning from operational spillovers. Those that are unable to do so perform relatively worse as they are unable to improve their INV capabilities and continue to absorb the costs of excess inventory. Firms on the right side of the curve have excessive INV capabilities. They are already too lean, and learning to be even more lean via INV spillovers results in lost sales and lower financial performance. They would be much better off if they focus solely on internal INV capability. While counterintuitive, it is a key finding that is nevertheless consistent with RBV. Hence, H3 is partially supported.

3.6.3.2 Sourcing Lead Time (SLT)

Models 12 and 13 (ROA & ROS respectively) in Table 3.6 present the results for the moderating role of SLT-spillover elasticity. The interaction of spillover elasticity with the quadratic term of SLT elasticity is significant with a p-value less than 0.001. In other words, spillover elasticity moderates the quadratic association between lead-time elasticity and financial performance. Figures 3.10 and 3.11 present the interaction results graphically for ROA and ROS respectively. The overall results for SLT are like those for INV, whereby not all firms benefit from an increased ability to learn from lead-time spillovers. For firms with longer SLTs, the only way to financially gain would be to positively enhance one's lead-time-spillover elasticity, that is learning to reduce their SLTs via operational

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spillovers. On the right side of the curve, there is little difference between the firms that learn via spillovers and those that do not learn from spillovers. Thus, the bulk of the moderation occurs in those firms that do not have excess capabilities related to SLT. Figures 3.10 and 3.11 together with Table 3.6 results partially confirm H3. The moderation effect is strongest in the case of SLT as observed in Table 3.6. Furthermore, in the case of SLT, firms tend to experience an even higher moderating impact of increase in spillover elasticity in the case of ROS.

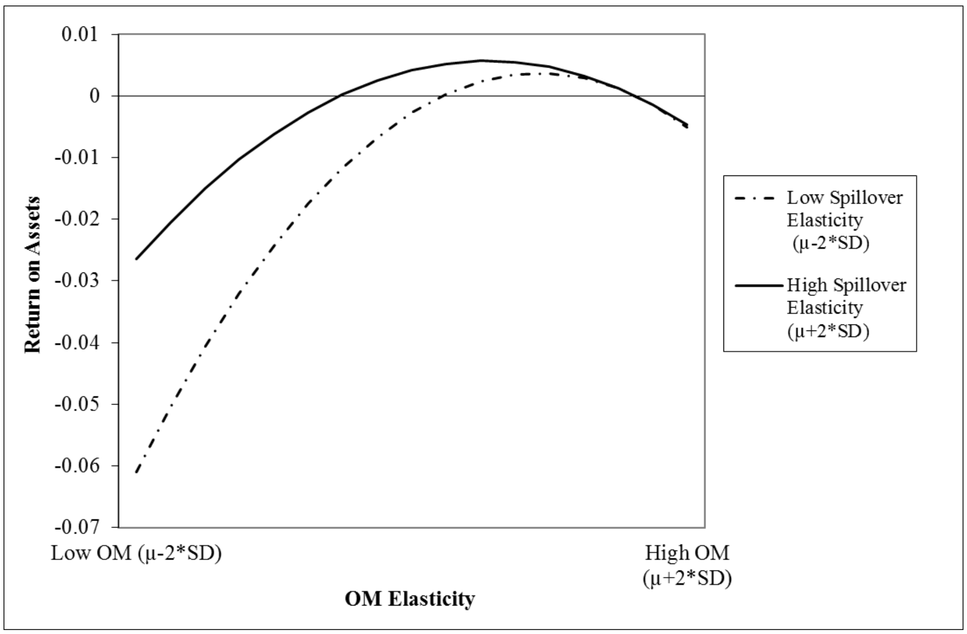

Figure 3.10. Interaction Plot: DV=ROA and OM = SLT

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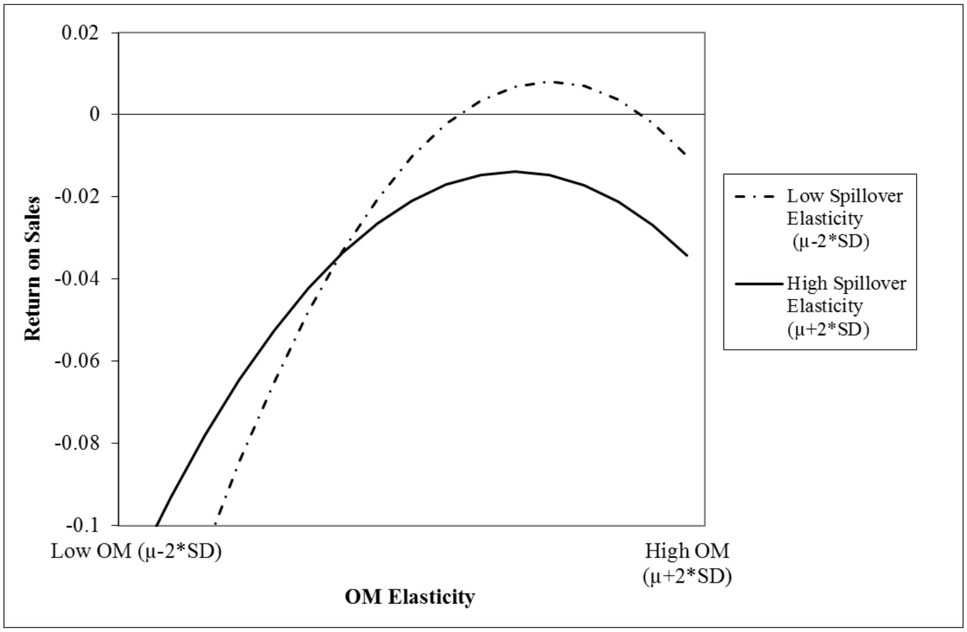

Figure 3.11. Interaction Plot: DV=ROS and OM = SLT

3.6.3.3 Volume flexibility (VF)

Models 14 and 15 (ROA & ROS respectively) in Table 3.6 present the results for the moderating role of VF spillover elasticity. The interaction of spillover elasticity with the quadratic term of VF elasticity is not significant (at a p-value less than 0.05). However, the magnitude of the interaction effect is considerable (0.553). Graphically the interaction is presented in Figures 3.12 and 3.13 for ROA and ROS respectively, and mirrors INV results except for the quadratic association. Learning helps when lacking VF capabilities, and hurts when excess VF capabilities are present. Recall that unlike INV and SLT, a higher value is considered better in terms of VF. The graphs indicate that, firms that can learn from spillovers perform better among the group of firms that rank too low on the VF scale compared to firms that cannot learn from spillovers. The opposite is true for the category of highly-flexible firms. On the left side of the curve, lie firms that already have too much VF such that any further increase hurts them financially.

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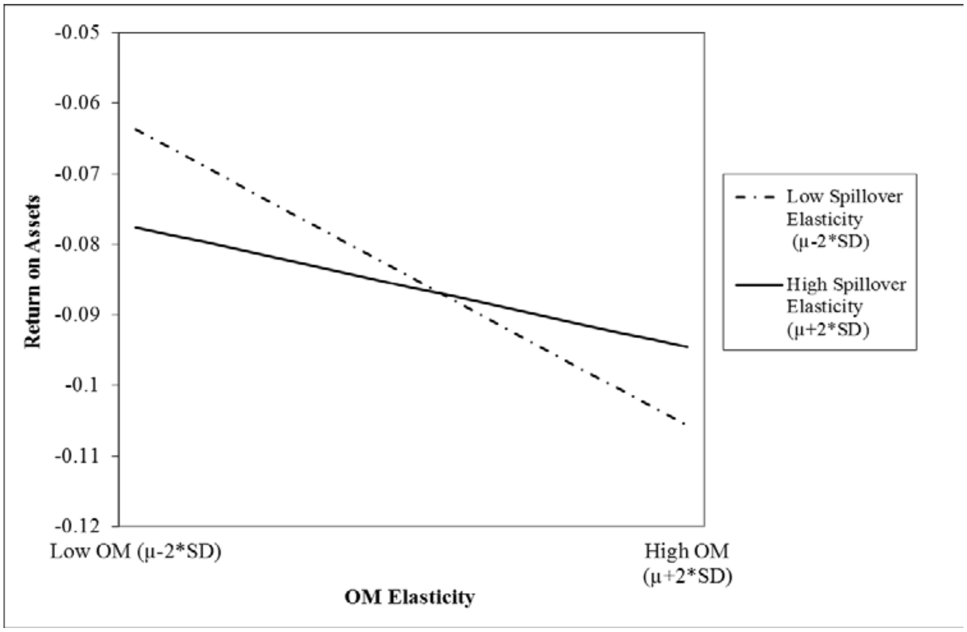

Figure 3.12. Interaction Plot: DV=ROA and OM = VF

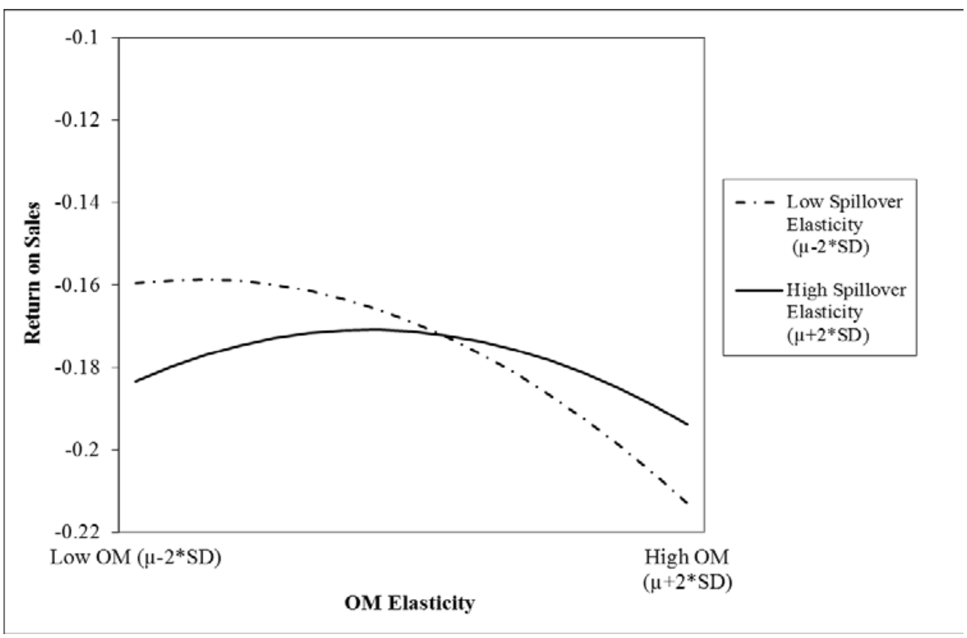

Figure 3.13. Interaction Plot: DV=ROS and OM = VF

Among these firms, those that do not learn from external spillovers tend to perform better than firms that do learn. This is because since these firms already have too much VF,

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any further increase resulting from learning from spillovers will negatively impact them. Hence H3 is partially supported.

Firms on the right side of the curve are the ones that can in fact benefit from an increase in VF. Hence, these firms might be able to extract benefit from VF spillovers that compensates for their low levels of VF. Unlike INV, VF as an operational capability comprises many sub-capabilities like processing of different types of products, improving quality of products, reduction in production cost, and responding to uncertain spikes in demand. The spillover pools used in the analysis reflect the gap between the leader firm and the focal firm in terms of VF as a whole, but does not differentiate between the different types of spillovers in terms of the different types of sub-capabilities within the umbrella of VF. Hence, it can be argued that the highly capable firm might learn about improving a sub capability, for example, reduction in time when changing between products. This can potentially bring down the costs for the focal firm, in turn positively affecting ROA and ROS. In such a scenario, the recommendation would be to learn from external spillovers on how to improve the various sub-capabilities.

3.6.4 Endogeneity Test

Stata's -IVREG2H- module that implements Lewbel's approach was used to test for endogeneity of the two elasticity measures (Baum et al., 2012; Lewbel, 2012). Lewbel's approach allows for testing of endogeneity including overidentification tests in the absence of traditional type of instrumental variables, as long as the model has at least one exogenous variable. His method generates instruments from within the data instead by using the available set of exogenous regressors. These generated instruments can then be tested for validity and overidentification as part of postestimation of -IVREG2H-. For the purposes

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of this research, the control variables used in all six models, served as exogenous regressors for the procedure. Double-clustered (firm and time) error structure was used to estimate the instrumental variables regression. -IVREG2H- reports the Hansen's J statistic of overidentifying restrictions of the generated instruments. Table 3.7 presents the results for each of models 4 to 9. All p-values are greater than 0.05. Failure to reject the null hypothesis collectively lead us to conclude that the generated instruments are valid for all six models and endogeneity is not a concern. An interaction of two 'non-endogenous' regressors cannot itself be endogenous. Hence, the endogeneity test results verify the robustness of the analyses done, in turn confirming the moderating relationship between firm profitability, OM elasticity, and OM-spillover elasticity.

Table 3.7. Instrumental Variables Regression Results

	Inventory		**Sourcing Lead Time**		**Volume Flexibility**	
	ROA	**ROS**	**ROA**	**ROS**	**ROA**	**ROS**
Hansen's J statistic	15.3	15.6	16.0	15.5	14.4	13.8
df	10	10	10	10	10	10
p-value	0.12	0.11	0.10	0.11	0.16	0.18

3.7. Discussion

First, the existence spillovers of operational-knowledge in terms of inventory, sourcing lead time, volume flexibility is confirmed using formal empirical methods. Second, it is confirmed that firms in fact differ in their ability to make use of their internal operational capabilities as well as the external spillovers of operational-knowledge. Third, statistical evidence was found that the relationship between OM elasticity and firm performance is in an inverted U-shaped form. Furthermore, it is shown that operational spillovers interact with OM elasticity such that operational spillovers are only beneficial to firms that are

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lacking in operational knowledge resources. Counterintuitively, the results suggest that firms can even be hurt financially from learning from operational spillovers. As shown in Figures 3.8-3.13, the firm the is itself lacking in operational capabilities can move closer to an optimal capability level by gaining additional capabilities via spillovers. However, operational spillovers hurt all other firms. While on the face this is a counterintuitive result, it is nevertheless consistent with RBV in that these firms are not lacking in operational knowledge resources, thus and additional operational knowledge moves them further away from the optimal level and reduces financial performance. Conversely, firms lacking in operational capabilities benefit from gaining additional operational knowledge via spillovers.

3.7.1 Managerial Implications

There are several key managerial insights that stem from this research. First, firm performance is a function of not just the absolute levels of operational knowledge, but rather the firm's internal ability to benefit from these operational-knowledge resources. Various organizational practices can enhance or diminish the relationship between operational capabilities and firm profitability thus managers should be cognizant to supplement their operational models with their internal capabilities. Secondly, any efforts to improve firm profitability (by changing operational capability levels and/or firm's internal OM elasticity) need to be harmonized with their own OM-spillover elasticity and changes in the amount of the available spillover pool. Firm with excessive operational capabilities are at greater risk of not reaching their potential in terms of ROA & ROS when trying to match their absolute levels of operational capabilities to that of the industry leader. Managerially speaking, firms need to realize that there is no one magic standard to any

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operational capability. Becoming leaner in inventory, achieving shorter lead times, and/or attaining highest VF does not necessarily give the optimal financial results. Getting more out of less is not always the only strategy, and that it is also possible to get more out of more as well. Conversely, less operationally capable firms should increase their internal capabilities to increase their productivity levels. These findings and recommendations are customized at the firm level by generating firm-specific values for both elasticities. The kind of efforts a firm should focus upon based on their individual capabilities are identified. To conclude, managers should not blindly assume that imitating the industry leader in terms of operational practices will generate increased financial performance—in fact this research shows that the opposite almost always occurs.

