Enhancing the Financial Returns of R&D Investments through Operations Management

Daphne L. M. Yiu

School of Business, Macau University of Science and Technology, Taipa, Macau

Email address: lmyiu@must.edu.mo

Phone number: +853 2882 3281

Hugo K. S. Lam

Management School, University of Liverpool, Liverpool, United Kingdom

Email address: hugolam@liverpool.ac.uk

Phone number: +44 151 795 3621

Andy C. L. Yeung (corresponding author)

Faculty of Business, The Hong Kong Polytechnic University, Kowloon, Hong Kong

Email address: andy.yeung@polyu.edu.hk

Phone number: +852 2766 4063

T. C. E. Cheng

Faculty of Business, The Hong Kong Polytechnic University, Kowloon, Hong Kong

Email address: edwin.cheng@polyu.edu.hk

Phone number: +852 2766 5215

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Abstract

Although much research has been carried out to examine various contextual issues and moderating factors for successful R&D investments, very little research has been conducted to explore the role of a firm's operational and process characteristics. In this study, we explore how firms could possibly enhance the financial returns of R&D investments through quality management, using Six Sigma implementation as an example, and efficiency improvement, using the stochastic frontier estimation of relative efficiency as a proxy. Based on data from 468 manufacturing firms in the U.S. over the period 2007-2014, we construct a dynamic panel data model to capture the effects of R&D investments on firms' financial returns in terms of Tobin's *q*. Using the system generalized method of moments estimator, our results indicate that the financial returns of R&D investments are significantly enhanced when firms adopt Six Sigma and improve efficiency in operations. Our additional analyses further suggest that such an enhancement effect through quality and efficiency improvements is more pronounced under high operational complexity as approximated by labor intensity and geographical diversity. Instead of considering innovation activities and process management as contradictory functions, we show that quality and efficiency improvements indeed support firms' R&D investments, leading to higher financial returns.

Keywords: R&D investments; Tobin's *q*; Six Sigma; operational efficiency

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1. Introduction

The surge of research and development (R&D) activities has been demonstrated in a large body of research with a general consensus that R&D investments are critical to the long-term economic growth and competitiveness of firms (Howells, 2005; Li, 2011). However, the R&D literature has also suggested that the financial returns of R&D investments can vary significantly depending on a number of factors. R&D is inherently a high-uncertainty activity that involves tremendous and irrecoverable costs and time in discovery (Fung, 2006; Pandit et al., 2011). As the innovation process is highly complex and uncertain (Pandit et al., 2011; Wang et al., 2010), it is difficult to ensure a positive outcome. Research has shown that almost 80% of R&D investments fail before completion (García-Quevedo et al., 2018; Kocina, 2017) and many of them do not generate a positive financial return (Simester, 2016). For example, in the pharmaceutical industry, the success rate of a new drug development project is less than 25% (DiMasi et al., 2016; Paul et al., 2010).

Much research has been carried out to examine the factors that determine the financial returns of R&D investments (Evanschitzky et al., 2012). Despite the extensive literature, researchers mainly focus on how knowledge characteristics (e.g., Liu et al., 2014; Rundquist, 2012), project team interactions (e.g., Fang et al., 2015; Liu et al., 2011), environmental factors (Li and Atuahene-Gima, 2001), and marketing strategies (Rubera and Droge, 2013) affect the performance outcome of R&D activities. Very little research has been conducted to find out how operational and process characteristics of firms might potentially moderate the returns of R&D investments. In fact, a significant issue associated with R&D investments is related to the production and delivery of products, rather than the success of product technology *per se*. With compressed product life cycle and fierce market competition (Arnett et al., 2018), timely and reliable product delivery is increasingly critical. For instance, LG Electronics Inc. (LG) tried to differentiate its smartphones and embarked on an R&D project to develop the world's first modular smartphone. Although the product design itself was successful, LG failed to make a profit due to supply chain complexity (Kang, 2016). LG's carriers, distributors, and retailers were unable to work together in managing the complex modules and inventory. In fact, various scholars have investigated the common reasons for R&D and new product failures, most of which are highly related to operations, including timeliness to the market, a lack of real understanding of customer needs, product quality and reliability issues, and inadequate supply chain capabilities (e.g., Schneider and Hall, 2011). Accordingly, the financial returns of any R&D project might depend not only on the technical achievement of the product, but equally importantly, the firm's operational capability in product delivery and production.

We examine the impact of R&D investments on firms' financial returns in terms of Tobin's *q*, and investigate the moderating effect of quality management and operational efficiency initiatives on R&D's performance outcomes. From the traditional operations management (OM) perspective, a firm's process management capability is important in ensuring the delivery of customer value (e.g., Linderman et al., 2003; Zu et al., 2008). Yet there are conflicting views in the literature about the roles of quality and operational efficiency in innovating activities like R&D. Some scholars, particularly those from the organizational behavior perspective, argue that process and quality management techniques, Six Sigma in particular, impede creativity and obstruct R&D activities (Benner and Tushman, 2002, 2003; Naveh and Erez, 2004; Piao and Zajac, 2016). For example, it has been widely reported that Six Sigma hinders the innovativeness in 3M (Huang, 2013), and the pursuing of process efficiency and innovativeness simultaneously would lead to negative organizational outcomes (Hurren, 2015; Klein, 2013). On the other hand, quality and process efficiency are fundamental to an organization, including its R&D activities. The success of R&D investments does not simply depend on technical creativity, but the overall production and delivery of products through quality and efficiency management. In fact, R&D does not stand alone in an organization but is pursued as part of the business under intense competition where quality and process capability are important to success. We examine the effects of Six Sigma and operational efficiency on the financial returns of R&D investments in this study.

Based on a sample of 468 publicly-traded manufacturing firms in the U.S., we investigate if firms enhance their financial returns from R&D investments through implementing Six Sigma and efficiency improvement efforts. Our results show that Six Sigma and operational efficiency positively interact with R&D investments, leading to stronger financial returns. Our additional analyses further demonstrate that such a positive interaction is more pronounced under high operational complexity as approximated by labor intensity and geographical diversity of firms. We contribute to the OM literature by examining how the financial value of R&D investments could possibly be enhanced through quality management and efficiency improvement efforts, and the operating environment in which such an enhancement effect becomes more prominent. Prior studies have examined the moderating effects of developing marketing capability (Ngo and O'Cass, 2012; Rubera and Kirca, 2012) and deploying firms' knowledge assets (Zhou and Li, 2012) on firms' realization of R&D benefits (Kotabe et al., 2011). Yet little is known about the importance of quality management and operational capability to R&D activities. Our results suggest that strong quality and operational capabilities of firms are important in enhancing the financial returns of R&D investments.

2. Theoretical Framework and Hypothesis Development

2.1. R&D and Process Management: Conflicting or Complementary?

Managing R&D process is challenging as it involves sophisticated technological elements and can be ambiguous to non-technical specialists (Mudambi and Swift, 2014). R&D processes are highly risky, and they involve search, experimentation, discovery and often radical changes in firms' product portfolio that require different organizational capabilities. R&D processes often require firms to search, look for deviating alternatives that involve uncertain and experimenting behaviors for discovering new ideas and creating novel solutions (Andriopoulos and Lewis, 2009; Koryak et al., 2018). On the other hand, quality and process management are considered as systematic, structured enabling activities for implementation and execution. Quality management techniques such as Six Sigma often rely on structured organizational framework and routines to ensure efficiency, safeguard reliability and reduce errors (Farjoun, 2010). Quality and process improvements entail systematic refinements of a firm's existing knowledge, while R&D activities require searching for novel ideas. Process routines and quality techniques that prize stability and reliability are likely to drive out innovative activities that pursue experimentation and risk-taking. As the micro-foundations in managing R&D activities and pursuing quality and continuous process improvements appear to be very different, there is potentially a conflict when product innovations and process stability or efficiency are pursued simultaneously (Boumgarden et al., 2012). As a result, the adoption of structured and repetitive routines such as Six Sigma could impair the innovativeness of a firm, impeding R&D activities.