3.7.2 Theoretical Implications

This work also has academic implications. First, majority of the OM empirical research on US manufacturing firms thus far has evaluated only the 'mean' response of a set of explanatory inputs on firm's financial and/or operational performance across a given sample of firms. The empirical assumption made in prior research is that all firms behave in the same way. The utility and advantages of the application of random coefficient models (RCM) in predicting firm-level differences are demonstrated. Since firm-specific elasticities are obtained from financial data, they can be calculated for any firm, even those that exist outside the study sample. Such an approach can aid in developing the theoretical interface between strategy and OM, and open doors to eliciting more practical implications of that research (Alcácer et al., 2013).

Second, the introduction of operational-knowledge type of spillovers enriches the spillover literature in general. Majority of the past studies have focused on knowledge

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spillovers and innovativeness in the context of R&D to the point that external knowledge was only viewed in the form of R&D or patents. R&D can be performed in any sector or division of the firm, not necessarily limited to the manufacturing division. However, there is much knowledge to be gained from operational models of different firms. Finally, this research provides support for the idea of resource orchestration and/or curatorship (Breton-Miller and Miller, 2015; Grewal and Slotegraaf, 2007; Paeleman and Vanacker, 2015). While it is typically suggested within the RBV framework that “more is better”, resource orchestration/curatorship perspectives suggest that what firms do with those resources is at least as important as which resources it has. These results highlight that only firms which are resource constrained are benefitted by obtaining additional resources via spillovers. While when firms have a sufficient level of resources, the imperative should then shift towards an optimal orchestration of those resources (e.g. moving their OM elasticity to zero) and not simply on obtaining additional resources.

3.7.3 Limitations and Directions for Future Research

Like any other empirical study doing exploratory work, ours is not beyond limitations. First, the OM-spillover pools were generated from the spillovers available from firms within the same industry as that of the focal firm. However, spillover knowledge can be obtained from outside the industry as well (Jaffe, 1986). Including spillover knowledge from other industries would further enrich the findings by building on the current work. Second, due to limitations of secondary data, the choice of valid exogenous instruments was limited for both elasticity measures. Instruments were generated from the control variables instead. Third, Compustat only offers data on publicly-traded firms, so the study sample does not include private firms. Future studies can look at lifting these restrictions

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and reevaluating the relationship between firm capabilities and firm performance for both public and private firms. Obtaining data on private firms can be more expensive and time-consuming since the government does not regulate them. However, few data sources including Dun & Bradstreet (D&B), ReferenceUSA, PrivCo, Hoover's etc. provide data for private firms. Data can also be obtained via company websites, market research reports, trade publications etc.

It has been shown that outsourcing to firms in other countries can lead to some firms gathering relatively more spillover benefits; specifically Foreign Direct Investment (FDI) spillovers (Kathuria, 2000). This raises an interesting research possibility as to whether the extent of operational spillovers differs domestically and internationally. More importantly, future researchers are encouraged to also explore organizational practices that impact their capabilities (both OM elasticity and spillover elasticity). For example, cross-cooperation between internal divisions, employee mindsets regarding changes in operating model, organizational mindset about following leader firms, patenting to appropriate knowledge and fend off imitation etc. are organizational practices that can be further examined. Such work would promote cross-disciplinary research between OM and Strategy. This work can also be extended to include non-US manufacturing firms to promote cross-country comparative research. Another possibility is to explore spillovers in service industries as they present very different needs and objectives in terms of their operations. Another research opportunity lies in exploring whether firms should rely more on operational spillovers, or only confine themselves to their in-house operational capabilities, or do both. For example, Samsung took a leaf out of Apple's book and has

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been increasingly outsourcing production in the last few years, instead of investing in developing internal production capabilities to keep everything in-house (Ross, 2015).

3.8. Conclusion

To conclude, despite certain limitations, an important yet understudied research avenue is explored in this chapter. Our findings indicate that taking a capability-based perspective contributes to our understanding of the impact of operational spillovers on firm profitability. Equally importantly, the idea of operational spillovers also feeds into the bigger umbrella of the relationship between operational innovation and firm performance.

An important contextual factor that can potentially impact the relationships explored in this chapter is related to the industry-level environment in which the firm operates, specifically in terms of the degree of uncertainty created by that environment. The latter influences a firm's strategic decisions, as well as its performance (Pagell and Krause, 2004). The degree of uncertainty in a firm's external environment has been measured along three dimensions- munificence, dynamism, and complexity (Pagell and Krause, 2004). The next chapter examines if the external operating conditions, especially as they pertain to these different dimensions of uncertainty, enable, or prohibit firms to benefit from either operational innovation or operational spillovers.

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CHAPTER 4

Examining Contextual Factors of the Relationship between Operational Spillovers and Financial Performance of Manufacturing Firms

4.1. Introduction

Facing increasingly advancing technology and ever-growing competition, manufacturing firms continually seek to excel operationally to maintain their position in the market. Firms need to unceasingly adapt their operational practices to respond to the frequently changing environmental conditions (Hammer, 2005; Miller and Friesen, 1983). Changes in the external environment of an industry can be driven by changes in the technological innovativeness of its firms as well as changes in the market conditions that move an industry towards either a more stable or a more volatile structure (D'Aveni, 2015; D'Aveni et al., 2010). Given the role that innovation plays in the competitiveness and subsequent uncertainty of an industry, this chapter evaluates both industry innovativeness as well as industry environmental uncertainty as two main components of a firms operating environment.

Research in strategy strongly advocates the interaction of environmental conditions, managerial decision-making and firm performance (Miller and Friesen, 1983; Stevenson et al., 1994). Thus it is suggested that firm performance is dependent not only on the actions of the firm, but also on the influence of the competitive environment (Grimpe et al., 2007; Miller and Friesen, 1983). According to the Resource-Based View (RBV), the

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resources and capabilities developed by a firm play a role as to what extent the firm is able to take advantage of the environmental conditions in which it operates and exploit valuable knowledge through imitating rival firms (Barney, 2001; García-Sánchez et al., 2017). Within the RBV domain, this paper draws upon resource orchestration and curatorship perspectives to tie the role of industry-level environment and operational spillovers to the financial performance of firms (Breton-Miller and Miller, 2015; Lavie, 2006; Sirmon et al., 2007).

Under reasonable and stable levels of market demand, competition, and technological intensity, firms are not sufficiently compelled to make changes to their operational practices. For example, an industry comprising a countable few monopolistic firms, is relatively less complex and less competitive. For example, the airline industry fits this scenario. Firms within such an industry need to worry less about what their competitors are doing and will be relatively less compelled to seek outside resources to transform their operational practices. However, changes in those conditions for example, unpredictable spikes in market demand, growing uncertainty of resource availability, increase in research and development (R&D), and/or shortening of product life-cycles can negatively impact the management of firm resources (Sirmon et al., 2007; Stevenson et al., 1994), thus compelling firms to seek additional resources. Spillovers represent an effective channel for acquiring valuable resources and knowledge while circumventing the high associated cost and time demands to develop operational capabilities in-house (Agrawal et al., 2015; Cheng and Nault, 2007, 2012; Jaffe, 1986). In this chapter, it is posited that the importance of operational spillovers increases with increasing levels of uncertainty and technological innovativeness in the environment. Volatility of the environment incentivizes firms into

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developing the required capabilities to manage operational resources in order to avoid situations of resource shortages and resource under-utilization (Sirmon and Hitt, 2009; Sirmon et al., 2007). Hence, it is also posited that changes in environmental conditions could drive firms into developing capabilities to successfully learn from operational spillovers, and that firms operating in highly uncertain and highly technologically innovative environments would possess better-developed capabilities to leverage operational spillovers (Lichtenstein and Brush, 2001).

Firm performance in terms of inventory, sourcing lead time, and volume flexibility is a function of both its resources and capabilities to leverage those resources; hence, lower performance by a firm may not necessarily imply inferior quality of its operational knowledge resources. It is also possible that the firm has an under-developed capability to fully exploit its resources leading to lower operational performance, as also suggested by resource curatorship literature (Breton-Miller and Miller, 2015). Given this, a firm might try to exploit operational knowledge that *spills over* from all kinds of firms in its industry (including leader and laggards) in case it is able to utilize that knowledge as well (in the case of leaders) or better (in the case of laggards) than the firm it originated from. A firm may potentially develop different capabilities to exploit different types of knowledge spillovers, in this case, spillovers from leader firms and spillover from laggard firms. In this chapter, they are referred to as *leader spillover elasticity* and *laggard spillover elasticity* respectively depending on the source of the external knowledge. Tying this with the argument on environmental conditions, this chapter explores if external environment influences both spillover types differently.

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To summarize, this chapter builds on the framework created in Chapter 3 through a more granular examination of operational spillovers via leader and laggard spillovers. The relative impact of leader and laggard spillovers is further examined for generalizability by exploring how the external environment in which the firm operates influences the results.

The remainder of the chapter is structured as follows. The next section describes the framework for testing the phenomenon of leader and laggard spillovers. Section 4.3 builds upon this framework to create the resulting hypotheses. Subsequent sections present the data, the methodology, and the results. The implications of the impact of the industry-level environment for future OM research are discussed in the concluding section of the chapter.

4.2. Theoretical Background on Spillovers

Spillovers have been shown to have both positive and negative performance effects for a firm (Eeckhout and Jovanovic, 2002; Knott et al., 2009; Spence, 1984). Exploitation of spillovers by the imitating firm brings down the innovation-related investment costs, as well as potentially reduces the risk of failure. This, in turn, augments the imitating firm's profits. On the other hand, spillovers challenge the monopoly of the innovating firm as they can diminish the innovative firm's financial returns from that innovation, in turn diminishing its incentives to innovate. As such, spillovers are an important determinant of firm performance, but operational-knowledge spillovers remain an under-studied area.

In Chapter 3 of this dissertation, a theoretical framework explaining the different types of operational-knowledge spillovers, how they occur, and their impact on performance was developed and presented. The framework is mathematically summarized

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next by adopting the terminology used by Levin and Reiss (1989) and Knott (2009). The operating profit is calculated as a function of the focal firm i's internal operational capabilities (measured as either inventory investments, sourcing lead time, or volume flexibility) as well as the external operational-knowledge the focal firm accumulates from the rival firm within its industry as presented below in equation 1.

$$Y_{it} = OM_{it}^{\alpha} \ S_{it}^{\gamma} \tag{1}$$

where Y is the operating profit of firm i in year t and OM is the internal operational capability of the firm. S is the entire pool of external operational knowledge available to the focal firm and is referred to as the *spillover pool* throughout the chapter. Thus, α is the elasticity of internal operational capability, OM to operating profit and is referred to as *OM elasticity*; while γ is the elasticity of spillover pool, S to operating profit and is referred to as *spillover elasticity* throughout the chapter. In other words, OM elasticity gauges the extent to which an additional unit of operational capability (in terms of inventory investments, sourcing lead time, and volume flexibility) impacts operating profit. Spillover elasticity gauges the extent to which an additional unit of the corresponding spillover pool (in terms of inventory investments, sourcing lead time, and volume flexibility) impacts operating profit. The term *spillovers* refer to the overall phenomenon of leakage of knowledge (in this case, operational knowledge) that is generated by a rival firm to the focal firm. The developed framework for this chapter does not capture the actual mechanism by which leaked knowledge transfers from one firm to another. Previous studies have examined various mechanisms like outsourcing, merger and alliances, employee mobility between firms etc. and sometimes refer to the actual transfer as spillovers (Knott et al., 2009; Rosenkopf and Almeida, 2003; Song et al., 2003). However,

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identifying actual mechanisms by which external knowledge is transferred is beyond the scope of this dissertation.

Following the literature on endogenous growth models (Eeckhout and Jovanovic, 2002; Nelson and Winter, 1982), the framework of Chapter 3 assumed that firms are heterogeneous in nature and that flow of spillovers have a directionality. The assumption made about the directionality was that the focal firm imitates only the industry leader firm. That is the industry leader firm generates knowledge that leaks out. The spillover pool for rest of the firms operating in that industry is their relative operational knowledge to that leader firm. Recall that the term ‘industry leader’ does not necessarily imply a firm that has the highest financial performance. In fact, industry leader is characterized in terms of its standing with respect to inventory, sourcing lead time, and volume flexibility. In terms of inventory, the industry leader is the firm that has the lowest inventory investments relative to all other firms in that industry. In terms of sourcing lead time, the industry leader is the firm that has the shortest lead times relative to all other firms in that industry. In terms of volume flexibility, a higher value is considered to be better, thus the industry leader is the firm that has the highest volume flexibility relative to all other firms in that industry.

In this chapter, the aforementioned assumption about directionality is extended to include industry laggards as another source for operational spillovers. An industry laggard firm is also a rival to the focal firm just like the leader firm, but lies on the opposite end of the spectrum. That is, in terms of inventory, the industry laggard is the firm that has the highest inventory investments relative to all other firms in that industry. In terms of sourcing lead time, the industry laggard firm has the longest sourcing lead times relative to

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all other firms in that industry. In terms of volume flexibility, the industry laggard is the firm that has the lowest volume flexibility relative to all other firms in that industry.

Chapter 3 detailed the calculation of the operational capability OM, the spillover pool S, the elasticity components (α, γ), as shown in equation 1, and how they may together affect the financial performance (return on assets, ROA and return on sales ROS) of manufacturing firms. As previously explained, this chapter extends the measurement of spillover pool (S) to include industry laggards and the resulting changes to the framework in equation 1 are explained in the following section.

4.2.1 Leader and Laggard Spillover Pool

Previous literature on spillovers has used different mathematical forms to measure the spillover pool and each has its own set of merits and demerits. Knott in her (2009) paper describes the most popular forms used and their individual advantages and limitations. In Chapter 3, the spillover pool available to a firm was calculated using the 'leader distance' functional form (Eeckhout and Jovanovic, 2002; Nelson and Winter, 1982). This form calculates spillover pool as the relative difference in operational knowledge between the focal firm and the industry leader firm. In this chapter, the functional form is broadened to include industry laggards as well and is referred to as 'leader- laggard distance' (Knott et al., 2009). This leads us to two different spillover pools now available to the focal firm, one where the leader is the source called the 'leader spillover pool' and one where the laggard is the source called the 'laggard spillover pool'. This results in the following modification to equation 1.

$$Y_{it} = OM_{it}^{\alpha}\ SD_{it}^{\gamma}\ \ SG_{it}^{\delta} \qquad (2)$$

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where SD is the leader spillover pool and SG is the laggard spillover pool. Thus, γ is the elasticity of leader spillover pool with respect to operating profit and is referred to as *leader spillover elasticity* throughout the chapter. Similarly, δ is the elasticity of laggard spillover pool with respect to operating profit and is referred to as *laggard spillover elasticity*.

4.3. Hypotheses Development

Per RBV, different firms possess different types and quality of operational-knowledge resources. This is a necessary but not sufficient condition in RBV for improving firm performance. Firms also need to develop the ability to bundle different knowledge resources and successfully employ them in the appropriate contexts to sustain competitive advantage (Barney and Arikan, 2001; Sirmon et al., 2007). Firms differ in their ability to assess the correct value of a knowledge resource and then apply them in the right context (Breton-Miller and Miller, 2015). This implies that even firms that are lacking in operational performance (laggards), may have the potential to supply valuable operational-knowledge resources to other relatively better-performing firms in the industry. Laggard firms may simply not possess a capability level required to successfully exploit their operational knowledge. Given this, a firm might try to exploit operational knowledge that *spills over* from all kinds of firms in its industry (including leaders and laggards) as it might be able to utilize that knowledge better than the firm it originated from.

In Chapter 3, the existence of an inverted-U relationship between OM elasticity in terms of operating profit (for inventory, sourcing lead time, volume flexibility) and financial performance (ROA and ROS) of manufacturing firms was empirically shown. Evidence for heterogeneity of firms in terms of leader spillover elasticity was also found.