Yet another school of thoughts considers R&D investments not solely experimenting and technical inventing activities, but part of on-going economic and organizational activities for product innovation undertaken in a competitive market. R&D is seen as part of regular business functions carried out in complex organizational systems under severe time constrains and cost restrictions. A dualistic view of organizational design (Farjoun, 2010) suggests that the chances of R&D success are likely to be enhanced by a considerable amount of formalization and control such as those advocated by Six Sigma. In particular, organizational routines through process improvement serve as high-level premises that constitute enabling organizational structures, supporting effective new product development (Farjoun, 2010; Swift, 2016). Organizational routines simultaneously regulate and enable R&D activities, enhancing the financial returns from new product development (Benner and Tushman, 2003; Farjoun, 2010).

Teece (2007) argued that distinct processes, well-established operational procedures, and well-structured decision rules are essential requirements for firms to adapt to fast-changing technological cycles. In particular, R&D intensive firms are often exposed to opportunities and threats associated with rapid emergence and decline of new products and technologies. Scholars in technology management (e.g., Eisenhardt and Martin, 2000; Teece, 2007) suggest that technical change itself is systemic in that multiple inventions and methods are integrated, and various organizational routines and skills are combined to create new products. Accordingly, both process management and R&D are required in a high-tech environment, enhancing the dynamic capabilities of firms and leading to competitive advantages (Anand et al., 2009; Helfat and Peteraf, 2015).

Overall, various theoretical perspectives lead to different propositions on the relationships between organizational adaptation and technological innovation. Therefore, we develop alternative hypotheses on the relationships between operational initiatives and R&D investments.

2.2. Alternative Research Hypotheses

2.2.1. R&D and Six Sigma implementation

Six Sigma is defined as "an organized, parallel-meso method to reduce variation in organizational processes by using improvement specialists, a structured method, and performance metrics with the aim of achieving strategic objectives" (Schroeder et al., 2008, p. 540). In general, the principles of Six Sigma programs are developed under a set of systematic and repeatable operational processes. In adherence to the Six Sigma principles, the management attention of firms is oriented towards improvements in quality, reduction in errors, and attack on the variability of process outcomes, achieving speedy, cost-effective operations and efficiency outcomes. However, since the core tenant of Six Sigma is on reducing variation in organizational processes and routines, it is likely to be contradictory to R&D efforts for introducing novel, deviating new products.

Instead of focusing on enhancing exiting designs, successful new products emerge when there is variation, and when new design deviates significantly and is untried totally from previous ones. Product innovativeness is of critical concern in new product developments because lack of innovation is considered as a common cause for new product failure (Sethi and Sethi, 2009). Innovativeness requires more divergent thinking that increases variance, relying on diversifying search rather than closed examinations. Strong emphasis on quality and reliance on statistical and fact-based decision-making may affect the types of new products that are selected and supported (Canato et al., 2013). Applying the Six Sigma principles in new product planning and selection, novel inventions and radically new designs that deviate from firms' current product lines are likely to be screened out, particularly when the quality and reliability of such deviating products are difficult to ascertain (Sethi and Sethi, 2009). In addition, as a key principle of Six Sigma, customer orientation could lead organizations to focus on improvements of existing customer requirements rather than radical solutions to future problems, weakening the innovativeness of R&D activities (Atuahene-Gima, 1996). Such a conflict leads to a negative perspective on the impact of Six Sigma on the financial returns of R&D:

H1a. Six Sigma implementation hampers the financial returns of firms' R&D investments.

Yet, another school of thoughts suggests that like other organizational functions operating in the competitive marketplace, R&D and new product developments require well-organized processes and well-structured routines such as those advocated by Six Sigma. Six Sigma is a structured and systematic method to identify and eliminate the root causes of problems, reducing the defect rate while pursuing continuous process improvement (Choo et al., 2007; Kovach and Fredendall, 2013; Linderman et al., 2003; Zu et al., 2008). By implementing Six Sigma, new product development and innovation deployment are systematically supported (Anand et al., 2010; Parast, 2011). Also, firms adopting Six Sigma normally embrace a parallel-meso organizational structure, involving quality and technology specialists at multi-functional levels (Schroeder et al., 2008; Sinha and Van de Ven, 2005). With Six Sigma programs, firms improve their new product development processes continuously through using quality management tools and techniques (Kovach and Fredendall, 2013; Scholtes et al., 2003; Schroeder et al., 2008). Previous research has shown that knowledge creation through Six Sigma implementation enables fast response to process uncertainty and reduces risk in product launch (Arumugam et al., 2013; Shah and Ward, 2003; Zu et al., 2008).

The five phases of the Six Sigma structured method are used to define, measure, analyze, improve, and control (DMAIC) variations in operations (Hammer, 2002; Linderman et al., 2006; Patyal and Koilakuntla, 2015; Schroeder et al., 2008). Through the DMAIC process, firms' innovative endeavors are likely to be embedded and carried out within a systems framework (Swink and Jacobs, 2012). With accumulated experience through Six Sigma, firms would develop a stronger problem-solving capability (Kale and Singh, 2007), making the product development process more stable (Kumar, 2012; Sitkin and Stickel, 1996) and enhancing financial returns. Hence, we develop an alternative hypothesis:

H1b. Six Sigma implementation enhances the financial returns of firms' R&D investments.

2.2.2. R&D and efficiency improvements

Operational efficiency refers to a firm's relative efficiency (versus its industry peers) in converting resources into operating outcomes (Kim et al., 2011; Miller and Roth, 1994; Roth and Jackson III, 1995). Operational efficiency is related to distinct sets of firm-specific skills, processes, and routines for improving organizational effectiveness (Peng et al., 2008; Wu et al., 2010). A different theoretical perspective suggests that the financial returns from R&D investments are hindered by firms' efforts in pursuing operational efficiency. Viewing from a knowledge management perspective, firms pursuing efficiency improvements tend to develop and refine their existing organizational knowledge that could lead to immediate benefits, rather than carrying out remote, boundary-spanning search into an uncharted area that is unlikely to benefit the firms immediately (Gupta et al., 2006; Andriopoulos and Lewis, 2009). Firms focusing on process and efficiency incline to collect, apply, and refine their current capabilities, while firms aggressively pursuing R&D need to explore unrelated technological domains and develop discrete skill sets (Stettner and Lavie, 2014). Process improvements lead to immediate, measurable benefits, which in turn reinforce firms' attention towards short-term efficiency targets (Gupta et al., 2006). As a result, firms with a focus on efficiency improvements are likely to lose sight on radical innovation (Benner and Tushman, 2002; Stettner and Lavie, 2014), leaving them vulnerable in the fast-changing technology market.

Benner and Tushman (2003) pointed out that organizational structures and communication channels are also very different between R&D-intensive firms and efficiency-focused organizations. Specifically, firms pursuing efficiency improvements need to strictly stabilize organizational routines and tighten links among organizational boundaries, making cross-functional, cross-community communications for innovations more difficult. In an organization with closely-connected systems and streamlined processes, each activity is carried out in a strictly prescribed manner, and each functional area is measured for its immediate contribution, impeding creativity and radical inventions. Overall, the philosophies behind efficiency improvements and R&D activities in a firm are very different. While the former fosters commitment, narrowness, and cohesiveness, the latter entails thoughtfulness, breath, and openness (March, 1991; Gupta et al., 2006). These fundamentally incompatible philosophies of process management and innovation render efficiency improvements harmful to R&D activities:

H2a.High operational efficiency hampers the financial returns of firms' R&D investments.

However, the literature also highlights the importance of integrating R&D activities into the organizational context in terms of organizational routines, management structures, and process systems (Prajogo and Sohal, 2006; Teece, 2007; Helfat and Peteraf, 2015). Rather than viewing R&D activities in isolation, OM scholars consider both process improvement and innovation as a bundle of closely matched routines and capabilities (Terziovski and Guerrero, 2014; Kortmann et al., 2014). Organizational routines help guide, promote, and systematize the process of new product development, and allow R&D activities to be reliably executed over time (Farjoun, 2010). Process improvement may help institutionalize R&D and product development activities, guarding against excessive experimentation and enabling early detection of problems (Farjoun, 2010; Koryak et al., 2018). Even though individual elements of creativity in R&D activities are difficult to be systematically and efficiently organized, firms might still benefit from the use of some structured enabling systems in new product development. Technology advancements take place in continuous interaction with organizational structures, information systems, and communication channels. The success of a new technology product requires strong operational capability and a culture of continuous process improvement. Accordingly, innovation and efficiency are likely to be highly related at the organizational level, reinforcing each other (Smith et al., 2017).

Zollo and Winter (2002) argued that firms with efficient, reliable processes and procedures are more likely to obtain a stable condition for ideas search and discovery, supporting R&D activities. Organizational routines provide a framework guiding sense-making and putting ideas into practice (Farjoun, 2010). High-efficient firms consistently improve their organizational routines to stay current, making their processes more compatible with ongoing innovations (Eisenhardt and Martin, 2000; Helfat and Peteraf, 2015). Through pursuing both efficiency improvements and R&D, organizations develop, integrate, and configure internal and external resources, enabling organizational changes and enhancing their adaptation in rapid-evolving technology markets (Kortmann et al., 2014; Su et al., 2014). As pointed out by Teece (2007), technology innovation is not merely inventing new products, but revamping business processes and building entirely new markets that entail operational capability. By focusing on both R&D investments and efficiency improvements, firms develop a dynamic capability in an R&D-intensive environment, leading to stronger competitive advantage (Kortmann et al., 2014; Su et al., 2014). Thus, we hypothesize:

H2b. High operational efficiency enhances the financial returns of firms' R&D investments.

3. Methods

3.1. Sample and Data Collection

In this study we focus on firms in the manufacturing sector listed in the U.S. with SIC codes in the range 2000-3999. We obtain firms' accounting and financial information from Standard and Poor's COMPUSTAT and corporate 10-K reports over the period 2007-2014. By the end of 2014, there were a total of 2,393 publicly-listed manufacturing companies. The sample used in our research is reduced due to missing data of some manufacturing firms for measuring research variables such as financial returns, R&D investments, and operational efficiency. For example, many small firms do not report R&D investments in their annual reports as it is not required by the U.S. Securities and Exchange Commission. We also remove firms with negative R&D investments or unreasonably high R&D investments to reduce the influence of outliers. Moreover, we exclude industries (four-digit SIC codes) with fewer than ten firms as it is not meaningful and practical to measure some industry-adjusted variables such as operational efficiency based on small industry size, as discussed below. As a result, we have 468 manufacturing firms with sufficient data for all the measures in the final sample. These 468 firms represent 19 industries based on two-digit SIC codes. Table 1 shows the top 13 industries of our sample, which includes a wide variety of manufacturing sectors. The top four sectors are (a) electronic and other electric equipment, (b) instruments and related products, (c) chemicals and allied products, and (d) industrial machinery and equipment, representing 77% of the total sample of 468.

[Insert Table 1 about here]

Similar to prior studies on Six Sigma (e.g., Shafer and Moeller, 2012; Swink and Jacobs, 2012), we search for Six Sigma adoption announcements using keywords such as the names of our sample firms and "Six Sigma" in conjunction with "adopt", "implement", "introduce", or "deploy" through publicly available documents, including all the publication sources in Factiva, 10-K reports, and the corporate websites of these firms. We search for all the possible news related to Six Sigma for the 468 firms and obtain a sample of 181 firms (39%) that have adopted Six Sigma. Based on the above publication sources, we further determine the first years of their Six Sigma adoptions. If a firm announces its first Six Sigma adoption in a certain year, we consider the firm as a Six Sigma adopting firm in that year and the subsequent years. Table 2 provides a few examples of the Six Sigma announcements. Table 3 shows the years of first Six Sigma adoption for the 181 firms and the highest frequency is between 1999 and 2006. Table 4 shows the sector related to chemicals and allied products with the most Six Sigma adopting firms.

[Insert Table 2, Table 3, and Table 4 about here]

We further classify the 181 Six Sigma adopting firms into two different types, attempting to quantify the potentially different levels of implementation efforts. In particular, we view firms as *advanced* Six Sigma adopters if they obtain independent, external awards for their Six Sigma implementation or their Six Sigma implementation is advocated internally by the top management team. This is because independent, external Six Sigma awards are often viewed as an indicator of a high level of comprehensive and successful Six Sigma implementation (Goh et al., 2003; Hendricks and Singhal, 1997). Prior research has also regarded winning quality awards as a recognition of firms' comprehensive and effective implementation of quality management programs (Hendricks and Singhal, 1997; Yang and Hsieh, 2009). Similarly, the strategic initiation and positioning of Six Sigma by top management is an important indicator of a high-level, organization-wide quality management initiative (Schroeder et al., 2008; Yeung et al., 2005). For example, Six Sigma was widely and strategically adopted in GE following the advocacy of the CEO Jack Welch in early years. We search archival data from firms' annual reports and letters to shareholders, company news from Factiva and other Six Sigma related sources to identify whether a firm's Six Sigma implementation wins any external Six Sigma awards or advocated by its top management such as CEO and Chairman. We are able to identify 118 such firms among the 181 Six Sigma adopting firms. For the remaining 63 firms without any external Six Sigma awards or top management's advocacy, we view them as *general* Six Sigma adopters. As a result, our 468 sample firms consist of 118 or 25% *advanced* Six Sigma adopters (Level 2), 63 or 13% *general* Six Sigma adopters (Level 1), and 287 or 61% non-Six Sigma adopters (Level 0).

3.2. Measurements

Financial Returns. Consistent with prior studies (e.g., Jacobs et al., 2016; Krasnikov et al., 2009; Miller et al., 2015), we measure a firm's financial returns based on its Tobin's q, a ratio of the firm's market value to the replacement cost of its assets. As Tobin's q reflects the market's evaluation of a firm's prospects when taking all the available information into account (Miller et al., 2015), it is a forward-looking, market-based measure of a firm's financial returns. This measure well suits our research context as R&D investments are expected to affect firms' future returns. In this research we adopt the widely-used approach proposed by Chung and Pruitt (1994) to measure Tobin's q. Mathematically, the Tobin's q of firm i in year t is computed as

$$Tobin's\ q_{it} = (Common\ Shares\ Outstanding_{it} \times Share\ Price_{it} + Liquidation\ Value\ of\ Preferred\ Stock_{it} + Long\text{–}term\ Debt_{it} + Current\ Liabilities_{it} - Current\ Assets_{it})\ /\ Total\ Assets_{it}\ . \qquad (1)$$

As Tobin's q varies significantly across industries, we measure a firm's financial returns as its industry-adjusted Tobin's q, which is the firm's Tobin's q minus the median Tobin's q in the firm's industry (four-digit SIC code), to account for industry heterogeneity (Bebchuk and Cohen, 2005). The use of industry-adjusted Tobin's q can also help reduce the potential bias due to market-wide systematic movements arising from unexpected events. This is especially the case for our research context in which the great recession occurred within our sample time period from 2007 to 2014.

R&D Investments. We measure a firm's R&D investments as its R&D intensity, i.e., the ratio of R&D expenses to sales (Ehie and Olibe, 2010; Jacobs et al., 2016; Xia et al., 2016). To ensure the validity of our test results, we remove R&D investments with unreasonable values. In particular, we remove R&D investments with negative values, which are mainly due to the negative sales as recorded in firms' balance sheets. On the other hand, as it is unusual for firms to spend more on R&D than they are receiving in revenues, we remove firms whose R&D expenses are higher than their sales, i.e., R&D investments > 100%. This practice is also consistent with the maximum cut-off of R&D investments documented in prior studies (e.g., Anwar and Sun, 2013; Nunes et al., 2012). Nevertheless, as a robustness check, we also apply 25% as an alternative maximum cut-off point for R&D investments and obtain consistent results.

Six Sigma Implementation. We use Six Sigma implementation to represent the quality management programs of firms. Six Sigma initiatives aim to initiate a persistent effort to improve organizational processes (Linderman et al., 2004), fostering improvement through identifying the root causes of variations and eliminating defects in the process (Choo et al., 2007; Kovach and Fredendall, 2013; Schroeder et al., 2008). As discussed above, we assign a score of 0 to 2 to non-adopting firms, *general* adopting firms, and *advanced* adopting firms, respectively. It should be noted that we code the *general* and *advanced* adopting firms as 0 for all the years before their Six Sigma adoptions, enabling a dynamic measure of their Six Sigma implementation across time.