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It was further shown that, for leader spillovers, manufacturing firms with a higher spillover elasticity benefit financially when complemented by their own OM elasticity, given the right conditions. Consistent with the breakdown of spillover elasticity in Chapter 3, a positive (or high) spillover elasticity indicates that operating profit increases (decreases) as the spillover pool increases (decreases). A firm with a positive spillover elasticity possesses an enhanced ability to learn from the spillover pool compared to a firm with a negative (or low) spillover elasticity. This is expected to hold true for each of the two spillover elasticities i.e. leader and laggard.

Drawing upon the resource curatorship view as explained above, the question that arises in the context of the current research, then is if the focal firm can distinguish between leader and laggard spillover pools, and if it possesses varying ability to exploit both types of operational knowledge. Hence, it is posited that firms differ in their ability to exploit the leader spillover pools (leader spillover elasticity) vs. its ability to exploit the laggard spillover pools (laggard spillover elasticity).

Regarding the individual impact of both leader as well as laggard spillover elasticity on a firm's financial performance (ROA and ROS), it is posited that firms will financially benefit from both, when complemented with OM elasticity, per RBV (Barney and Arikan, 2001). It is further expected that the strength of the moderating effect of one elasticity type on a firm's financial performance will differ from the other. The focal firm needs to invest in the accumulated external knowledge resource (leader or laggard) to verify its value, synchronize it with its other resources, and develop a capability to turn it into operating profits. For the focal firm to gain financially, the payoff that results from exploiting one type of knowledge (leader or laggard) should monetarily outweigh the costs incurred by it

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in leveraging its value. However, when the associated costs outweigh the payoff instead, the firm will experience a decrease in net income, and in turn, ROA and ROS.

More specifically, it is posited that the strength of moderation effect of leader spillover elasticity will be greater than that of the laggard spillover elasticity because of the differences in expected payoff vs. associated costs between leader knowledge and laggard knowledge. Since, industry leaders represent best practices in the industry, the knowledge that they generate is already established to be valuable. On the other hand, industry laggards have under-developed operational capabilities in terms of inventory, sourcing lead times, and volume flexibility. Hence, the knowledge generated via laggards does not reflect industry best practices and the value is mostly unidentified. This implies that the focal firm would have to invest more to assess the value of laggard knowledge vs. leader knowledge and how to better use it, to build a capability (spillover elasticity) around it. Thus, the difference between the costs and resulting payoff might be relatively higher in the case of laggard spillover elasticity. In turn, its impact on financial performance (ROA and ROS) can be reasonably expected to be weaker than that of leader spillover elasticity. This argument leads to the following hypothesis:

Hypothesis 1: *The strength of the moderating effect of leader spillover elasticity on the inverted-U relationship between OM elasticity (in terms of inventory, sourcing lead time, volume flexibility) and financial performance of manufacturing firms is greater than that of the moderating effect of laggard spillover elasticity.*

The next two sets of hypotheses are aimed at testing how industry-specific characteristics are linked to the relative importance of both leader and laggard spillover elasticity for reaping financial returns.

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In Hypothesis 2, it is posited that the impact of both leader and laggard spillover elasticity changes with the degree of environmental uncertainty at the industry level. The concept of environmental uncertainty comes from the field of strategy and is measured as a composite across the three dimensions of munificence, dynamism, and complexity (Boyd, 1995; Dess and Beard, 1984). Munificence measures a firm's access to resources and opportunities to financially grow in the industry in which it operates. Deficiency of resources increases uncertainty in the environment; hence, munificence is inversely proportional to environmental uncertainty. For example, the computer industry is relatively more munificent than steel industry because of its higher availability of resources (Boyd, 1995). Dynamism, on the other hand, is directly proportional to environmental uncertainty. Dynamism gauges the degree of volatility or turbulence of the environment in which the firm competes i.e. higher level of dynamism indicates higher levels of environmental volatility or uncertainty. For example, an industry where market demand changes frequently and unpredictably will be considered more dynamic than one with a stable demand over long periods of time. The third element creating environmental uncertainty is complexity. Complexity pertains to the concentration of firms in an industry and the heterogeneity between them. An industry with a few large monopolistic firms would be considered less complex compared to an industry with a high number of competitors ranging from large incumbents to new entrants. A higher complexity (or industry concentration) indicates higher uncertainty. Taken together, these three factors reflect the levels of competition, unpredictability, and volatility in the industry's environment.

Previous literature across disciplines has frequently looked at how the uncertainty of the environment in which a firm operates influences a firm's strategic decisions, as well

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as its performance (Sirmon et al., 2007). For instance, munificence, dynamism, and complexity were found to significantly impact the relationship between operational slack in terms of inventory and safety violations made by a firm (Wiengarten et al., 2017). Kovach et al. (2015) also found that operational slack improved performance of firms operating in unstable (more dynamic) environments. RBV emphasizes on building resources to sustain competitive advantage, and firms often look towards other rival firms to acquire new and improved knowledge especially when internal development is inadequate and/or takes longer (King et al., 2003). A strong focus on external knowledge and resources is more common in uncertain environments where competition levels are high and time is not luxury. For example, firms that invest heavily in technology; and operate in highly munificent and dynamic environments are more prone to getting acquired by a rival firm, to access its technology and expertise, compared to those operating in stable environments (Heeley et al., 2006). Market concentration (or complexity) has been shown to impact the performance sensitivity to both leader and laggard R&D spillovers in the banking industry (Knott et al., 2009). Recognizing the importance of both internal as well as external knowledge, as laid out by RBV, and the past research on the influencing effects of environmental uncertainty; it is posited the firms will value external knowledge more under highly uncertain environments. Whereas in more stable and certain environments, firms are not sufficiently incentivized to look beyond in-house resources for increasing operational excellence. When operating in highly uncertain environments, firms are expected to try even harder to capitalize on external operational-knowledge resources to improve their operational practices, and financial outcomes (Sirmon et al., 2007). In order to do so, firms would need to strengthen their internal capability of successfully learning

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from the available spillover pools (both leader and laggard). Those firms that are able to do so, and are able to successfully complement the external resources with their internal operational capabilities are expected to perform better financially (Breton-Miller and Miller, 2015). Taken together, the following hypothesis is proposed:

Hypothesis 2a: *The higher the environmental uncertainty of the industry in which the manufacturing firm operates, the stronger is the moderating effect of leader spillover elasticity on the inverted-U relationship between OM elasticity and financial performance (in terms of inventory, sourcing lead time, volume flexibility).*

Hypothesis 2b: *The higher the environmental uncertainty of the industry in which the manufacturing firm operates, the stronger is the moderating effect of laggard spillover elasticity on the inverted-U relationship between OM elasticity and financial performance (in terms of inventory, sourcing lead time, volume flexibility).*

The last hypothesis is aimed at examining if the level of innovativeness of an industry influences how firms within that industry benefit (or suffer) from leader and laggard spillovers. Innovation does not happen in a vacuum and spillovers help firms in acquiring new sources of knowledge and expertise which is essential to developing new and improved products (Jaffe, 1998). This makes the level of innovativeness as an industry characteristic particularly relevant to the study of operational spillovers. Highly innovative industries are synonymous to rapid technological advancements (Thornhill, 2006). This is because firms operating in highly innovative industries need to continuously innovate and introduce new and better products to the market, or else they will perish (Greenhalgh and Rogers, 2010; Scheck and Glader, 2009; Sood and Tellis, 2009). To do so, they can be

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expected to require higher amounts of new and improved knowledge and expertise. These firms are faced with increased time pressures, shorter product life-cycles (Mackelprang et al., 2015), higher levels of competition, unpredictability, and volatility since new products and ideas need to be introduced at a much faster pace. Firms are expected to continuously improve their existing pool of resources as well as their internal capabilities to maintain their competitive edge. This pressure is substantially greater for firms operating in highly innovative industries given the aforementioned characteristic. One way to reduce time and cost demands is to exploit external knowledge resources that spill-over from rival firms. Per hypothesis H1, firms are expected to exploit different levels of operational knowledge and develop internal capabilities to learn from both leader and laggard spillover pools. It is now posited that the hypothesized effects in H1 will be stronger in the case of highly innovative industries compared to less innovative industries. To conclude, the following hypothesis is proposed:

Hypothesis 3a: *The higher the industry innovativeness in which the manufacturing firm operates, the stronger is the moderating effect of leader spillover elasticity on the inverted-U relationship between OM elasticity and financial performance (in terms of inventory, sourcing lead time, volume flexibility).*

Hypothesis 3b: *The higher the industry innovativeness in which the manufacturing firm operates, the stronger is the moderating effect of laggard spillover elasticity on the inverted-U relationship between OM elasticity and financial performance (in terms of inventory, sourcing lead time, volume flexibility).*

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4.4. Data and Measures

The dataset used for this chapter is the same as that created in Chapter 3 i.e. financial data of US manufacturing firms (with SIC codes in the range of 2000 and 3999) collected over the period 1990-2016 from COMPUSTAT. The final data set consists of 220 industries and 5668 firms, with a grand total of 66,569 firm-year observations. Tables 4.1 and 4.2 present the sample distribution with respect to industry at the two-digit level and time in years respectively. The creation of measures is discussed next.

Table 4.1. Sample Distribution by Industry

SIC	N	Percent of Data
20	3,798	5.71
21	206	0.31
22	794	1.19
23	1,551	2.33
24	834	1.25
25	904	1.36
26	1,623	2.44
27	1,662	2.5
28	10,010	15.04
29	1,143	1.72
30	1,710	2.57
31	495	0.74
32	1,009	1.52
33	2,383	3.58
34	2,178	3.27
35	9,082	13.64
36	12,656	19.01
37	3,555	5.34
38	9,402	14.12
39	1,574	2.36
Total N	66569	100

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Table 4.2. Sample Distribution by Time in Years

Year	N	Percent of Data
1990	2,337	3.51
1991	2,507	3.77
1992	2,690	4.04
1993	2,859	4.29
1994	2,975	4.47
1995	3,185	4.78
1996	3,303	4.96
1997	3,257	4.89
1998	3,233	4.86
1999	3,124	4.69
2000	2,950	4.43
2001	2,777	4.17
2002	2,682	4.03
2003	2,577	3.87
2004	2,519	3.78
2005	2,447	3.68
2006	2,378	3.57
2007	2,267	3.41
2008	2,208	3.32
2009	2,157	3.24
2010	2,077	3.12
2011	2,010	3.02
2012	1,953	2.93
2013	1,923	2.89
2014	1,863	2.8
2015	1,720	2.58
2016	591	0.89
Total N	66,569	100

4.4.1 Dependent Variables and Control Variables

To calculate firm-specific elasticities, the dependent variable used is firm's operational performance, which is operationalized as *Operating Profit (OP)*. Operating profit is calculated as the difference between a firm's revenues and its cost of goods sold (COGS).

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For testing the hypotheses, the dependent variable used is firm financial performance, which is measured in two ways (a) *Return on Sales (ROS)*, and (b) *Return on Assets (ROA)*. ROS is calculated as net income divided by total sales, and ROA is calculated as net income divided by total assets. All three variables were winsorized (95 5 percentile) to remove outliers. Finally, the following variables are used as firm-level controls. Net property, plant, and equipment is used as a proxy for firm capital, and number of employees is used as a proxy for labor. Third, a one-year lagged value of R&D expenditure is included to account for the potential lag between innovation initiatives (as reflected by R&D investment) and realization of financial profits (Knott, 2008). Fourth, Leverage, which is calculated as total liabilities divided by total assets of a firm i in year t, is included. Table 4.3 shows the descriptive statistics of the aforementioned variables.

Table 4.3. Descriptive Statistics

Variable	Obs	Mean	SD	Median	Min	Max
ln(Capital)	48,798	3.538	2.568	3.460	-6.215	12.517
ln(Labor)	48,798	-0.027	1.977	-0.089	-6.908	6.414
ln(R&D)	48,798	-0.900	5.377	1.080	-9.210	9.549
ln(OP)	48,798	4.140	2.127	4.117	-0.794	9.175
Leverage	48,712	0.514	0.521	0.464	0.007	62.721
ROS	48,797	-0.056	0.286	0.030	-1.605	0.235
ROA	48,797	-0.019	0.176	0.033	-0.790	0.201

4.4.2 Operational-Capability Measures

The three operational-capability measures (OM), inventory investments (INV), sourcing lead time (SLT), and volume flexibility (VF) are operationalized in the same manner as in Chapter 3.

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4.4.3 Operational-Knowledge Spillover Pool

Taking the example of inventory (INV), industry leader will have the minimum inventory investments, min(INV), and the industry laggard will have the maximum inventory investments, max(INV). So, for a focal firm i within an industry y (at the 4-digit SIC level) in year t, the leader spillover pool is the difference between the focal firm i and the industry leader in terms of the inventory investments i.e. INV_{iyt} - $\min(INV)_{yt}$. The laggard spillover pool is then calculated as $\max(INV)_{yt}$ - INV_{iyt}. The leader and laggard spillover pools for SLT are calculated in a similar fashion. In terms of volume flexibility, a higher value is considered to be better, thus the industry leader and the industry laggard swap positions. So, the leader spillover pool is calculated as $\max(VF)_{yt}$ - VF_{iyt} and the laggard spillover pool is calculated as VF_{iyt} - $\min(VF)_{yt}$.

4.4.4 OM Elasticity and Spillover Elasticity

Firm-specific OM elasticities and spillover elasticities for each of three operational-capability measures (INV, SLT, and VF) were calculated using the procedure described in Chapter 3 by means of random-coefficient modeling (RCM). Section 4.5.1 provides the RCM results and the descriptive statistics for both elasticities.

4.4.5 Environmental Uncertainty

The degree of uncertainty in the external environment was measured across three dimensions-munificence, dynamism, and complexity in line with Boyd (1995). For an industry y in year t, munificence and dynamism were obtained by regressing annual industry sales over a five-year period. The slope coefficient thus derived was used as a measure of munificence, and the corresponding standard error of that coefficient was used

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as a measure of dynamism (Boyd, 1995; Wiengarten et al., 2017). Scores for munificence and dynamism were missing for 10,681 observations in the data. Higher level of munificence is indicative of an environment where firms have access to more opportunities and resources to grow financially. Higher level of dynamism is indicative of higher levels of environmental volatility/uncertainty. Finally, the Herfindahl-Hirschman Index (HHI) was used to operationalize complexity (Wiengarten et al., 2017). For an industry y in year t, the squared values of market share in terms of sales is calculated for each firm in that industry, and then summed to calculate HHI. HHI score was missing for 13 observations in the data. HHI ranges from zero to one. HHI scores close to one imply lower market concentration (i.e. countable few monopolistic firms) in that industry and so lower complexity. Scores closer to zero imply higher concentration with several competing firms and thus higher complexity. An average of all three dimensions was taken to arrive at a single composite measure of environmental uncertainty. To do so, first, the direction of all three dimensions needed to be altered such that a lower value on the composite measure indicated lower levels of uncertainty and a higher value indicated a higher level of uncertainty. So, the munificence and HHI scores were multiplied by (-1) to alter their direction. This means that now a low munificence would indicate low uncertainty; dynamism remains same in that lower value indicates low uncertainty; and a low HHI indicates low complexity, in turn, low uncertainty. Next, all three dimensions were standardized by year. The composite measure for environmental uncertainty was only calculated if values for all three dimensions were present and considered missing otherwise. Table 4.4 presents the descriptive statistics for the three dimensions and the composite measure of environmental uncertainty for the entire sample.