Operational Efficiency. Operational efficiency is the relative efficiency of a firm in its ability to convert organizational resources into business outcomes in comparison with its industry peers (Peng et al., 2008; Alan and Lapré, 2018; Chuang et al., 2019). We use the stochastic frontier estimation (SFE) methodology to measure a firm's operational efficiency in transforming its resources such as the number of employees (EMP), capital expenditure (CEX), and inventory (INV) into its operating income (OI), and measure the efficiency of each firm relative to its competitors in the same industry (Dutta et al., 2005; Li et al., 2010). The SFE is a sound approach to measure a firm's operational efficiency in its transformative framework of converting various operational inputs into operational outputs. Also, it incorporates a composite error term composed of random effects and pure inefficiency (Coelli et al., 2005). It can isolate any influences from random factors other than inefficient behavior to prevent possible upward bias of inefficiency associated with deterministic methods (Vandaie and Zaheer, 2014). Specifically, we model a firm's operational output (OI) as a function of its inputs (EMP, CEX, and INV) as follows:

$$ln(OI_{ijt}) = \beta_0 + \beta_1 ln(EMP_{ijt}) + \beta_2 ln(CEX_{ijt}) + \beta_3 ln(INV_{ijt}) + \varepsilon_{ijt} - \gamma_{ijt}, \quad (2)$$

where ε_{ijt} is the purely stochastic random error term affecting operating income and γ_{ijt} captures the operational inefficiency of a firm *i* in industry *j* (four-digit SIC code) in year *t*. γ_{ijt} ranges from 0 to 1, with 0 meaning no operational inefficiency (relative to the industry). Thus, γ_{ijt} is a relative measure to indicate how inefficient a firm is in comparison with the corresponding frontier in the same industry and in the same year. The composite error term ($\varepsilon_{ijt} - \gamma_{ijt}$) is estimated based on the difference between the maximum achieved operating income (in an industry) and the observed operating income so as to obtain a consistent estimate of firm-specific operational inefficiency $\hat{\gamma}_{ijt}$. As we classify industries based on four-digit SIC codes, some industries based on this classification only include a few firms. To reduce the bias due to small sample size, we focus our estimation of $\hat{\gamma}_{ijt}$ on those industries with ten or more firms. Finally, the operational efficiency of firm *i* in industry *j* in year *t* is

$$Operational\ Efficiency_{ijt} = 1 - \hat{\gamma}_{ijt}. \quad (3)$$

Control Variables. We consider several pertinent control variables, including firm size, firm age, firm leverage, marketing expense, tangible assets, industry Tobin's *q*, and industry size in this research. We measure firm size as the natural logarithm of total assets (Modi and Mishra, 2011). Prior research (e.g., Bharadwaj et al., 1999; Modi and Mishra, 2011) has suggested that firm size is negatively associated with Tobin's *q*. We take firm age as the natural logarithm of the number of years from the date of incorporation (Zhang, 2015). Older firms are usually viewed as having greater structural inertia in organizations and being more resistant to changes, thus might be more difficult to improve financial returns (Hoisl et al., 2017). We measure firm leverage as the ratio of total debt to total assets (Zhang, 2015). Firms with a higher leverage might be more capable of capitalizing on external financial resources to enhance their returns (Bae et al., 2017). We measure marketing expense as the difference between selling, general and administration (SG&A) expense and R&D expense divided by total assets (Raithel et al., 2012). Prior Marketing research (e.g., Kurt and Hulland, 2013; Oh et al., 2016) has shown that firms' spending on marketing is positively related to their financial returns. We measure tangible assets as property, plant and equipment divided by total assets (O'brien, 2003). A firm with a higher level of tangible assets might be in a better position to leverage its resources for financial returns (Baker and Wurgler, 2002). We control for industry Tobin's *q*, measured as median Tobin's *q* based on four-digit SIC codes, as there might be a positive correlation between firm-level Tobin's *q* and industry-level Tobin's *q* (Bardhan et al., 2013). We also include industry size, measured as the natural logarithm of all firms' total assets in the same industry based on four-digit SIC codes (Lo et al., 2013), because a larger industry might provide a more stable operating environment (Brunnermeier and Cohen, 2003). Finally, we include year dummies to account for the influences of time-specific economic events that firms cannot control such as the great recession and industry dummies (two-digit SIC codes) to control for industry-specific effects.

3.3. Estimation Strategy

Firm performance such as financial returns could be persistent over time such that past firm performance is highly correlated with current firm performance. Prior research has also emphasized the importance of controlling for past firm performance, especially when the current firm performance is used as the dependent variable (Suarez et al., 2013; Vandaie and Zaheer, 2014). This can ensure a more robust estimation of the effects of other firm-level variables such as firms' strategies and practices on the current firm performance. As our research views firms' current financial returns as the dependent variable and considers the effects of several firm-level variables such as R&D investments and Six Sigma implementation on the current financial returns, we follow prior research to control for past financial returns in our analysis. As a result, we construct a dynamic panel data (DPD) model as shown in equation (4) to investigate the roles that Six Sigma implementation (H1) and operational efficiency (H2) play in moderating the R&D investments-financial returns relationship.

$$
\begin{aligned}
& Financial\ Returns_{it} \\
& = \alpha_0 + \alpha_1 Financial\ Returns_{i(t-1)} + \alpha_2 Firm\ Size_{it} + \alpha_3 Firm\ Age_{it} + \alpha_4 Firm\ Leverage_{it} \\
& + \alpha_5 Marketing\ Expense_{it} + \alpha_6 Tangible\ Assets_{it} + \alpha_7 Industry\ Tobin's\ q_{it} \\
& + \alpha_8 Industry\ Size_{it} + \alpha_9 Six\ Sigma\ Implementation_{it} + \alpha_{10} Operational\ Efficiency_{it} \\
& + \alpha_{11} R\&D\ Investments_{it} + \alpha_{12} R\&D\ Investments_{it} \times Six\ Sigma\ Implementation_{it} \\
& + \alpha_{13} R\&D\ Investments_{it} \times Operational\ Efficiency_{it} + \varepsilon_{it}\ , \qquad (4)
\end{aligned}
$$

where *i* and *t* are firm and year indices, respectively, and ε_{it} is the error term consisting of two components, namely firm-specific fixed effects and idiosyncratic disturbances. We rely on α_{12} to determine how Six Sigma implementation (H1) moderates the R&D investments-financial returns relationship, while the moderating role of operational efficiency (H2) is indicated by α_{13}. To reduce the multicollinearity concern, we center R&D investments, Six Sigma implementation, and operational efficiency when computing the interactions among them (Balli and Sørensen, 2013; Coombs and Gilley, 2005). In line with prior DPD research (e.g., Suarez et al., 2013; Vandaie and Zaheer, 2014), we include the one-year lag of financial returns, i.e., $Financial\ Returns_{i(t-1)}$, as a regressor in our DPD model. We also control for an additional lag of financial returns, i.e., $Financial\ Returns_{i(t-2)}$, in our robustness tests and obtain similar results as shown in Section 5.

Although this DPD model helps control for the influence of firms' past financial returns, it gives rise to the "dynamic panel bias" or Nickell bias (Nickell, 1981) as the lagged financial returns are correlated with the fixed effects in the error term by construction. This correlation makes the conventional ordinary least squares (OLS) estimation inconsistent (Roodman, 2009). Although a more advanced least squares dummy variables (LSDV) estimator can address this bias (Kiviet, 1995), it does not deal with the other endogeneity concerns such as unobservable heterogeneity and simultaneity arising from the other regressors included in our research (Roodman, 2009). For example, considering R&D investments, it is possible that some unobservable firm-specific characteristics such as managerial ability may affect firms' decisions to invest in R&D and also their ability to improve financial returns, making the relationship between R&D investments and financial returns biased. Moreover, although we expect R&D investments to affect financial returns, it is also possible that firms' financial returns will influence their decisions to invest in R&D, leading to two-way causality. If this possible reverse causation is not addressed, the impact of R&D investments on financial returns could be overestimated. These arguments about the unobservable heterogeneity and simultaneity concerns also apply to the other regressors such as Six Sigma implementation and operational efficiency that are included in our research. Although the endogeneity concerns can be addressed by employing conventional instrumental variables (IV) techniques that use external variables as instruments, prior research has demonstrated the difficulty of obtaining such strictly exogenous instruments externally (Roodman, 2009; Wintoki et al., 2012). This difficulty is particularly evident in our research in view of the large number of endogenous variables included in our research and the limited availability of appropriate external datasets that cover our sample firms. As a result, we adopt the more advanced system Generalized Method of Moments (GMM) estimation technique that relies on transformations of existing variables rather than the use of external variables to address the endogeneity concerns (Arellano and Bover, 1995; Blundell and Bond, 1998).