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Table 4.4. Descriptive Statistics for Environmental Variables

Variable	Obs	Mean	SD	Min	Max
Munificence	55,888	0.000	1.000	-11.260	21.953
Dynamism	55,888	0.000	1.000	-1.177	32.645
Complexity	66,556	0.000	1.000	-4.630	1.350
Environmental Uncertainty	55,888	0.003	0.533	-2.202	15.968
Industry Innovativeness	64,750	19.791	36.388	0.000	1014.340

4.4.6 Industry Innovativeness

R&D expenditure has been widely considered as an indicator of knowledge creation and an input to the process of innovation (Hirschey et al., 2012). Past research has used R&D spending as a way to measure the level of innovativeness at both the firm and industry level (Han et al., 2013; Heeley et al., 2007; Lantz and Sahut, 2005). Hence, in this chapter, R&D intensity is used to measure level of innovativeness of an industry. For an industry y in year t, industry innovativeness is calculated as the median value of R&D intensity for all firms in that industry. R&D intensity at the firm level in year t is calculated as R&D expenditure per firm employee (Wiengarten et al., 2017). Table 4.4 presents the descriptive statistics for industry innovativeness for the entire sample.

4.5. Analysis and Results

The entire analysis is done separately for each of the three operational measures (INV, SLT, and VF). The analysis begins by first calculating the firm-specific values for both OM elasticity; and leader and laggard spillover elasticity. The results for each of hypotheses is discussed subsequently.

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4.5.1 Calculation of Firm-Specific Elasticities

Stata's linear-mixed-model command was used to run RCM in order to generate firm-specific elasticities. The procedure as outlined in Chapter 3 was followed. A separate model was run for each operational measure (INV, SLT, and VF). Capital, labor, and one-year lagged value of R&D expenditure were used as control variables. The model includes both the leader (SD) and laggard (SG) spillover pools and thus a separate spillover elasticity is calculated for each of the two pools, referred to as the leader spillover elasticity (γ) and the laggard spillover elasticity (δ) respectively. Table 4.5 shows the RCM results for INV, SLT, and VF. Table 4.5 only provides information about the direct/average component of OM elasticity; and the leader and laggard spillover elasticity.

Table 4.5. RCM Results

DV = Ln(OP)	**(1)**	**(2)**	**(3)**
Variables	**OM = INV**	**OM = SLT**	**OM = VF**
Ln(Capital)	0.190***	0.079***	0.180***
	(0.007)	(0.007)	(0.008)
Ln(Labor)	0.670***	0.581***	0.690***
	(0.010)	(0.011)	(0.013)
Ln(Lagged R&D)	0.051***	0.034***	0.058***
	(0.003)	(0.002)	(0.003)
Ln(OM)	-0.174***	-0.302***	0.016
	(0.013)	(0.011)	(0.014)
Ln(Leader Spillover Pool)	0.016*	0.055***	0.002
	(0.007)	(0.008)	(0.004)
Ln(Laggard Spillover Pool)	-0.029***	-0.005**	-0.030***
	(0.005)	(0.002)	(0.006)
Constant	3.027***	3.447***	3.520***
	(0.030)	(0.025)	(0.036)
N	48201	48798	26125

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Standard errors are in parentheses.

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To verify that these effects differ across firms, the variance of the direct component was checked for statistical significance. Stata reports these statistics postestimation. For each of the three measures (INV, SLT, and VF), the variance for the direct component of OM elasticity was found to be statistically significant with a p-value<0.001 (t-statistic for INV = -41.5, for SLT = -46.94, for VF = -28.09). Similarly, the variance for the direct component of the corresponding leader spillover elasticity was found to be statistically significant with a p-value<0.001 (t-statistic for INV = -43.57, for SLT = -13.13, for VF = -48.34). Finally, the variance for the direct component of the corresponding laggard spillover elasticity was also found to be statistically significant with a p-value<0.001 (t-statistic for INV = -40.88, for SLT = -68.29, for VF = -15.53). Next, for each of the three operational measures (INV, SLT, and VF), *firm-specific* elasticities were calculated. The descriptive statistics for the three elasticities for each of the three operational measures are shown in Table 4.6.

Table 4.6. Descriptive Statistics for Firm-Specific Elasticities

Elasticities	Obs	Mean	SD	Min	Max
Model 1- Inventory (INV)					
OM Elasticity	48,201	-0.181	0.165	-1.032	1.300
Leader Spillover Elasticity	48,201	0.015	0.068	-0.546	0.675
Laggard Spillover Elasticity	48,201	-0.030	0.068	-0.509	0.633
Model 2- Sourcing Lead Time (SLT)					
OM Elasticity	48,798	-0.316	0.208	-1.517	1.698
Leader Spillover Elasticity	48,798	0.054	0.024	-0.136	0.485
Laggard Spillover Elasticity	48,798	-0.007	0.027	-0.284	0.219
Model 3- Volume flexibility (VF)					
OM Elasticity	26,125	0.016	0.114	-0.870	0.642

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Leader Spillover Elasticity	26,125	0.002	0.060	-0.527	0.535
Laggard Spillover Elasticity	26,125	-0.030	0.015	-0.145	0.088

For example, in the case of inventory (Model 1 in Table 4.5), the inventory elasticity of a firm is its ability to generate operating profit from its own inventory investments and it ranges from -1.032 (lowest) to 1.3 (highest). The leader inventory-spillover elasticity ranges from -0.546 (lowest) to 0.675 (highest). The histograms for all the three firm-specific elasticities were also drawn to verify firm heterogeneity in terms of these three elasticities, but are not shown here in the interest of brevity. The reported t-test results along with the histograms, and the results from Table 4.6. collectively verify that there is considerable variance across firms in terms of all three elasticity types. Consistent with the results from Chapter 3, all three elasticities are negative for a subset of firms in the sample, and positive for the rest. <u>A negative elasticity value is referred to as low elasticity and a positive elasticity value is referred to as high elasticity from here onwards.</u>

4.5.2 Moderating Effect of Leader and Laggard Spillover Elasticity

To test the first hypothesis H1, an OLS regression was run as shown in equation 3, with a double-clustered robust error structure (Cameron et al., 2011; Mackelprang and Malhotra, 2015). Firm size, R&D, leverage, time, and industry (4-digit level) effects were included as control variables.

$$Y_{it} = \beta_1 \ln(X1)_{it} + \beta_2 X2_{it} + \beta_3 (X2*X2)_{it} + \beta_4 X3_{it} + \beta_5 (X2*X3)_{it} + \beta_6 (X2*X2*X3)_{it} + \beta_7 X4_{it} + \beta_8 (X2*X4)_{it} + \beta_9 (X2*X2*X4)_{it} + \beta_{10} \mathrm{Ln}(L)_{it} + \beta_{11} \mathrm{Ln}(R)_{it-1} + \beta_{12} \mathrm{Ln}(Z)_{it} + \beta_{13} (\text{no. of years}) + \text{industry dummies} + \varepsilon_{it} \quad (3)$$

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where Y is the financial performance (ROA/ROS) of firm i in year t, X1 is one of the three operational measures, X2 is the corresponding OM elasticity of that operational measure, X3 is the leader spillover elasticity, X4 is the laggard spillover elasticity, Ln(L) is Ln(#employees) used as a proxy for firm size, R is the one-year lagged R&D value, and Z denotes leverage. H1 results for both ROA and ROS are summarized in Table 4.7.

Table 4.7. Regression Results for Hypothesis 1

	(4)	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
	OM = INV		**OM = SLT**		**OM = VF**	
Variables	**ROA**	**ROS**	**ROA**	**ROS**	**ROA**	**ROS**
Ln(Lagged R&D)	-0.004***	-0.007***	-0.004***	-0.008***	-0.002***	-0.004***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
No. of Years	-0.002***	-0.001	-0.003***	-0.003***	-0.000	0.001
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Ln(Labor)	0.031***	0.052***	0.004	0.025***	0.022***	0.031***
	(0.002)	(0.004)	(0.003)	(0.005)	(0.001)	(0.002)
Leverage	-0.020	-0.026	-0.078**	-0.088**	-0.076***	-0.092***
	(0.012)	(0.014)	(0.027)	(0.030)	(0.017)	(0.018)
Ln(OM)	-0.004	0.050***	-0.031***	-0.031***	-0.067***	-0.107***
	(0.003)	(0.009)	(0.003)	(0.004)	(0.005)	(0.009)
OM Elasticity	-0.143***	-0.265***	-0.038	-0.085	-0.101*	-0.067
	(0.017)	(0.035)	(0.024)	(0.047)	(0.048)	(0.085)
OM Elasticity^2	-0.307***	-0.587***	-0.219***	-0.473***	-0.096	-0.531
	(0.051)	(0.089)	(0.033)	(0.064)	(0.142)	(0.289)
Leader ES	-0.139**	-0.262**	-0.025	-0.174	0.041	0.077
	(0.043)	(0.085)	(0.100)	(0.208)	(0.044)	(0.082)
OM Elasticity*	0.078	0.101	-0.735*	-1.225	0.574***	1.020**
Leader ES	(0.084)	(0.155)	(0.366)	(0.746)	(0.137)	(0.323)
OM Elasticity^2*	0.718***	1.189***	1.551***	3.054***	0.607	1.428*
Leader ES	(0.128)	(0.232)	(0.196)	(0.444)	(0.315)	(0.685)

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Laggard ES	-0.098** (0.034)	-0.150* (0.064)	0.311*** (0.082)	0.795*** (0.191)	0.165 (0.175)	0.240 (0.320)
OM Elasticity* Laggard ES	-0.111 (0.114)	-0.163 (0.220)	0.916*** (0.253)	1.849*** (0.522)	0.240 (0.911)	2.749 (1.553)
OM Elasticity^2* Laggard ES	0.039 (0.161)	0.079 (0.296)	-0.929** (0.356)	-1.664* (0.728)	0.774 (1.858)	2.204 (3.351)
N	48128	48128	48711	48711	26085	26085

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Standard errors are in parentheses and are two-way cluster robust. ES=Spillover Elasticity

Results of industry dummies are not shown in the interest of brevity. The Variance Inflation Factor (VIF) for all models was either less than or equal to 5.83. Wald tests of the relevant coefficients were also performed to confirm that there is a significant difference between the moderating effect of leader spillover elasticity and that of laggard spillover elasticity on the quadratic association between OM elasticity and financial performance (ROA and ROA), for each of the three operational measures. Table 4.8 presents the Wald test results of the relevant coefficients.

Table 4.8. Wald Test Results for Hypothesis 1

	OM = INV		**OM = SLT**		**OM = VF**	
Coefficients	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Leader ES = Laggard ES	-0.04	-0.11	**-0.34**	**-0.97**	-0.12	-0.16
OM Elasticity*Leader ES = OM Elasticity* Laggard ES	0.19	0.26	**-1.65**	**-3.07**	0.33	-1.73
OM Elasticity^2*Leader ES = OM Elasticity^2* Laggard ES	**0.68**	**1.11**	**2.48**	**4.72**	-0.17	-0.78

Difference estimate = leader coefficient-laggard coefficient. A positive value implies that leader coefficient is larger in magnitude. Values in bold are significant at the 5% level. The rest are not significant.

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For example, in the case of INV and ROA (Model 4 in Table 4.7), the interaction effect of leader spillover elasticity with the quadratic term of inventory elasticity is significantly different than that of laggard spillover elasticity, as shown in bold. The difference between the two coefficients is 0.68 (=0.718-0.039). Wald test results indicate that there is a statistically significant difference (at p-value <0.05) between leader and laggard spillover elasticity for INV and SLT for both ROA and ROS; however, not so for VF. Also, for INV and SLT, the moderating impact of leader spillover elasticity is stronger than that of the laggard spillover elasticity. Hence, Wald test results support H1 for INV and SLT, but not for VF. The interpretation of the H1 results for each of the three measures is discussed next.

4.5.2.1 Inventory (INV)

Models 4 and 5 (ROA & ROS respectively) present the results for the moderating effect of both leader and laggard types of inventory-spillover elasticity. The interaction of leader spillover elasticity with the quadratic term of inventory elasticity is significant with a p-value < 0.001. The interaction of laggard spillover elasticity with the quadratic term of inventory elasticity is however not significant for both ROA and ROS. Although, per Wald test results in Table 4.8, the said coefficients are significantly different from each other. Also, the strength of moderation effect of leader spillover elasticity is greater than that of laggard spillover elasticity. Hence, H1 is supported. Graphically the interaction effects for leader spillover elasticity are presented in Figures 4.1 and 4.2 for ROA and ROS respectively.

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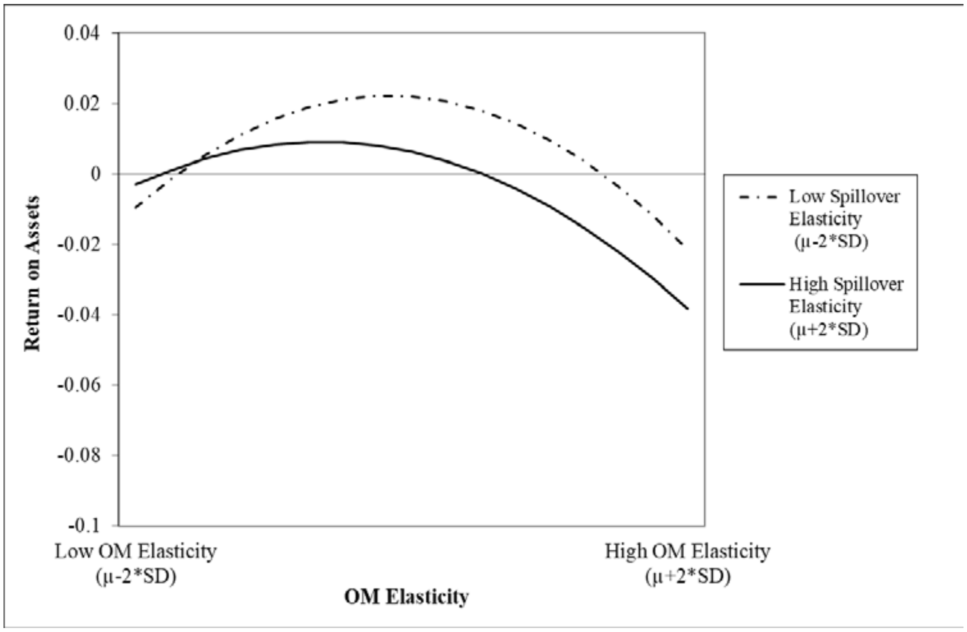

Figure 4.1. Plot: DV = ROA, OM = INV, and Leader Spillover Elasticity

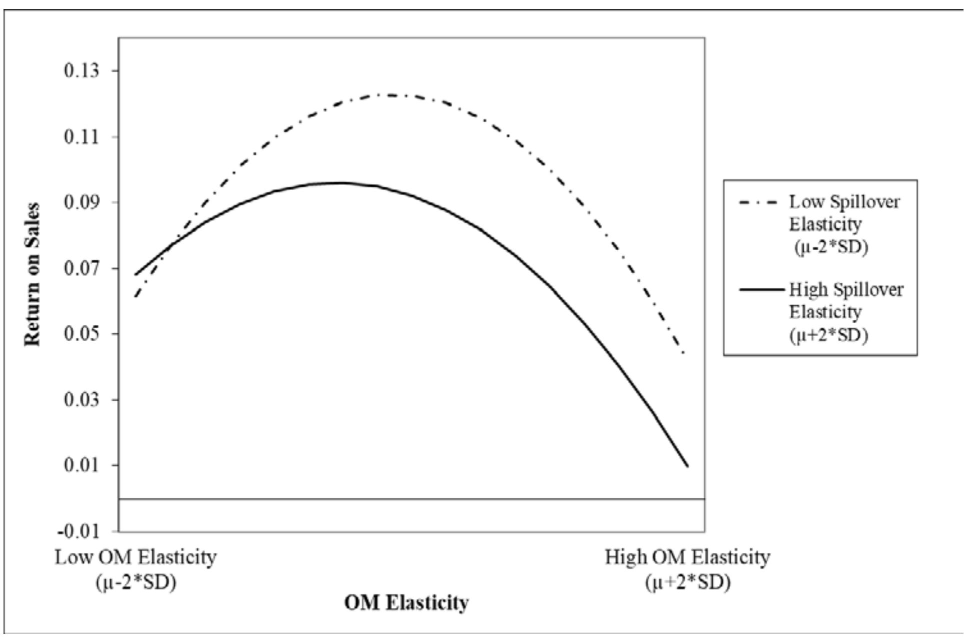

Figure 4.2. Plot: DV = ROS, OM = INV, and Leader Spillover Elasticity

The results for leader spillover elasticity are consistent with those in Chapter 3. That is the impact of leader spillover elasticity varies depending on the firm's position on the inverted-U curve of inventory elasticity. Not all firms benefit from an increased ability

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to learn from leader inventory spillover pool as explained in Chapter 3. The interaction effects for laggard spillover elasticity are presented in Figures 4.3 and 4.4 for ROA and ROS respectively.