The system GMM estimator is suitable for our research context for several reasons. First, this estimator is applicable to "small *T*, large *N*" panels (Roodman, 2009), which fits our research focused on a small number of years (2007-2014) and a large number of firms (468 firms). Second, as the system GMM estimator is one of "the most robust methodologies for unbalanced panels with endogenous variables" (Flannery and Hankins, 2013, p. 13), it is appropriate for our research with some firms having more observations than the others and in which a number of endogenous variables are presented. Third, the system GMM estimator enables us to address the Nickell bias by transforming the error term to remove the fixed effects (in difference equation) and by instrumenting the lagged financial returns with variables orthogonal to the fixed effects in the error term (in level equation). Finally, the system GMM estimator relies on the transformation of existing variables rather than the use of external variables to construct instruments (Roodman, 2009; Wintoki et al., 2012). This is an important advantage for our research due to the difficulty to obtain appropriate exogenous instruments externally.

We now provide a detailed explanation of how the system GMM estimator is implemented in our research. First, we transform the DPD model in the level equation (4) into its first difference form in the difference equation (5), as follows:

$$\begin{aligned}
&\triangle\, Financial\ Returns_{it} \\
&= \alpha_1 \triangle Financial\ Returns_{i(t-1)} + \alpha_2 \triangle Firm\ Size_{it} + \alpha_3 \triangle Firm\ Age_{it} + \alpha_4 \triangle Firm\ Leverage_{it} \\
&+ \alpha_5 \triangle Marketing\ Expense_{it} + \alpha_6 \triangle Tangible\ Assets_{it} + \alpha_7 \triangle Industry\ Tobin's\ q_{it} \\
&+ \alpha_8 \triangle Industry\ Size_{it} + \alpha_9 \triangle Six\ Sigma\ Implementation_{it} + \alpha_{10} \triangle Operational\ Efficiency_{it} \\
&+ \alpha_{11} \triangle R\&D\ Investments_{it} + \alpha_{12} \triangle R\&D\ Investments_{it} \times Six\ Sigma\ Implementation_{it} \\
&+ \alpha_{13} \triangle R\&D\ Investments_{it} \times Operational\ Efficiency_{it} + \triangle\, \varepsilon_{it}\ , \qquad (5)
\end{aligned}$$

where $\triangle X_{it}$ represents $X_{it} - X_{i(t-1)}$ and $\triangle X_{i(t-1)}$ represents $X_{i(t-1)} - X_{i(t-2)}$ for each variable X included in equation (5). After the transformation, the constant term and the fixed effects in the error term are removed, so the concern of the Nickell bias is addressed. However, the lagged dependent variable could still be endogenous as the one-year lagged financial returns, i.e., $Financial\ Returns_{i(t-1)}$, in $\triangle Financial\ Returns_{i(t-1)}$ [1] is correlated with the one-year lagged idiosyncratic disturbances in $\triangle\, \varepsilon_{it}$ [2]. The same applies to the other endogenous regressors included in equation (5). Arellano and Bond (1991) proposed a difference GMM estimator that uses longer lags of the endogenous regressors as instruments for the differenced endogenous regressors included in the difference equation as the longer lags are correlated with the differenced endogenous regressors but orthogonal to $\triangle\, \varepsilon_{it}$. For example, the two-year lagged financial returns, i.e., $Financial\ Returns_{i(t-2)}$, is mathematically related to $\triangle Financial\ Returns_{i(t-1)}$ but not to $\triangle\, \varepsilon_{it}$ as long as the idiosyncratic disturbances in the error term are not serially correlated. However, if the idiosyncratic disturbances are

[1] $\triangle Financial\ Returns_{i(t-1)} = Financial\ Returns_{i(t-1)} - Financial\ Returns_{i(t-2)}$

[2] $\triangle\, \varepsilon_{it} = \varepsilon_{it} - \varepsilon_{i(t-1)}$ and the one-year lagged idiosyncratic disturbances are in $\varepsilon_{i(t-1)}$.

serially correlated, the two-year lagged financial returns are endogenous and thus an invalid instrument. In this case, the instrument set may have to start from the three-year lagged financial returns instead (Roodman, 2009).

We choose instruments for the difference equation (5) in the following ways. First, we adopt a conservative approach to view all the regressors included in equation (5) as endogenous variables. This approach is consistent with prior GMM research that regards firms' characteristics and strategies as endogenous variables (Bardhan et al., 2013; Fremeth and Shaver, 2014; Wintoki et al., 2012). Following Roodman's (2009) suggestion, for each endogenous variable, we use its second lag to its maximum available lag, i.e., (*t*-2, *t*-maximum), as instruments. As a robustness check, we also use (*t*-2, *t*-4) as alternative instruments and obtain consistent results as shown in Section 5. Moreover, we conduct the Arellano-Bond test of autocorrelation in Section 4 to check whether there are serial correlations in the idiosyncratic disturbances that will make the second lags, i.e., *t*-2, invalid as instruments.

A major concern about the difference GMM estimator is that the lags can be weak instruments for the difference equation if the dependent variable is close to a random walk (Blundell and Bond, 1998). To address this weak instruments concern, Arellano and Bover (1995), and Blundell and Bond (1998) proposed a new estimator, called system GMM estimator, to use lagged differences as instruments for the original level equation (e.g., equation (4)), in addition to the use of lagged levels as instruments for the transformed difference equation (e.g., equation (5)) as discussed above. This means that this estimator estimates a system of two equations (the level and difference equations; e.g., equations (4) and (5)) simultaneously, which helps address the weak instruments concern and improve the estimation efficiency (Roodman, 2009). As the error term in the level equation still includes the fixed effects, the system GMM estimator addresses the Nickell bias by differencing the instruments to make them uncorrelated with the fixed effects in the level equation (Wintoki et al., 2012). As our instruments for the difference equation (5) start from the second lags of the levels as discussed above, the first lags of the differences are used as our instruments for the level equation (4) (Roodman, 2009). We conduct the Hansen test of overidentifying restrictions in Section 4 to check whether the instruments used in our research are orthogonal to the error term.

4. Test Results

Table 5 reports the descriptive statistics and correlations of our research variables. The results show that the variable of firms' financial returns is highly correlated with its lagged value (r = 0.763, p <

0.01). Thus, controlling the lagged variable of firms' financial returns in our research is necessary. Table 6 presents the system GMM test results. Model 1 is the basic model including a list of independent variables, year dummies, and industry dummies. Models 2 and 3 add the moderating effects of Six Sigma implementation and operational efficiency, respectively. Finally, Model 4 is the full model in which the moderating effects of both Six Sigma implementation and operational efficiency are included simultaneously. All the four models are statistically significant ($p < 0.01$) based on the Wald chi-squared tests. The number of observations is 2,920 in the four models, suggesting that on average there are about six observations for each of the 468 sample firms (unbalanced panel). Such repeated measurements of the same firms over years enable us to cluster the standard errors by firms to obtain more robust results. Therefore, we report the robust standard errors clustered by firms in Table 6.

[Insert Table 5 and Table 6 about here]

We conduct two specification tests to verify the validity of the instruments used in our system GMM estimation. The first test is the Hansen test of overidentifying restrictions, which is used to check whether the instruments used in our research are correlated with the error term. Valid instruments, by definition, should be correlated with the endogenous variables but orthogonal to the error term (Alessandri and Seth, 2014). The Hansen test results shown in Table 6 are not significant ($p > 0.1$) across the four models, failing to reject the null hypothesis that the instruments are orthogonal to the error term. These statistics confirm a crucial assumption for valid system GMM estimation, i.e., the instruments are exogenous (Roodman, 2009).

The second test is the Arellano-Bond test of autocorrelation, which is used to assess whether some instruments (e.g., the second lags) are rendered invalid due to autocorrelation in the idiosyncratic disturbances (Alessandri and Seth, 2014). As we apply this test to the residuals in differences, first-order autocorrelation (AR1) should be significant by construction (Roodman, 2009). Therefore, we need to use the second-order correlation in differences (AR2) to check for the first-order serial correlation in levels (Lam et al., 2016). The Arellano-Bond test results shown in Table 6 suggest that although the AR1 statistics are significant ($p < 0.01$) across the four models (as they should be), the AR2 statistics are not significant ($p > 0.1$). We thus cannot find serial correlation in the idiosyncratic disturbances. This suggests that the second lags of levels are valid instruments for the difference equation and we need not force our instruments to start from the third lags, i.e., t-3. Taken together, these two specification tests demonstrate the validity of the instruments used in our system GMM estimation.

The system GMM test results documented in Table 6 show that lagged financial returns, firm size, marketing expense, operational efficiency, and R&D investments are significant ($p < 0.1$) across the four models. In particular, the coefficients of lagged financial returns are positive in the four models, suggesting that previous year's financial returns have a positive impact on current year's financial returns. It thus confirms the persistence of firm performance over time as suggested in the literature (Baños-Caballero et al., 2014; Lam et al., 2016; Vandaie and Zaheer, 2014). The coefficients of marketing expense, operational efficiency, and R&D investments are also positive across the four models, indicating that firms' investments in marketing, operations, and R&D can help improve financial returns. On the other hand, the coefficients of firm size are negative in the four models, showing that smaller firms have the advantage of improving financial returns. These results are generally consistent with prior studies' findings (e.g., Bardhan et al., 2013; Bharadwaj et al., 1999; Kurt and Hulland, 2013; Modi and Mishra, 2011; Oh et al., 2016).

Although Six Sigma implementation does not have a direct significant impact on financial returns ($p > 0.1$) as shown in Models 1 to 4, Models 2 and 4 indicate that its interaction with R&D investments is positive and significant ($p < 0.05$). Six Sigma implementation thus enhances the financial returns of firms' R&D investments, supporting H1b but rejecting H1a. Finally, Models 3 and 4 also show a positive and significant ($p < 0.05$) interaction between R&D investments and operational efficiency, showing the positive moderating role of operational efficiency in the R&D investments-financial returns relationship. Therefore, H2a is rejected but H2b is supported.

4.1 Additional Tests

The test results as shown in Table 6 support H1b and H2b but reject H1a and H2a, confirming a complementary rather than contradictory view on the moderating roles of Six Sigma implementation and operational efficiency improvement. These findings motivate us to further explore the conditions under which such complementary or contradictory effects are more likely to occur. In particular, we examine whether the moderating roles of Six Sigma implementation and operational efficiency improvement might vary across different operating environments that exhibit different levels of operational complexity. This investigation direction is in line with the dynamic capability view which suggests that a firm's competitive advantage arising from its dynamic capability might depend on the dynamism and complexity of its operating environment (Schilke et al., 2018). Consistent with prior OM research (e.g., Hendricks et al., 2009; Lam, 2018; Lo et al., 2014; Swink and Jacobs, 2012), we approximate operational complexity in terms of labor intensity and geographical diversity. This is because it should be more complex and challenging for firms to manage a large number of employees in operations and to deal with geographically dispersed customers across different countries.

In order to investigate the roles of Six Sigma implementation and operational efficiency under different levels of operational complexity, we split our sample firms into different sub-samples based on their labor intensity and geographical diversity. Specifically, for each manufacturing firm, we first measure its labor intensity as number of employees divided by sales and geographical diversity as the distribution of sales across different countries (Hendricks et al., 2009; Lam, 2018; Lo et al., 2014; Swink and Jacobs, 2012). We then put firms in the high labor intensity sub-sample if their labor intensity is higher than the industry median based on four-digit SIC codes, and the low labor intensity sub-sample otherwise. Similarly, we put firms in the high geographical diversity sub-sample if their geographical diversity is higher than the industry median based on four-digit SIC codes, and the low geographical diversity sub-sample otherwise. Finally, we perform system GMM estimation for each of these four sub-samples and document the test results in Table 7.

[Insert Table 7 about here]

As shown in Table 7, Six Sigma implementation positively moderates the R&D investments-financial returns relationship ($p < 0.1$) for firms with high labor intensity and high geographical diversity, but we cannot find a significant interaction between Six Sigma implementation and R&D investments ($p > 0.1$) for firms with low labor intensity and low geographical diversity. Similarly, our test results show that the interaction between R&D investments and operational efficiency is more significant for firms with high rather than low labor intensity and geographical diversity. Taken together, these findings suggest that the complementary effects are more (less) likely to occur under more (less) complex operating environments as approximated by labor intensity and geographical diversity.

Our sub-sample analysis also suggests that Six Sigma implementation is positively and significantly related to financial returns ($p < 0.1$) for firms with high labor intensity and high geographical diversity, but there is no significant relationship between Six Sigma implementation and financial returns ($p > 0.1$) for firms with low labor intensity and low geographical diversity[3]. These

[3] We also check the number of Six Sigma adopting firms in each sub-sample. In particular, we find that among the 181 Six Sigma adopting firms, 100 of them (or 55%) are in the low labor intensity sub-sample, while 107 (or 59%) are in the low geographical diversity sub-sample. Therefore, there is no evidence that the non-significant effects for firms with low labor intensity and low geographical diversity are driven by a limited number of Six Sigma adopting firms in these sub-samples.

findings are consistent with those in prior research (e.g., Swink and Jacobs, 2012) and demonstrate the important role that Six Sigma implementation plays in more complex operating environments.

5. Robustness Tests

We also conduct various tests to check the robustness of our findings based on alternative measurement approaches and different estimation strategies. Table 8 reports the robustness test results and we discuss the detailed testing procedures below. Overall, the robustness tests provide further support for the conclusion drawn in our research and help rule out some alternative explanations of our research findings.

[Insert Table 8 about here]

First, we adopt an alternative measure of operational efficiency based on inventory turnover. Specifically, we compute inventory turnover as cost of goods sold divided by inventory and then normalize inventory turnover based on four-digit SIC codes to account for the difference in inventory turnover across industries (Mishra et al., 2013; Sakakibara et al., 1997; Wu et al., 2019). We perform the system GMM estimation with this alternative measure of operational efficiency and the corresponding test results shown in Model 1 suggest that the moderating effects of Six Sigma implementation and operational efficiency remain positive and significant ($p < 0.05$).

As we classify firms' efforts to implement Six Sigma into two different categories, i.e., advanced implementation and general implementation, a valid concern is whether advanced implementation indeed has a stronger moderating effect and thus can be coded as a higher level. To address this concern, we create two dummy variables: one representing advanced implementation and the other indicating general implementation. We then include the interactions between these two variables and R&D investments in the DPD model. The test results shown in Model 2 suggest that advanced implementation has a more positive and significant moderating effect than general implementation, supporting our classification of Six Sigma implementation.

Moreover, we re-estimate the DPD model by replacing Six Sigma with ISO 9000, a popular quality management system widely adopted by manufacturing firms. We identify whether or not our sample firms adopt ISO 9000 via searches in Factiva. The keywords we use for the searches include the names of the sample firms and ISO 9000. We then code firms with and without ISO 9000 adoption as 1 and 0, respectively. The test results as shown in Model 3 indicate a significant positive interaction between ISO 9000 adoption and R&D investments ($p < 0.1$), demonstrating the robustness of our findings.

We also apply an alternative maximum cut-off point for R&D investments to remove firms with unusual high R&D intensities. Specifically, instead of applying the 100% cut-off point, we set the cut-off points to 25%. The test results based on this alternative cut-off point remain consistent, as shown in Model 4, suggesting that our research findings are robust to outliers with very high R&D investments. Moreover, we add the squared term of R&D investments to our DPD model to examine the possible non-linear relationship between R&D investments and financial returns. The test results shown in Model 5 suggest that although the squared term of R&D investments is negative (inverted U-shape), it is not statistically significant ($p > 0.1$). On the other hand, R&D investments remain positive and significant ($p < 0.01$) after adding the squared term, confirming the linear relationship between R&D investments and financial returns.