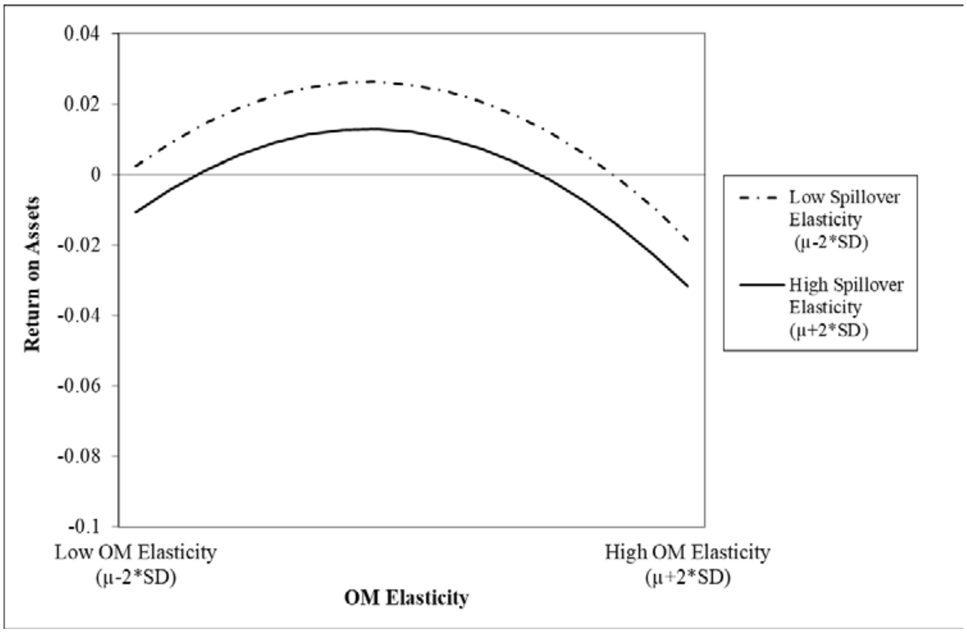

Figure 4.3. Plot: DV = ROA, OM = INV, and Laggard Spillover Elasticity

In the case of laggard spillover elasticity, the figures indicate that, contrary to leader spillover elasticity, position of the firm on the inverted-U curve of inventory elasticity is not relevant. There is a difference between firms with low and high laggard spillover elasticity. Firms that increasingly learn from laggard spillover pools perform *worse* than those that do not. This implies that learning to increase inventory via laggard spillover pool hurts all firms and decreases their financial performance. A possible explanation for this is the difference in the payoff vs. costs associated. The costs of imitating laggard knowledge are outweighing its potential benefits on this side of the curve. Unless the financial benefits from building and utilizing the capability of laggard spillover elasticity more than cover those costs, these firms would experience net loss. Firms with well-developed (or high)

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laggard spillover elasticity are incurring even more costs than benefits from laggard knowledge and hence, performing worse than those with low laggard spillover elasticity.

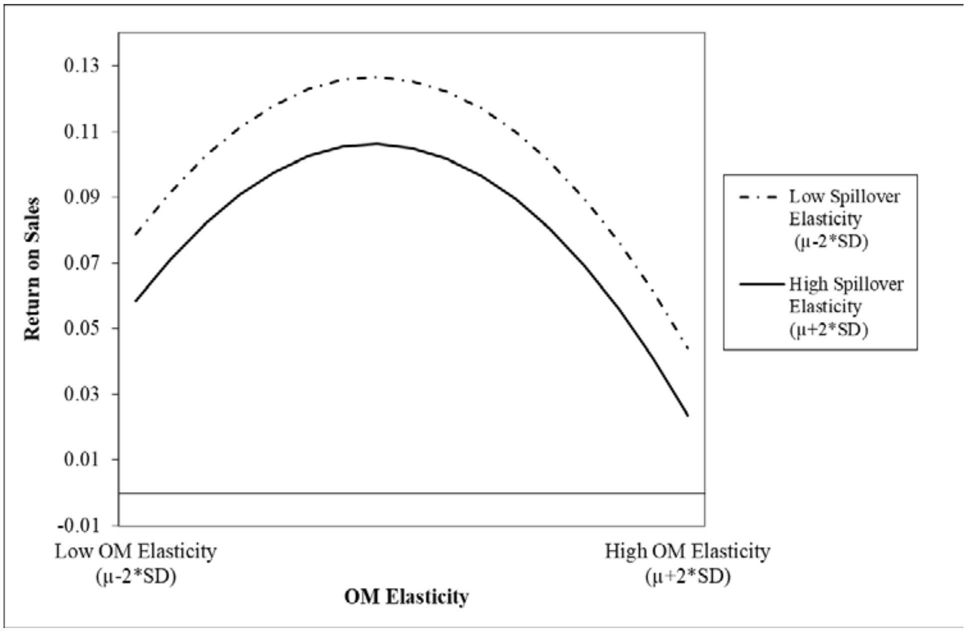

Figure 4.4. Plot: DV = ROS, OM = INV, and Laggard Spillover Elasticity

Finally, these results are consistent across ROA and ROS except that in the case of ROS, (a) relatively more positive returns are realized overall, and (b) the difference between low and high spillover elasticity is stronger.

4.5.2.2 Sourcing Lead Time (SLT)

Models 6 and 7 (ROA & ROS respectively) present the results for the moderating effect of both leader and laggard types of SLT-spillover elasticity. The moderation effect for leader spillover elasticity is strongest in the case of SLT compared to inventory and VF, as observed in Table 4.7. The interaction of leader spillover elasticity with the quadratic term of SLT elasticity is significant with a p-value < 0.001 for both ROA and ROS. The interaction of laggard spillover elasticity with the quadratic term of SLT elasticity is also significant with a p-value < 0.05, unlike inventory.

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The results show that, both the leader and laggard spillover elasticities individually moderate the quadratic association between SLT elasticity and financial performance. Moreover, per Wald test results in Table 4.8, the said coefficients are significantly different from each other. Also, the strength of moderation effect of leader spillover elasticity is greater than that of laggard spillover elasticity. Hence, H1 is supported. The results are consistent across ROA and ROS except that in case of ROS, the overall results are more pronounced. Graphically, the interaction effects for leader spillover elasticity is presented in Figures 4.5 and 4.6 for ROA and ROS respectively.

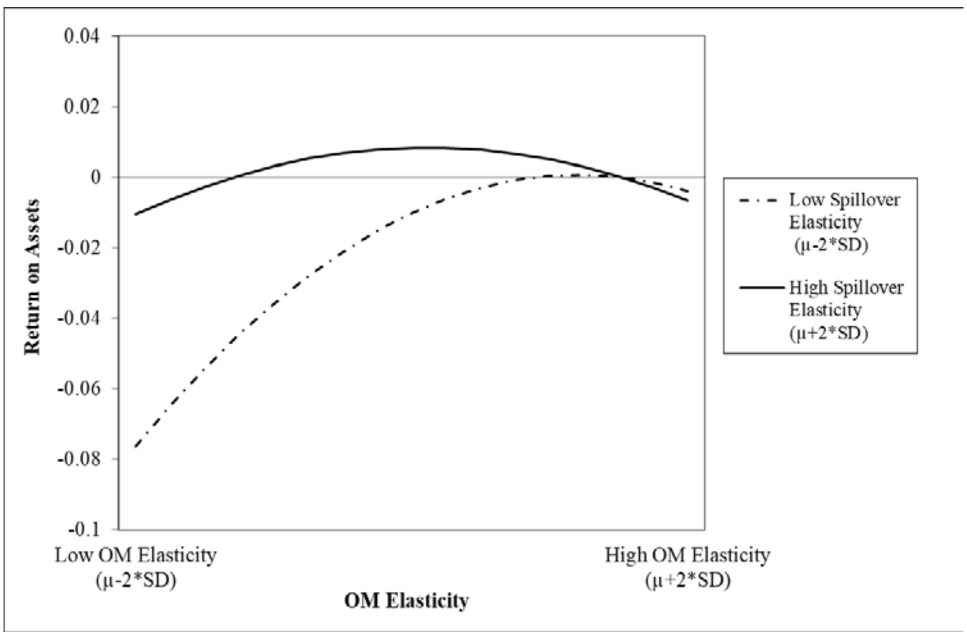

Figure 4.5. Plot: DV = ROA, OM = SLT, and Leader Spillover Elasticity

The results for leader spillover elasticity are consistent with those in Chapter 3. That is, the impact of leader spillover elasticity varies depending on the position of the firm on the inverted-U curve of SLT elasticity. Not all firms benefit from an increased ability to learn from their SLT spillover pool.

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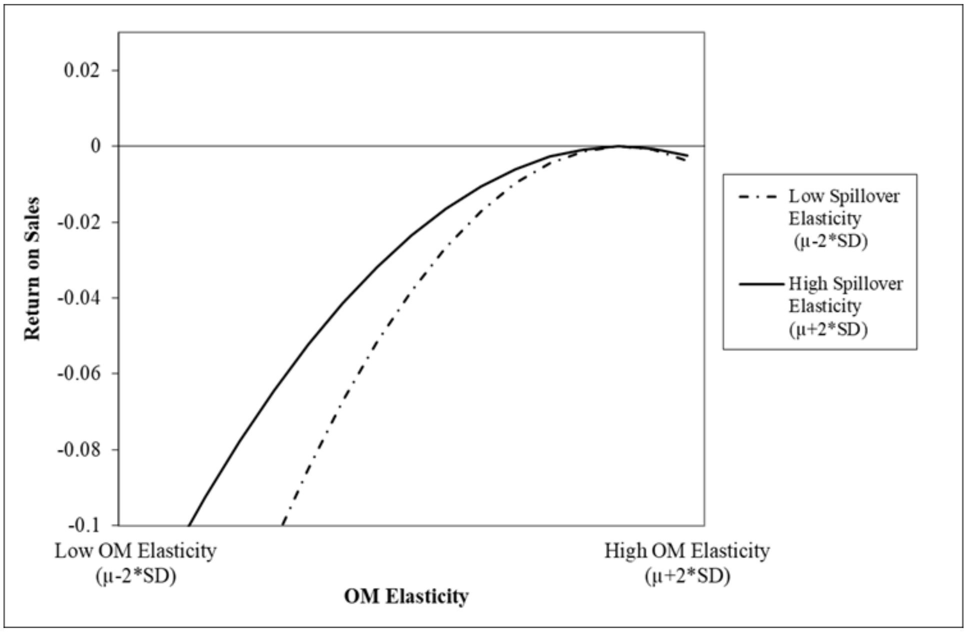

Figure 4.6. Plot: DV = ROS, OM = SLT, and Leader Spillover Elasticity

For laggard spillover elasticity, the interaction effects are presented in Figures 4.7 and 4.8 for ROA and ROS respectively. The graphs indicate that unlike inventory, firm behavior in fact depends on its position on the inverted-U curve of SLT elasticity. Also, the interaction effects of laggard spillover elasticity results are opposite to those of leader spillover elasticity. Within firms lying on the left side of the curve, firms with lower laggard spillover elasticity perform better than those with higher spillover elasticity. Firms on the left side have longer SLT and learning from laggard spillover pool implies that these firms further lengthen their SLT, hence firms with an ability to successfully exploit laggard spillover pool perform relatively worse. Firms on the right side behave in the opposite way. Since these firms have increasingly shorter SLT, those with an ability to successfully learn from laggard spillover pool are prevented from becoming excessively lean in terms of SLT and hence experience relatively better financial outcomes.

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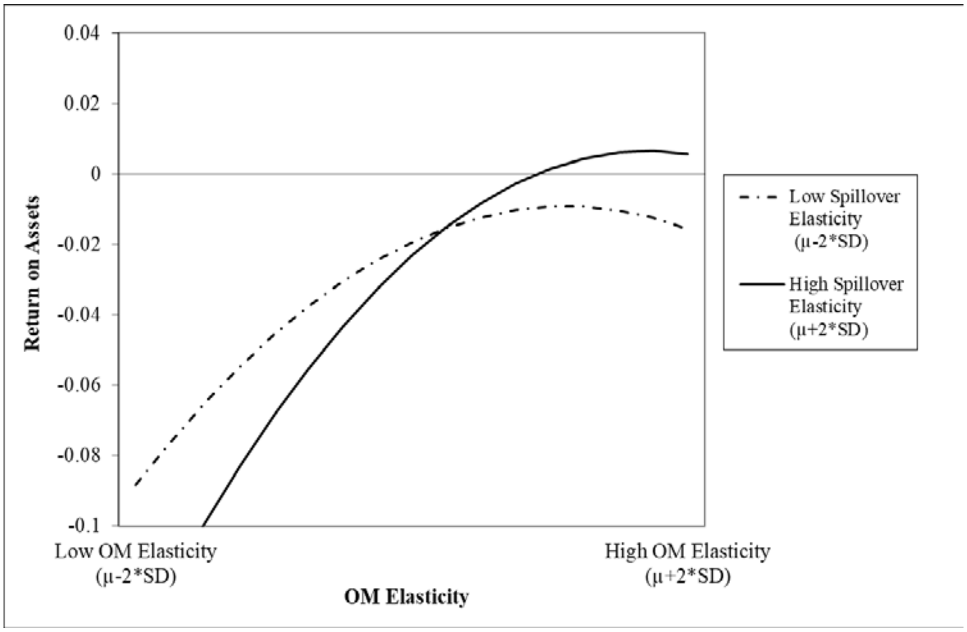

Figure 4.7. Plot: DV = ROA, OM = SLT, and Laggard Spillover Elasticity

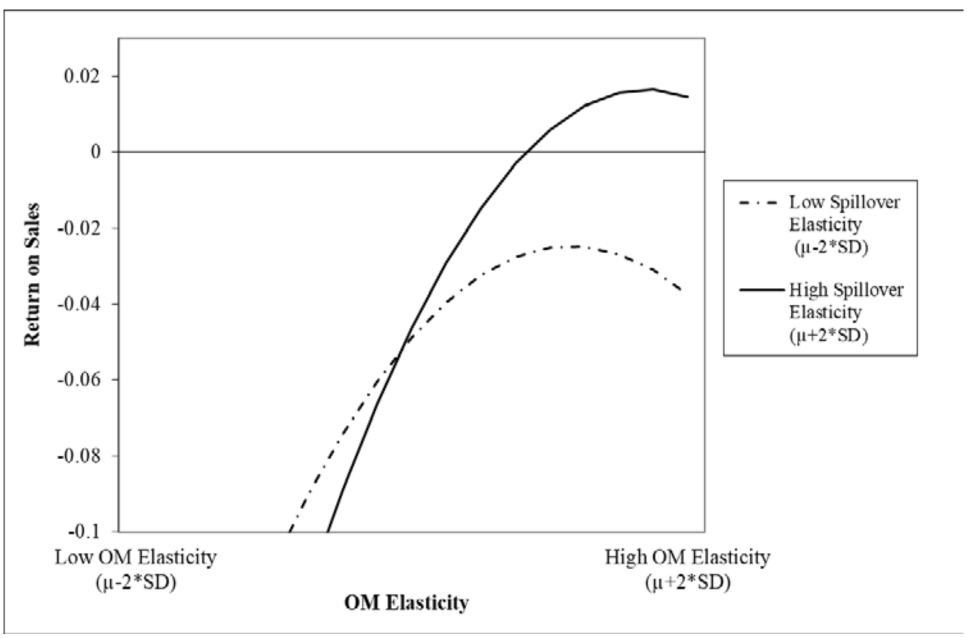

Figure 4.8. Plot: DV = ROS, OM = SLT, and Laggard Spillover Elasticity

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4.5.2.3 Volume Flexibility (VF)

Models 8 and 9 (ROA & ROS respectively) present the results for the moderating effect of both leader and laggard types of VF-spillover elasticity. The interaction of leader spillover elasticity with the quadratic term of VF elasticity is not significant for ROA but is significant for ROS with a p-value less than 0.05. The interaction of laggard spillover elasticity with the quadratic term of VF elasticity is not significant for both ROA and ROS. Hence, overall the moderation effect of both leader and laggard spillover elasticity on the quadratic association between OM elasticity and financial performance is not statistically significant. Furthermore, per Wald test results in Table 4.8, there is no significant difference between the moderating effects of leader and laggard spillover elasticity. Hence, no support is found for H1a and H1b in the case of VF.