On the other hand, as prior R&D investments might affect current financial returns, we include additional time lags of R&D investments in the DPD model to control for the effects of prior R&D investments. The test results shown in Model 6 suggest that one-year lagged R&D investments have a positive impact on current financial returns, although the impact is significant at the 0.1 level only ($p = 0.098$). There is no significant relationship between two-year lagged R&D investments and current financial returns ($p > 0.1$). Moreover, the impact of current R&D investments remains positive and significant ($p < 0.05$) after controlling prior R&D investments. These findings suggest that although prior R&D investments have some positive effects on current financial returns, such effects are not as strong as that of current R&D investments. A possible reason for the stronger effect of current R&D investments is that our measure of financial returns is based on the forward-looking, market-based Tobin's *q*, which reflects the market's evaluation of a firm's prospects when taking all the available information into account (Miller et al., 2015).

As firm performance such as financial returns could be quite persistent over time, we control for an additional time lag of financial returns, i.e., t-2, in our DPD model when performing the system GMM estimation. The test results with this additional control variable remain consistent as shown in Model 7. Moreover, the coefficient of this control variable, although positive, is not statistically significant ($p > 0.1$), suggesting that it is sufficient to control for the one-year lag of financial returns in our research.

We also check the sensitivity of our findings to an alternative set of instruments used in the system GMM estimation. Specifically, instead of using all the available lagged values starting from t-

2, i.e., (t-2, t-maximum), as instruments for the difference equation, we choose a smaller set of instruments by limiting the maximum number of lags to t-4, i.e., (t-2, t-4). The test results based on this alternative set of instruments are shown in Model 8. The Hansen and AR2 test results are not significant ($p > 0.1$) in this model, confirming the validity of these alternative instruments used in our system GMM estimation. This model also shows consistent test results for all the research variables.

Finally, we perform a random effect estimation of the DPD model as shown in Model 9. The test results remain consistent, although the lagged financial returns' coefficient and the t-statistic are much higher than those in the system GMM estimation because the random effect estimation is less capable of addressing the dynamic panel bias (Roodman, 2009).

6. Discussions

R&D activities are often carried out in fierce market competition environments and the financial returns of R&D investments are highly uncertain. Previous research has examined how the success of R&D investments is associated with marketing capabilities (Arunachalam et al., 2018), human capital (Chen and Huang, 2009), and environmental turbulence (Wong, 2014), identifying several critical success factors for R&D activities. We approach this problem from a different perspective. We examine how the financial returns of R&D investments could possibly be enhanced from a process capability point of view. A large body of literature suggests that R&D activities are in conflict with process and efficiency improvements. Many believe that while process management enhances a firm's operational efficiency, it could create organizational inertia and innovation traps, restricting the effectiveness of R&D efforts (Benner and Tushman, 2002). As a result, firms focusing on both R&D and efficiency improvements may encounter inconsistency elements that diminish the firms' overall effectiveness (Boumgarden et al., 2012). Our analyses based on the interactive effects between quality and efficiency improvements and R&D investments on firms' Tobin's q, however, do not support this argument.

Our results show that the financial returns of R&D investments are significantly enhanced when firms adopt Six Sigma and improve operational efficiency. Firms might establish stronger process systems and routines to reduce the uncertainty and enhance the chance of success of R&D investments. Our empirical results suggest that quality management and operational initiatives are supportive to R&D investments. Although certain management skills for R&D activities (e.g., inducing variation and idea generation) are very different from those for continuous process improvement (e.g., variation reduction and standardization), operational capability and the success of R&D efforts can be highly related to the extent that continuous improvement can help install robust processes and enhance the financial returns of new product development.

The positive interaction results in our research indicate that quality and efficiency initiatives and R&D investments are supportive to each other, which are in line with a dynamic capability view (Eisenhardt and Martin, 2000; Teece, 2007) on the relationship between the two different constructs. A dynamic capability comprises two dimensions, namely ability to sense and shape product and market opportunities through various means such as R&D investments, and competence in seizing opportunities through "distinct skills, processes, procedures, organizational structures, decision rules and disciplines" (Teece, 2007, p. 1319). A dynamic capability is essential in adapting to changing market requirements and technological opportunities (Teece, 2007; Helfat and Peteraf, 2015). Quality and efficiency underpin an enterprise's capability in realizing the value of innovative ideas and reinforcing robust disciplines to deliver superior financial value from R&D investments.

In fact, the uncertainties associated with R&D activities are multi-layered, and many of these issues are highly related to OM. Lev et al. (2016) suggested that the financial returns of R&D investments hinge on firms' capability in managing product and process uncertainties. While product uncertainty refers to the technical feasibility of new products and their market acceptance, process uncertainty concerns the risks associated with the economic production and timely delivery of R&D and new products. Research suggests that one of the most critical issues associated with R&D-intensive firms is that firms need to restructure themselves and renew their organizational processes from time to time (Lev et al., 2016). Six Sigma adoption and efficient operations enhance firms' capability in dealing with product and process uncertainties as firms carry out R&D and develop new products (Aoki and Wilhelm, 2017). More importantly, process and operational capabilities are extremely critical as firms need to re-orientate their processes, and re-organize and renew themselves periodically (Floyd and Lane, 2000) so as to reduce the related uncertainties and enhance the returns of their R&D investments.

In the R&D-intensive industries, firms need to periodically develop the best practice, strengthen business processes, and reinvent and restructure operational systems through various quality and efficiency initiatives (Eisenhardt et al., 2010). A dynamic capability perspective on the relationship between efficiency and R&D also implies that not only R&D investments are supported by quality and efficiency improvements, but quality and efficiency initiatives are reinforced by R&D. This suggests that firms may not obtain full benefits from their disciplined organizational processes and decision rules if they do not renew themselves periodically through exploring new products and markets, i.e., R&D

investments. Taking the dynamic capability view on the positive interaction results documented in our study, it is possible that firms will become less inert in their quality and efficiency initiatives if they also invest heavily in R&D (Eisenhardt et al., 2010; Piao and Zajac, 2016).

Our results further show that the enhancement effect of quality and efficiency initiatives on R&D investment is more pronounced under high operational complexity as approximated by labor intensity and geographical diversity. Operational complexity refers to the variety and uncertainty coming from the customers, operations and supply chains and the amount of information necessary for organizing the processes. The result is consistent with previous findings that a competitive and complex operational environment provides a more fertile ground for quality and efficiency improvements (Lo et al., 2013; Swink and Jacobs, 2012). In a complex operating environment (e.g., labor-intensive operations with global markets), the support of R&D investments through quality and efficiency improvements becomes more essential, while in a less complicated operational environment (e.g., highly automated processes focusing on domestic markets) such a dual focus is less critical. When R&D and new product development activities are undertaken in a dynamic and multifaceted environment, firms need to strengthen their quality and efficiency initiatives to a greater extent.

A rapid-changing technology environment not only leads to volatility and dynamism in operations, but also makes the processes more complex and more difficult to manage. In this case, operations managers not only need to rigorously control their processes, but dramatically renew themselves from time to time, making the interaction between R&D and process management more important. Overall, operational complexity in terms of dynamism, variety and uncertainty may drive such a complementary effect. Our results show that the more complex the operations, the higher the synergy effect between R&D and process management.

7. Conclusions and Limitations

Previous research has examined a number of contextual factors for successful R&D activities. However, very little is known about the role of quality management programs and efficiency improvement initiatives in enhancing the financial returns of R&D investments. Based on operational and financial data from U.S. manufacturing firms, we construct a DPD model to capture the effects of R&D investments on the financial returns of firms. Performing system GMM estimation of the DPD model, we show that firms' financial returns from R&D investments are significantly enhanced when they adopt Six Sigma and improve operational efficiency. Our additional analyses show that such a complementary effect is more pronounced under higher operational complexity. Our research supports the dynamic capability view on the competitive advantage of firms and the dualistic perspective that operational initiatives and R&D investments are mutually enabling and supplement each other in an organization. R&D and process improvements are highly dependent and complementary under dynamic and complex operating environments, driving the financial returns of R&D investments.

There are some limitations in this research. Like most other studies using secondary data, the measurements of constructs are one of the biggest challenges of our study. The objective of our research is to examine whether the financial returns of R&D investments are enhanced or hindered as a result of Six Sigma implementation and operational efficiency improvement. While the amounts of R&D investments can be directly extracted from firms' accounting data, the measurements of Six Sigma implementation and operational efficiency are less straightforward. In this study we determine whether or not a firm has adopted Six Sigma and the level of its implementation based on publicly available information, instead of conducting a direct investigation into the firm. Similarly, we can only assess operational efficiency by using the stochastic frontier estimation of the relative efficiency of a firm in its industry. We realize that the relative efficiency of a firm is not affected by process management alone, but an array of complex organizational factors (e.g., effective human resources). The stochastic frontier estimation of the relative efficiency of a firm in its industry cannot be a perfect indicator of effective operational routines, although it is a commonly accepted indicator of operational efficiency at the macro-level.