4.5.3 Moderating Effect of Environmental Uncertainty

To test H2, OLS regression was run with a double-clustered robust error structure. Firm size, R&D, leverage, time, and industry (4-digit level) effects were included as control variables. A traditional three-way interaction model to test the moderating effect of environmental uncertainty was showing high multi-collinearity. Hence, median-split method was used instead on the base model described in equation 3 (Mackelprang et al., 2015; Wiengarten et al., 2014). Environmental uncertainty was split at its median value into two groups (low and high) and analysis was done separately for each group. Both groups were later compared if the relevant coefficients are significantly different using Wald tests. Table 4.9 summarizes results using ROA as the dependent variable. Taking the example of inventory, Model 10 in Table 4.9 shows the results for low environmental-uncertainty and Model 11 shows the results for high environmental-uncertainty group.

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Table 4.9. Regression Results for Hypothesis 2, DV = ROA

	(10)	(11)	(12)	(13)	(14)	(15)
DV = ROA	**OM = INV**		**OM = SLT**		**OM = VF**	
	Low	**High**	**Low**	**High**	**Low**	**High**
Ln(Lagged R&D)	-0.004*** (0.001)	-0.004*** (0.000)	-0.004*** (0.000)	-0.004*** (0.001)	-0.002*** (0.000)	-0.002*** (0.000)
#Years	-0.001* (0.001)	-0.001 (0.001)	-0.003*** (0.001)	-0.002** (0.001)	0.000 (0.001)	-0.000 (0.001)
Ln(Labor)	0.032*** (0.002)	0.034*** (0.002)	0.001 (0.003)	0.008* (0.003)	0.021*** (0.002)	0.022*** (0.002)
Leverage	-0.013 (0.008)	-0.040* (0.018)	-0.098*** (0.022)	-0.062* (0.029)	-0.062*** (0.021)	-0.096*** (0.019)
Ln(OM)	-0.011* (0.005)	0.004 (0.004)	-0.037*** (0.003)	-0.030*** (0.003)	-0.068*** (0.007)	-0.064*** (0.006)
OM Elasticity	-0.187*** (0.023)	-0.125*** (0.019)	-0.053 (0.033)	-0.035 (0.025)	-0.145 (0.051)	-0.067 (0.060)
OM Elasticity^2	-0.398*** (0.071)	-0.241*** (0.053)	-0.246*** (0.043)	-0.205*** (0.038)	0.056 (0.150)	-0.197 (0.179)
Leader ES	-0.115* (0.054)	-0.131* (0.053)	0.095 (0.125)	-0.107 (0.134)	-0.010 (0.063)	0.072 (0.055)
OM Elasticity* Leader ES	0.198 (0.156)	0.068 (0.068)	-0.554 (0.471)	-0.827* (0.398)	0.255 (0.235)	0.716*** (0.144)
OM Elasticity^2* Leader ES	1.001*** (0.249)	0.593*** (0.133)	1.602*** (0.241)	1.528*** (0.246)	0.313 (0.601)	0.892* (0.369)
Laggard ES	-0.048 (0.052)	-0.131*** (0.039)	0.322** (0.118)	0.363*** (0.099)	0.086 (0.191)	0.174 (0.242)
OM Elasticity* Laggard ES	-0.157 (0.154)	-0.048 (0.150)	0.881* (0.422)	1.027*** (0.267)	-1.221 (0.869)	1.133 (1.095)
OM Elasticity^2* Laggard ES	0.240 (0.280)	0.049 (0.179)	-1.642*** (0.436)	-0.813 (0.444)	-0.010 (2.018)	1.269 (2.395)

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N	20262	21913	20528	22096	12420	13659

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Standard errors in parentheses and are two-way cluster robust. ES=Spillover Elasticity

Table 4.10 summarizes results using ROS as the dependent variable. Taking the example of inventory again, Model 16 in Table 4.10 shows the results for the low group and Model 17 shows the results for the high group. Results of industry dummies are not shown in the interest of brevity. The Variance Inflation Factor (VIF) for all models in both tables was either less than or equal to 6.

Table 4.10. Regression Results for Hypothesis 2, DV = ROS

	(16)	**(17)**	**(18)**	**(19)**	**(20)**	**(21)**
DV = ROS	**OM = INV**		**OM = SLT**		**OM = VF**	
	Low	**High**	**Low**	**High**	**Low**	**High**
Ln(Lagged R&D)	-0.007^{***}	-0.007^{***}	-0.008^{***}	-0.008^{***}	-0.004^{***}	-0.005^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
#Years	-0.000	0.000	-0.002^{*}	-0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ln(Labor)	0.052^{***}	0.059^{***}	0.015^{**}	0.036^{***}	0.029^{***}	0.034^{***}
	(0.004)	(0.004)	(0.005)	(0.007)	(0.002)	(0.003)
Leverage	-0.019	-0.050^{*}	-0.110^{***}	-0.074^{*}	-0.078^{***}	-0.114^{***}
	(0.010)	(0.021)	(0.023)	(0.033)	(0.022)	(0.019)
Ln(OM)	0.038^{**}	0.068^{***}	-0.040^{***}	-0.026^{***}	-0.107^{***}	-0.105^{***}
	(0.012)	(0.010)	(0.005)	(0.006)	(0.014)	(0.011)
OM Elasticity	-0.334^{***}	-0.252^{***}	-0.083	-0.086	-0.142	-0.012
	(0.047)	(0.041)	(0.061)	(0.050)	(0.086)	(0.119)
OM Elasticity^2	-0.700^{***}	-0.531^{***}	-0.492^{***}	-0.474^{***}	-0.255	-0.724^{*}
	(0.129)	(0.101)	(0.085)	(0.072)	(0.383)	(0.335)
Leader ES	-0.252^{*}	-0.256^{*}	-0.023	-0.335	0.013	0.108
	(0.120)	(0.107)	(0.273)	(0.273)	(0.103)	(0.108)

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OM Elasticity* Leader ES	0.336	0.075	-1.099	-1.474*	0.422	1.321**
	(0.275)	(0.150)	(1.005)	(0.744)	(0.359)	(0.377)
OM Elasticity^2* Leader ES	1.742***	1.048***	3.117***	3.189***	1.222	1.840*
	(0.445)	(0.280)	(0.526)	(0.521)	(1.025)	(0.753)
Laggard ES	-0.110	-0.187*	0.898***	0.876***	0.031	0.330
	(0.096)	(0.082)	(0.245)	(0.225)	(0.290)	(0.496)
OM Elasticity* Laggard ES	-0.214	-0.085	2.273**	1.784***	0.146	4.377*
	(0.283)	(0.301)	(0.864)	(0.526)	(1.696)	(1.793)
OM Elasticity^2* Laggard ES	0.617	-0.027	-3.292***	-1.275	1.837	2.327
	(0.556)	(0.357)	(0.891)	(0.897)	(3.666)	(4.218)
N	20262	21913	20528	22096	12420	13659

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Standard errors in parentheses and are two-way cluster robust.
ES=Spillover Elasticity

Wald tests of the relevant coefficients were performed to confirm the moderating effect of environmental uncertainty for each of the three operational measures. For example, in the case of inventory and ROA as the dependent variable, the relevant coefficients were compared between Models 10 and 11 to check if H2 was supported and so on. Results are summarized in Table 4.11. The moderating relationship between both leader and laggard spillover elasticity and the quadratic association between OM elasticity and financial performance does not differ between low and high environmental-uncertainty groups for INV and VF. In case of SLT and ROS, only the interaction between laggard spillover elasticity and the quadratic term of OM elasticity is significant. However, with ROA as the dependent variable, the same effect is not significant. As such, Wald tests failed to support H2 for both ROA and ROS overall. To conclude, failure to find support for H2 indicates that the results for H1 are robust to the effects of the environmental uncertainty.

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Table 4.11. Wald Test Results for Hypothesis 2

Low vs. High Group	OM = INV		OM = SLT		OM = VF	
Coefficients	**ROA**	**ROS**	**ROA**	**ROS**	**ROA**	**ROS**
OM Elasticity	**0.062**	0.082	0.018	-0.003	0.078	0.130
OM Elasticity^2	**0.157**	0.169	0.041	0.018	-0.253	-0.469
Leader ES	-0.016	-0.004	**-0.202**	-0.312	0.082	0.095
OM Elasticity*Leader ES	-0.130	-0.261	-0.273	-0.375	0.461	0.899
OM Elasticity^2*Leader ES	-0.408	-0.694	-0.074	0.072	0.579	0.618
Laggard ES	-0.083	-0.077	0.041	-0.022	0.088	0.299
OM Elasticity*Laggard ES	0.109	0.129	0.146	-0.489	2.354	4.231
OM Elasticity^2*Laggard ES	-0.191	-0.644	0.829	**2.017**	1.279	0.490

Difference estimate= coefficient of high group- coefficient of low group. Values in bold are significant at the 5% level. All other values are not significant.

4.5.4 Moderating Effect of Industry Innovativeness

To test H3, OLS regression was run with a double-clustered robust error structure. Firm size, R&D, leverage, time, and industry (4-digit level) effects were included as control variables. A traditional three-way interaction model to test the moderating effect of industry innovativeness was showing high multi-collinearity. Hence, median-split method was used instead on the base model described in equation 3, similar to H2 (Mackelprang et al., 2015; Wiengarten et al., 2014). Industry innovativeness was split at its median value into two groups (low and high) and analysis was done separately for each group. Both groups were later compared if the relevant coefficients are significantly different using Wald tests. Table 4.12 summarizes results using ROA as the dependent variable. Taking the example of inventory, Model 22 shows the results for low industry-innovativeness group and Model 23 shows the results for high industry-innovativeness group.

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Table 4.12. Regression Results for Hypothesis 3, DV = ROA

	(22)	(23)	(24)	(25)	(26)	(27)
DV=ROA	**OM = INV**		**OM = SLT**		**OM = VF**	
	Low	**High**	**Low**	**High**	**Low**	**High**
Ln(Lagged R&D)	-0.001***	-0.009***	-0.001***	-0.009***	-0.001*	-0.004***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
#Years	-0.001	-0.002***	-0.002***	-0.004***	-0.000	-0.000
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Ln(Labor)	0.019***	0.043***	0.006***	0.006	0.013***	0.029***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.001)	(0.002)
Leverage	-0.021	-0.019	-0.111***	-0.063*	-0.082***	-0.070**
	(0.012)	(0.012)	(0.015)	(0.030)	(0.016)	(0.023)
Ln(OM)	-0.003	-0.009*	-0.016***	-0.041***	-0.041***	-0.078***
	(0.004)	(0.004)	(0.002)	(0.004)	(0.004)	(0.007)
OM Elasticity	-0.085***	-0.183***	-0.055*	-0.042	0.051	-0.175**
	(0.019)	(0.024)	(0.027)	(0.028)	(0.047)	(0.066)
OM Elasticity^2	-0.175***	-0.370***	-0.295***	-0.206***	-0.238**	-0.212
	(0.048)	(0.074)	(0.046)	(0.036)	(0.089)	(0.195)
Leader ES	0.013	-0.206***	-0.009	-0.100	-0.040	0.050
	(0.054)	(0.059)	(0.079)	(0.157)	(0.039)	(0.076)
OM Elasticity* Leader ES	-0.194	0.215*	0.258	-0.834*	0.357	0.640***
	(0.142)	(0.107)	(0.351)	(0.396)	(0.214)	(0.166)
OM Elasticity^2* Leader ES	0.153	0.966***	0.728***	1.723***	0.181	0.808
	(0.230)	(0.182)	(0.117)	(0.247)	(0.359)	(0.508)
Laggard ES	-0.155***	-0.069	-0.031	0.485***	-0.337*	0.793*
	(0.039)	(0.052)	(0.104)	(0.103)	(0.151)	(0.366)
OM Elasticity* Laggard ES	0.045	-0.211	0.503	0.877**	1.106*	0.898
	(0.168)	(0.181)	(0.407)	(0.288)	(0.556)	(1.522)
OM Elasticity^2* Laggard ES	0.404	0.099	0.517	-1.323***	-0.899	0.457
	(0.334)	(0.239)	(0.434)	(0.400)	(1.908)	(2.003)

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N	22160	25238	22487	25446	12292	13487

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Standard errors in parentheses and are two-way cluster robust.
ES=Spillover Elasticity

Table 4.13 summarizes the results using ROS as the dependent variable. Taking the example of inventory again, Model 28 shows the results for the low group and Model 29 shows the results for the high group. Results of industry dummies are not shown for both ROA and ROS in the interest of brevity. The Variance Inflation Factor (VIF) for all models was either less than or equal to 6.6.

Table 4.13. Regression Results for Hypothesis 3, DV = ROS

	(28)	**(29)**	**(30)**	**(31)**	**(32)**	**(33)**
DV=ROS	**OM = INV**		**OM = SLT**		**OM = VF**	
	Low	**High**	**Low**	**High**	**Low**	**High**
Ln(Lagged R&D)	-0.002***	-0.015***	-0.003***	-0.017***	-0.001**	-0.009***
	(0.000)	(0.002)	(0.000)	(0.002)	(0.000)	(0.001)
#Years	-0.001	-0.001	-0.002***	-0.004***	0.000	0.001
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Ln(Labor)	0.029***	0.074***	0.016***	0.038***	0.018***	0.044***
	(0.003)	(0.005)	(0.004)	(0.007)	(0.002)	(0.003)
Leverage	-0.025*	-0.027	-0.110***	-0.077*	-0.091***	-0.089***
	(0.012)	(0.016)	(0.012)	(0.035)	(0.012)	(0.025)
Ln(OM)	0.016*	0.057***	-0.016***	-0.040***	-0.046***	-0.137***
	(0.007)	(0.010)	(0.003)	(0.006)	(0.005)	(0.013)
OM Elasticity	-0.138***	-0.344***	-0.093*	-0.096	0.113	-0.192
	(0.031)	(0.049)	(0.046)	(0.054)	(0.066)	(0.123)
OM Elasticity^2	-0.365***	-0.705***	-0.525***	-0.485***	-0.344*	-0.812*
	(0.080)	(0.121)	(0.100)	(0.068)	(0.136)	(0.380)
Leader ES	0.098	-0.406***	-0.022	-0.430	-0.050	0.105
	(0.087)	(0.118)	(0.135)	(0.325)	(0.054)	(0.138)

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OM Elasticity* Leader ES	-0.352 (0.214)	0.368* (0.180)	0.626 (0.617)	-1.496 (0.818)	0.206 (0.374)	1.190** (0.407)
OM Elasticity^2* Leader ES	-0.529 (0.424)	1.729*** (0.303)	0.823*** (0.202)	3.725*** (0.529)	2.004* (0.788)	1.287 (1.157)
Laggard ES	-0.219** (0.076)	-0.113 (0.097)	-0.013 (0.200)	1.190*** (0.251)	-0.730*** (0.217)	1.357 (0.728)
OM Elasticity* Laggard ES	0.108 (0.293)	-0.287 (0.357)	1.257 (0.825)	1.613** (0.575)	1.906* (0.884)	4.628 (2.663)
OM Elasticity^2* Laggard ES	0.537 (0.583)	0.186 (0.453)	1.339 (0.862)	-2.611*** (0.774)	8.328* (4.187)	0.852 (4.262)
N	22160	25238	22487	25446	12292	13487

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Standard errors in parentheses and are two-way cluster robust. ES=Spillover Elasticity

Wald tests of the relevant coefficients were performed to confirm the moderating effect of industry innovativeness for each of the three operational measures. Results are summarized in Table 4.14.

Table 4.14. Wald Test Results for Hypothesis 3

Low vs. High Group	**OM = INV**		**OM = SLT**		**OM = VF**	
Coefficients	**ROA**	**ROS**	**ROA**	**ROS**	**ROA**	**ROS**
OM Elasticity	**-0.098**	**-0.206**	0.013	-0.003	**-0.226**	-0.305
OM Elasticity^2	**-0.195**	**-0.340**	0.089	0.040	0.026	-0.468
Leader ES	**-0.219**	**-0.504**	-0.091	-0.408	0.090	0.155
OM Elasticity*Leader ES	**0.409**	**0.720**	-1.092	-2.122	0.283	0.984
OM Elasticity^2*Leader ES	**0.813**	**2.258**	**0.995**	**2.902**	0.627	-0.717
Laggard ES	0.086	0.106	**0.516**	**1.203**	**1.130**	**2.087**
OM Elasticity*Laggard ES	-0.256	-0.395	0.374	0.356	-0.208	2.722
OM Elasticity^2*Laggard ES	-0.305	-0.351	**-1.840**	**-3.950**	1.356	-7.476

Difference estimate = coefficient of high group- coefficient of low group. Values in bold are significant at the 5% level. All other values are not significant.

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For each of the three measures, Wald test results were consistent across ROA and ROS. The moderating effects of both leader and laggard spillover elasticity differs significantly between low and high groups for SLT but not for VF. In the case of INV, the moderating effects of only the leader spillover elasticity differs across the two groups. To summarize, Wald tests provide support to H3 for SLT, but failed to support H3 for VF. For INV, Wald tests only support H3a. Overall, the results for ROS are consistent with that of ROA in the two tables except for the small variation between the actual coefficient estimates and statistical significances. ROA regression results are slightly more conservative than those of ROS. Hence, interaction plots and interpretation are presented using only ROA results in the interest of brevity. The interpretation of these results for each operational measure is discussed next.

4.5.4.1 Inventory (INV)

Models 22 and 23 in Table 4.12 present the results for the low and high industry-innovativeness group respectively for ROA. Models 28 and 29 in Table 4.13 present the results for the low and high industry-innovativeness group respectively for ROS. In Table 4.12, the interaction of leader spillover elasticity with the quadratic term of inventory elasticity is significant for the high industry-innovativeness group ($p\text{-value} < 0.001$), but not for the low industry-innovativeness group. The interaction of laggard spillover elasticity with the quadratic term of inventory elasticity is not statistically significant for both groups. This is consistent with H1 results where the moderation effect of laggard spillover elasticity was not statistically significant to begin with. Wald tests came out statistically significant for leader spillover elasticity but not for laggard spillover elasticity.

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The results show that, only the moderation effect of leader spillover elasticity differs significantly between low and high industry-innovativeness groups. Graphically the interaction effects for leader spillover elasticity are presented in Figures 4.9 and 4.10 for low and high industry-innovativeness group respectively.

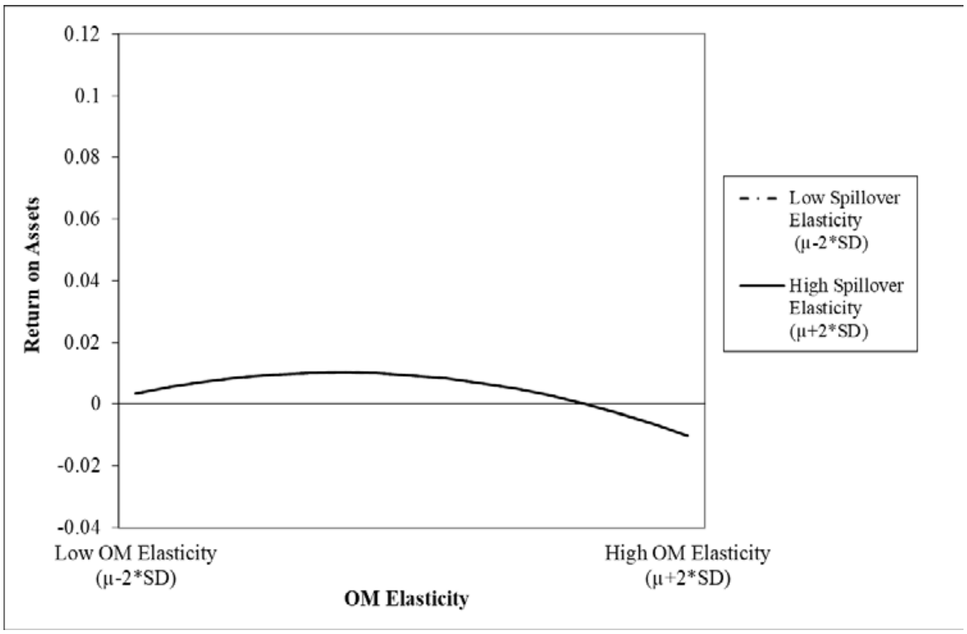

Figure 4.9. Plot: OM = INV, Leader Spillover Elasticity, and Low Innovativeness

For the high industry-innovativeness group (refer to Figure 4.10), results match those for H1 (refer to Figure 4.1), only more pronounced. Firms on the left side benefit from learning from leader spillover pool while firms on the right side are financially hurt when they rely more on leader spillover pools. For the low innovativeness group; however, no evidence is found of the moderating effect of leader spillover elasticity. All firms perform the same regardless of their ability to learn from the leader spillover pool. This indicates that firms in less innovative industries are (a) least inclined to exploit external operational knowledge since they are not confronted with the same time and market pressures as firms operating in highly innovative industries, and/or (b) all have comparable

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abilities to learn from leader's best practices and lack incentive to improve on this ability. Hence, H3a is supported. The Wald tests are not significant for laggard spillover elasticity results failing to support H3b.

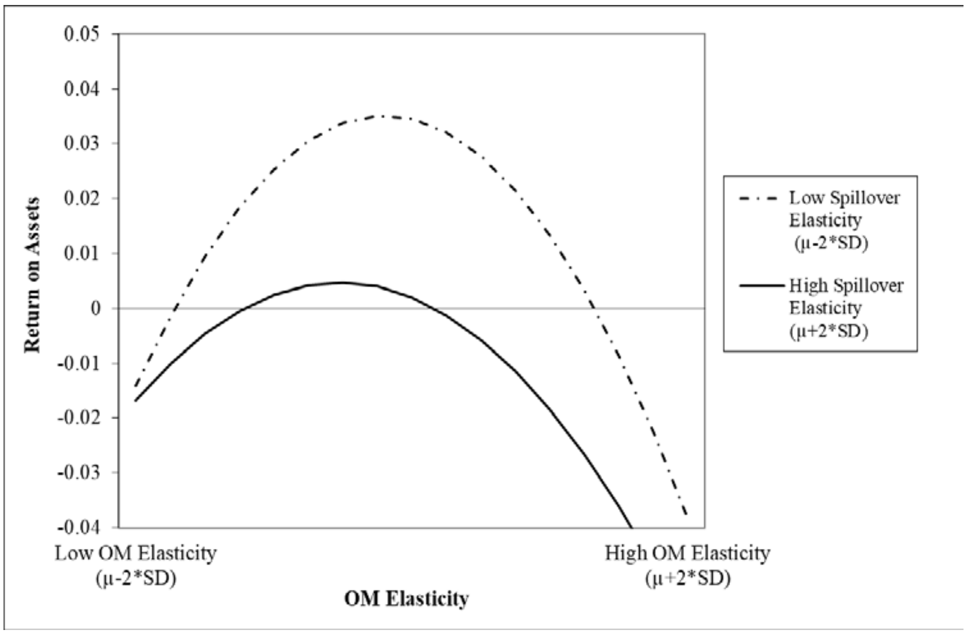

Figure 4.10. Plot: OM = INV, Leader Spillover Elasticity, and High Innovativeness

4.5.4.2 Sourcing Lead Time (SLT)

Models 24 and 25 in Table 4.12 present the results for the low and high industry-innovativeness group respectively for ROA. Models 30 and 31 in Table 4.13 present the results for the low and high industry-innovativeness group respectively when for ROS. The interaction of leader spillover elasticity with the quadratic term of SLT elasticity is significant with a p-value < 0.001 for both low and high industry-innovativeness groups, unlike inventory. The interaction of laggard spillover elasticity with the quadratic term of SLT elasticity is statistically significant with a p-value < 0.001 only for the high industry-innovativeness group. Wald tests came out statistically significant at a p-value < 0.05 for interactions with leader spillover elasticity as well as those with laggard spillover elasticity.

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Graphically the interaction effects for the high industry-innovativeness group are presented in Figures 4.11 and 4.12.

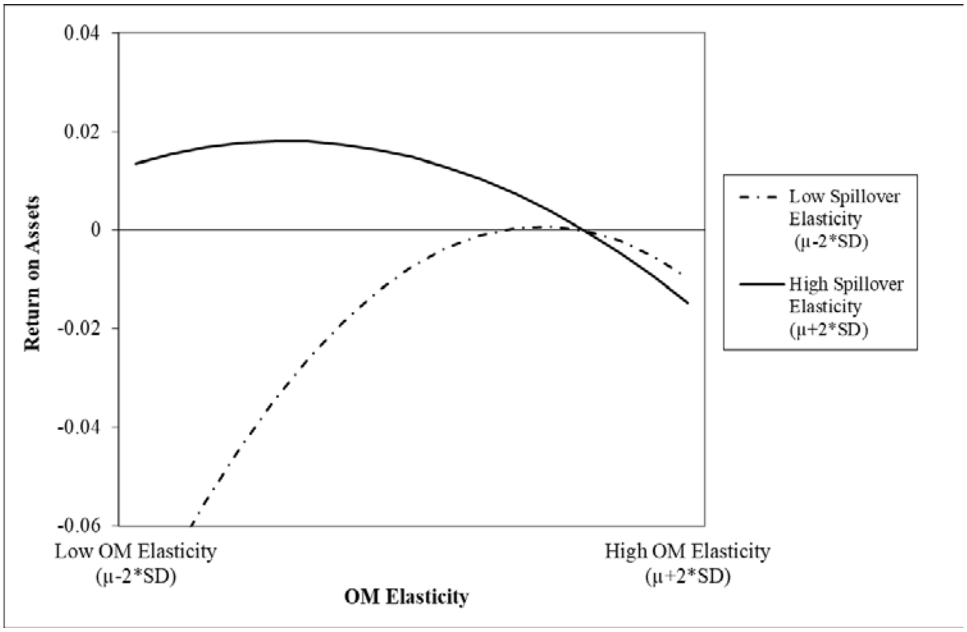

Figure 4.11. Plot: OM = SLT, Leader Spillover Elasticity, and High Innovativeness

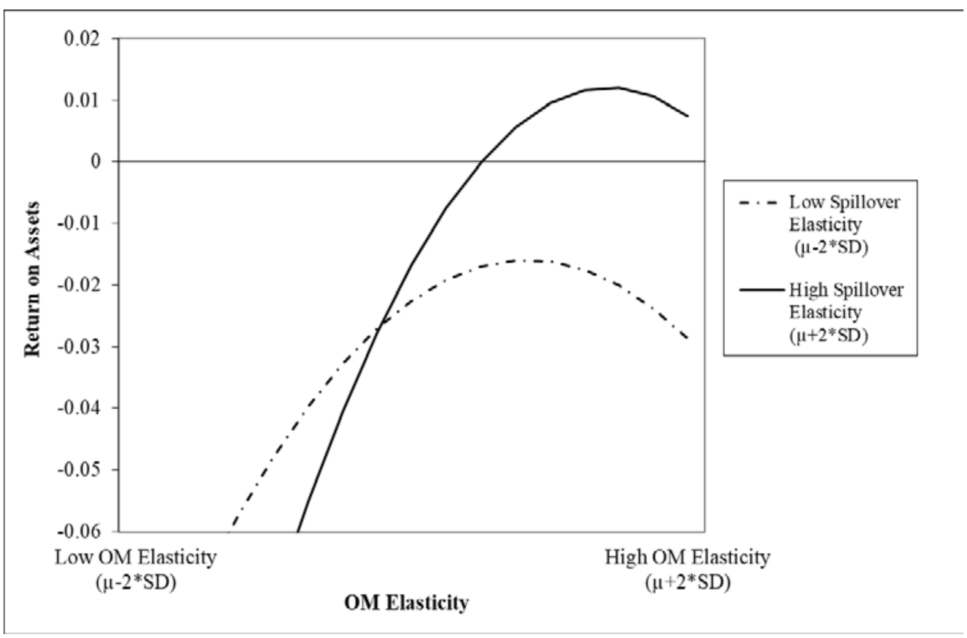

Figure 4.12. Plot: OM = SLT, Laggard Spillover Elasticity, and High Innovativeness

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For the high industry-innovativeness group, results match those for H1 for both leader and laggard spillover elasticity. The financial benefit from leader spillover pool is dependent on the position of the firm on the quadratic curve and this dependency is most pronounced in the left side of the curve. Firms on the left side benefit from learning from leader spillover pool in that they can reduce their long lead times while firms on the right-side experience little difference. In the case of laggard spillover elasticity, both sides of the curve show substantial difference between firms that are able to successfully learn and those that are not. Unlike leader spillover elasticity, firms on right side of the curve financially gain from learning from laggard spillover pool. Laggard pool is indicative of SLT practices that lead to longer lead times. Hence, firms on the right side that are already too lean in terms of SLT actually benefit from the knowledge provided by laggard spillover pools. Plots for the low industry-innovativeness group are shown in Figures 4.13 and 4.14.

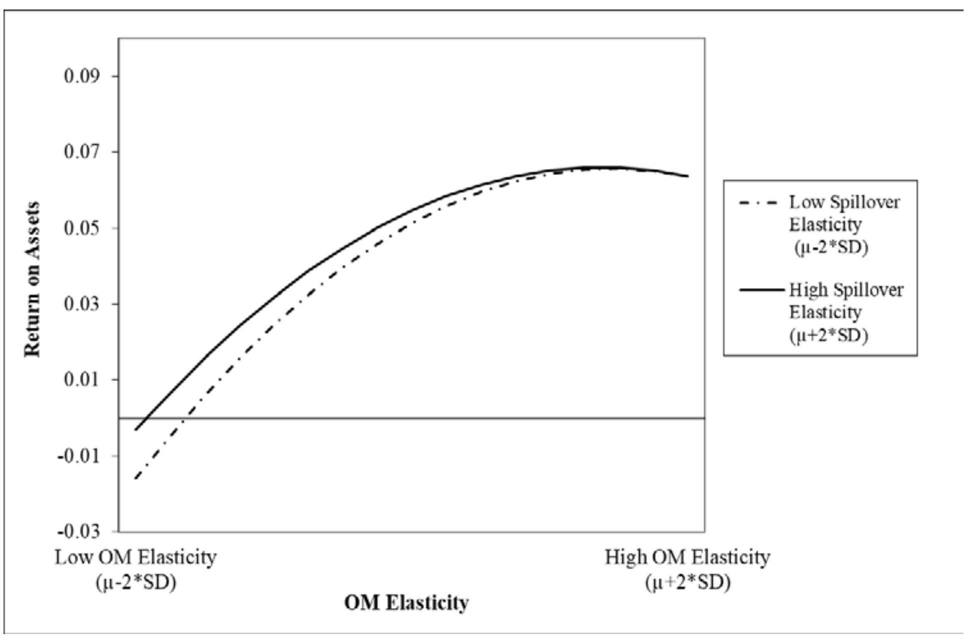

Figure 4.13. Plot: OM = SLT, Leader Spillover Elasticity, and Low Innovativeness

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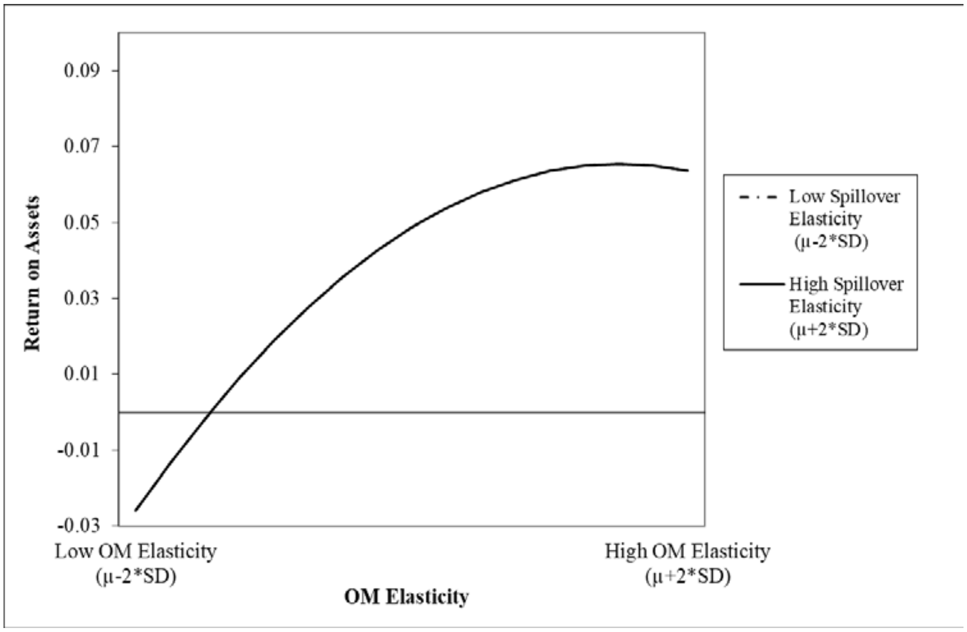

Figure 4.14. Plot: OM = SLT, Laggard Spillover Elasticity, and Low Innovativeness

For leader spillover elasticity in the low industry-innovativeness group, the same effects are evident albeit in a much weaker intensity compared to the high group. The difference between low and high leader spillover elasticity is almost non-existent, especially on the right side of the curve. Firms on the left side benefit slightly for high leader spillover elasticity. In the case of laggard spillover elasticity (refer to Figure 4.14), all firms perform the same regardless of their ability to learn from the laggard spillover pool. This indicates that firms in less innovative industries are not focusing as much on knowledge generated outside the firm as they face lesser competition and time pressures to build on the work in-house (Mackelprang et al., 2015). The interaction plots across the two groups together with the Wald test results, imply that both leader and laggard spillover elasticity moderation effects are stronger in the high industry-innovativeness group. This lends supports to both H3a and H3b.

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4.5.4.3 Volume Flexibility (VF)

Models 26 and 27 in Table 4.12 present the results for the low and high industry-innovativeness group respectively for ROA. Models 32 and 33 in Table 4.13 present the results for the low and high industry-innovativeness group respectively for ROS. The interaction of leader spillover elasticity with the quadratic term of VF elasticity is not statistically significant for either of the two groups. Same is true for laggard spillover elasticity. Furthermore, Wald tests were also not statistically significant suggesting that there is no difference between the low and high innovativeness groups in terms of the moderating effects of both leader and laggard spillover elasticity. Hence, the results do not support either H3a or H3b.

4.6. Discussion

Table 4.15 summarizes the results for the three sets of hypotheses.

Table 4.15. Summary of Findings

Hypothesis	OM = INV	OM = SLT	OM = VF
H1	H1: supported	H1: supported	H1: not supported
H2	H2: not supported	H2: not supported	H2: not supported
H3	H3a: supported H3b: not supported	H3a: supported H3b: supported	H3: not supported

First, the existence of laggard operational spillovers in terms of inventory, sourcing lead time, and volume flexibility is confirmed using formal empirical methods. Second, it is confirmed that manufacturing firms in fact differ in their ability to turn leader and laggard spillovers into operating profits. Third, even after the inclusion of laggard spillover

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elasticity, the overall interpretation for the moderating impact of leader spillover elasticity remains consistent with that in Chapter 3 across all three operational measures. That is, leader spillovers are only beneficial to firms that are lacking in operational-knowledge resources, regardless of the environmental conditions. Fourth, the moderating effects of both leader and laggard spillover elasticity are robust to the level of uncertainty in the industry-level environment. However, industry innovativeness does play an influencing role in the relationship between operational spillovers and financial performance. Overall, the results, though not fully supported and counterintuitive in places, are consistent with resource orchestration view.

4.6.1 Managerial Implications

The concept of leader and laggard spillovers has multiple implications for managers. First, consistent with the work in Chapter 3, firm performance is a function of not just the absolute levels of operational knowledge, but rather the firm's internal ability to benefit from these operational-knowledge resources. Managers need to not only be able to correctly assess the value of their external operational resources, but also use them in the correct context by orchestrating them with their existing operational capabilities. Simply stated, managers must be skilled in how they use the resources they possess, independent of how those resources were obtained. Second, industry laggards also have the potential of generating useful operational knowledge. Third, firms do not exploit leader's operational knowledge and laggard's operational knowledge in the same way, as demonstrated by the varying levels of leader and laggard spillover elasticities. The fourth implication pertains to augmenting financial performance from leader and laggard spillover elasticities. As such and somewhat counterintuitive, managers should not simply seek to imitate leader firms.

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Additionally, managers should be cognizant that while laggard firms may possess operational knowledge its value is largely unknown and payoffs are uncertain. Arguably, there are two possibilities behind this. It is possible that laggard firms have valuable operational knowledge but are unable to fully realize the benefits of their knowledge. It is also possible that laggards, while possessing adequate levels of capabilities, simply possess an inferior quality of knowledge; hence, end up lagging behind. For a firm to be successful, correct recognition of inferior knowledge is crucial so as not to waste precious money and resources in imitating inferior knowledge (Knott et al., 2009). Fifth, managers need to pay special attention to industry innovativeness because the impact of operational spillovers increases with increasing levels of innovativeness. In terms sourcing lead time, both leader and laggard spillovers become increasingly relevant with increasing levels of innovativeness. In terms of inventory, successfully imitating leaders is more crucial under high-innovativeness conditions, not so for imitating laggards. Finally, environment uncertainty does not seem to interact with the moderating effects of operational spillovers which implies that managerial decisions regarding operational spillovers need not be dependent on the levels of environmental uncertainty.

4.6.2 Theoretical Implications

This research builds the theoretical interface between operations management (OM) and strategy. First, further empirical support is provided to one of the foundational pieces of RBV, that firms are heterogeneous in terms of their capabilities and resources (Barney and Arikan, 2001). To the best of knowledge, empirical work is scarce on the heterogeneity aspect specific to operational capabilities in terms of inventory, SLT, and VF of manufacturing firms. Within RBV, there is dearth of research that explains how firms can

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actually use their unique set of resources and capabilities to create competitive advantage (Sirmon et al., 2007). With this work, an attempt is made to demonstrate how firms can orchestrate their different capabilities (OM elasticity and spillover elasticity) to augment profits. Second, results also provide support for the literature of resource orchestration and/or curatorship (Breton-Miller and Miller, 2015; Grewal and Slotegraaf, 2007; Paeleman and Vanacker, 2015).

Third, it is shown that operational spillovers do have directionality, and manufacturing firms seem to exploit operational knowledge from both industry leaders and laggards, in terms of inventory and sourcing lead time. Hence, there is much more granularity to be gained from delving deeper into the source of operational spillovers. Lower performance by a laggard firm in terms of inventory, SLT, and VF does not necessarily mean that it possesses inferior operational knowledge. Finally, this work ties together several research streams- operational practices; resource and capability orchestration; innovativeness, external environment, and firm performance. External environment in terms of industry innovativeness is found to be strongly associated with the exploitation of operational spillovers. Finally, the results of this essay further strengthen the results of essay two as the effect of operational spillovers on performance are insensitive to environmental uncertainty, suggesting a degree of generalizability with respect to environmental uncertainty.

4.7. Conclusion

To conclude this chapter advances the understanding of operational spillovers coupled with the influence of environment-specific characteristics. The work done does have some limitations. First, the study sample does not include private firms. The spillover pool, S, is

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modeled such that only the spillovers from within the industry are considered. Future research can extend this work to include inter-industry spillovers. This work can also be extended to examine if using a different functional form, other than the leader-laggard distance form, influences the results. Another profitable research opportunity lies in exploring other types of operational spillovers beyond those of inventory, SLT, and VF. One interesting finding of this research is the possession of potentially valuable operational knowledge in laggard firms. This is counterintuitive in that laggard firms are presumed to have inferior knowledge (Knott et al., 2009). Such a finding raises an interesting potential research avenue related to why laggard firms are laggards? Do laggard firms lack specific capabilities or is their knowledge simply not as broad as leader firms? A similar line of inquiry could be made for leader firms. Hence, the field of OM can benefit from more research on leveraging operational knowledge and capabilities. Sirmon et al. (2007) have called for more research on ways of leveraging resources in general. To conclude, it is hoped that future scholars will find the concept of operational spillovers useful and continue to enrich it with further research.

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CHAPTER 5

Conclusion

The complexity and ambiguity of converting new ideas into successful products and processes has provided operations management researchers a challenging yet fruitful research domain. Additional challenges facing researchers in this area is the lack of data for adequately measuring technological innovation and also the multi-disciplinary and multi-dimensional nature of innovation causing the need to use multiple different methods for research on this topic. Despite these challenges, the opportunity for research in this area is significant given its critical importance to most firms competing in today's complex operational environment. In its totality, this dissertation grapples with these challenging issues to delve deeper into technological innovation in general and more specifically operational knowledge spillovers.

The second chapter of this dissertation concentrates on the overarching construct of technological innovation and its inherent complexity. The contradictory findings on its impact on firm performance are quantitatively aggregated by using empirical data from relevant published studies from thirteen major journals across various research disciplines. Analysis via multivariate meta-analytic methodology sought to reconcile the relationship between technological innovation and firm performance. The results indicate a significant and positive relationship. The rate and direction of the impact of technological innovation on firm performance is however influenced by various contextual factors at play.

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Additionally, in the second chapter, the role of country-level contextual factors across the dimensions of culture and formal institutions is examined. Results show that firms operating in nations with a collectivistic mindset and/or lower tendency to avoid uncertainty reap better financial outcomes from innovation. Moreover, contrary to past research in this area, innovation endeavors by firms operating in nations with strong patent protection do not result in financial gains. Furthermore, two interesting patterns are revealed in the research done on technological innovation thus far. First, majority of the research done has assumed firms to be homogenous in nature, and second, imitation of rival firm(s) as a strategy for transforming financial performance is equally popular as in-house innovation among firms. Hence, the role of imitation of rival firm(s) as an influencing factor is explored in the analysis conducted in Chapters 3 and 4, under the assumption that firms are in fact heterogenous in their ability to financially benefit from innovation.

Imitation of rival firm(s) occurs by exploiting the innovative knowledge that leaks out of those firm(s) and this phenomenon is referred to as spillovers. In the third chapter of this dissertation, the concept of spillovers of operational knowledge, called *operational spillovers* is introduced. These operational spillovers are characterized in terms of inventory, sourcing lead time, and volume flexibility. Chapter 3 verifies the existence of operational spillovers in manufacturing firms across the three dimensions of inventory, lead time, and flexibility. The moderating role on the performance sensitivity of firms to their internal innovative operational practices is also examined. Results show that firms are indeed heterogenous in nature, and operational spillovers financially benefit only those firms which have underdeveloped operational capabilities. All other firms are hurt

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financially from operational spillovers, contrary to expectations. Using the resource-based view (RBV) of a firm, this chapter highlights the importance of learning from operational spillovers as a capability of a firm to sustain competitive advantage. The results have the following practical implications. First, firm performance is a function of both the absolute levels of internal and external operational knowledge as well as the firm's ability to successfully exploit these resources. Second, imitation of the industry's leading firm is not always the best idea for augmenting financial outcomes, and should be undertaken by firms keeping in mind their internal capabilities.

In Chapter 4 of the dissertation, external operational knowledge accumulated by a firm is further separated into leader and laggard spillover pools. The aim is to get a deeper understanding of the differences in the impact of both leader and laggard spillovers on the focal relationship studied in Chapter 3. Results indicate that there are significant differences in the moderating effects of both leader and laggard spillovers in terms of inventory and sourcing lead time, but not in the case of volume flexibility. The individual impact of leader and laggard spillovers is further evaluated in the context of industry-level environment to establish generalizability of results. The degree of environmental uncertainty and industry innovativeness are used to characterize the external environment in which the firm operates. Results show that the impact of both leader and laggard spillovers is insensitive to environmental uncertainty. However, the impact of both spillovers was found to be more pronounced in highly innovative industries compared to less innovative industries. These results indicate that (a) not all operational capabilities are equally relevant and valuable under all environmental conditions, and (b) the external knowledge gained via operational spillovers is more important in highly innovative

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industries. Hence, firms operating in highly innovative industries are recommended to focus on developing capabilities to leverage operational spillovers. Taken together, the essays contained within this dissertation advance the extant understanding related to technological innovation generally and operational spillovers more specifically. It is expected that the introduction of the operational-spillover concept in extant literature will spur further examination into the underlying processes that underpin successful (unsuccessful) innovation efforts.

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APPENDIX A

List of Studies in the Sample

No.	Author/s	Journal Name	Year	Country
1	Berchicci	Research Policy	(2013)	Italy (IT)
2	Han et al.	POM	(2013)	US
3	Zhang et al.	POM	(2012)	US
4	McDermott and Prajogo	IJOPM	(2012)	Australia
5	Jean et al.	DS	(2012)	Taiwan
6	Song et al.	JOM	(2011)	US
7	Lee et al.	IJOPM	(2011)	South Korea
8	Choi et al.	Research Policy	(2011)	China
9	Yam et al.	Research Policy	(2011)	Hong Kong
10	Liao and Rice	Research Policy	(2010)	Australia
11	Eddleston	JMS	(2008)	US
12	Durand et al.	SMJ	(2008)	France (FR)
13	Oke	IJOPM	(2007)	UK
14	Heeley et al.	AMJ	(2007)	US
15	Namara & Baden-Fuller	Research Policy	(2007)	US, UK, FR, IT, GR
16	Jansen et al.	MS	(2006)	Europe
17	Ettlie & Pavlou	DS	(2006)	US
18	Thornhill	JBV	(2006)	Canada
19	Mallick & Schroeder	POM	(2005)	US
20	Lantz & Sahut	IJB	(2005)	Europe
21	Qian & Li	SMJ	(2003)	US
22	Li and Atuahene-Gima	SMJ	(2002)	China
23	Li and Atuahene-Gima	AMJ	(2001)	China
24	Yamin et al.	IJPE	(1997)	Australia
25	Feeny & Rogers	AER	(2003)	Australia
26	Leiponen	EINT	(2000)	Finland
27	Terwiesch et al.	JPIM	(1998)	US, Japan, Europe
28	Kelm et al.	AMJ	(1995)	US

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