We measure R&D investments based on firms' R&D expenses as documented in their annual reports. Although this measurement approach is consistent with prior literature on R&D at the firm level, it cannot differentiate whether such investments are for incremental R&D, radical R&D, or both. It would be interesting for future research to provide a more direct measure of firms' incremental and radical R&D investments, and examine how incremental and radical R&D activities might benefit differently from Six Sigma implementation and operational efficiency improvement.

Finally, when hypothesizing the moderating roles of Six Sigma implementation and operational efficiency improvement, we assume that the corresponding disciplines and systematic orientation can "spill over" to R&D activities, making them more effective in driving financial returns. Although we do find that Six Sigma implementation and operational efficiency improvement positively moderate the financial returns of R&D investments, it is still possible that some firms might pursue their quality and efficiency initiatives and R&D activities separately, or loosely couple them. It is thus worth further investigating the possible “spill over” effects of quality management and efficiency improvement in the R&D context.

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Table 1 Distribution of Sample Firms across Industries

Two-digit SIC Code	Industry	Frequency	Percentage
36	Electronic and other electric equipment	108	23.08
38	Instruments and related products	91	19.44
28	Chemicals and allied products	86	18.38
35	Industrial machinery and equipment	74	15.81
37	Transportation equipment	27	5.77
34	Fabricated metal products	18	3.85
26	Paper and allied products	12	2.56
30	Rubber and miscellaneous plastics products	9	1.92
20	Food and kindred products	7	1.50
33	Primary metal industries	7	1.50
25	Furniture and fixtures	6	1.28
32	Stone, clay, and glass products	6	1.28
39	Miscellaneous manufacturing industries	6	1.28
Others	Other industries	11	2.35
Total		468	100

Table 2 Examples of Announcements about Six Sigma Implementation

Announcement 1	
Company Name	Caterpillar Inc. (NYSE: CAT)
Announced on	1 April 2010
Text extracted from article	In 2001, Caterpillar launched its 6 Sigma program to drive change to achieve the company's long-term strategic goals (Caterpillar uses 6 Sigma to identify its Six Sigma initiatives). This 6 Sigma process was, and continues to be, extremely successful. Some of the results include first-year benefits that exceeded implementation cost and achievement of the revenue goal two years earlier than planned.
Announcement 2	
Company Name	Select Comfort (NASDAQ: SNBR)
Announced on	7 February 2007
Text extracted from article	Complementing our investment in new product innovation is the Company's introduction of "Six Sigma" process improvement programs. Dedicated leaders and experts are now learning these data-driven, statistical processes as part of a company-wide focus to enhance customer satisfaction by improving our quality and sustaining the highest levels of consistency.
Announcement 3	
Company Name	Wabash National Corporation (NYSE: WNC)
Announced on	11 February 2008
Text extracted from article	In 2007, we focused on productivity enhancements within manufacturing assembly and sub-assembly areas, improving material flow and inventory levels within our supply chain, and waste reduction in key support areas. We deployed a Six Sigma team to work on key waste reduction initiatives across the enterprise.

Table 3 Distribution of Six Sigma Sample Firms across First Adoption Years

Year	Frequency	Percentage
2014	1	0.55
2013	10	5.52
2012	4	2.21
2011	4	2.21
2010	8	4.42
2009	7	3.87
2008	9	4.97
2007	9	4.97
2006	14	7.73
2005	16	8.84
2004	17	9.39
2003	15	8.29
2002	9	4.97
2001	18	9.94
2000	12	6.63
1999	13	7.18
1998	8	4.42
1997	7	3.87
Total	181	100

Table 4 Distribution of Six Sigma Sample Firms across Industries

Two-digit SIC Code	Industry	Frequency	Percentage
28	Chemicals and allied products	40	22.10
35	Industrial machinery and equipment	31	17.13
38	Instruments and related products	29	16.02
36	Electronic and other electric equipment	24	13.26
37	Transportation equipment	15	8.29
26	Paper and allied products	11	6.08
34	Fabricated metal products	6	3.31
20	Food and kindred products	4	2.21
25	Furniture and fixtures	4	2.21
30	Rubber and miscellaneous plastics products	4	2.21
33	Primary metal industries	4	2.21
32	Stone, clay, and glass products	3	1.66
Others	Other industries	6	3.31
Total		181	100

Table 5 Correlations and Descriptive Statistics

Variables	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.
1. Financial Returns	1											
2. Lagged Financial Returns	0.763	1										
3. Firm Size	-0.034	-0.031	1									
4. Firm Age	-0.077	-0.088	0.361	1								
5. Firm Leverage	-0.017	-0.016	0.379	0.254	1							
6. Marketing Expense	0.080	0.071	-0.339	-0.104	-0.099	1						
7. Tangible Assets	-0.018	-0.033	0.090	0.151	0.208	-0.100	1					
8. Industry Tobin's *q*	0.006	-0.016	0.042	-0.051	0.023	0.147	-0.118	1				
9. Industry Size	0.073	0.075	0.183	-0.085	-0.053	-0.063	-0.056	0.200	1			
10. Six Sigma Implementation	-0.042	-0.065	0.401	0.290	0.163	-0.119	0.184	-0.021	-0.044	1		
11. Operational Efficiency	0.287	0.271	0.379	0.127	0.086	-0.163	-0.132	0.023	-0.046	0.131	1	
12. R&D Investments	0.171	0.157	-0.025	-0.341	-0.169	-0.105	-0.329	0.184	0.369	-0.214	-0.050	1
Mean	0.194	0.205	7.011	3.874	0.180	0.204	0.184	1.730	10.806	0.617	0.534	0.063
Standard deviation	0.906	0.943	2.045	0.741	0.172	0.183	0.124	0.719	1.675	0.850	0.172	0.070
Minimum	-3.989	-5.301	1.252	1.386	0.000	0.005	0.001	0.739	4.470	0.000	0.002	0.000
Maximum	10.343	9.504	12.491	5.361	1.635	2.617	0.695	12.497	15.108	2.000	0.890	0.549

Note: Correlations with absolute value higher than 0.049 are significant at 0.01 level.

Table 6 System GMM Test Results

Variables	Model 1	Model 2	Model 3	Model 4
Intercept	-0.470 (2.768)	0.062 (2.680)	-0.353 (2.584)	0.079 (2.515)
Lagged Financial Returns	0.386*** (0.065)	0.393*** (0.065)	0.391*** (0.065)	0.399*** (0.065)
Firm Size	-0.183* (0.099)	-0.192** (0.097)	-0.198* (0.104)	-0.195* (0.101)
Firm Age	0.045 (0.206)	0.011 (0.189)	0.096 (0.202)	0.038 (0.189)
Firm Leverage	-0.026 (0.490)	-0.154 (0.483)	0.030 (0.475)	-0.121 (0.463)
Marketing Expense	1.036** (0.432)	0.987** (0.428)	0.770* (0.425)	0.777* (0.423)
Tangible Assets	0.814 (1.274)	0.980 (1.272)	0.667 (1.207)	0.863 (1.186)
Industry Tobin's *q*	0.019 (0.151)	-0.021 (0.156)	0.014 (0.141)	-0.015 (0.147)
Industry Size	0.093 (0.136)	0.054 (0.119)	0.070 (0.124)	0.039 (0.109)
Six Sigma Implementation	-0.202 (0.166)	0.178 (0.244)	-0.179 (0.157)	0.160 (0.228)
Operational Efficiency	1.174*** (0.450)	1.213*** (0.441)	1.166*** (0.410)	1.203*** (0.405)
R&D Investments	4.337* (2.485)	6.149** (2.605)	4.930** (2.156)	6.479*** (2.284)
R&D Investments × Six Sigma Implementation		4.912** (2.696)		4.440** (2.544)
R&D Investments × Operational Efficiency			5.858** (3.396)	5.645** (3.373)
Year Dummies	Included	Included	Included	Included
Industry Dummies	Included	Included	Included	Included
Number of Observations	2920	2920	2920	2920
Wald Chi-squared	199.48***	220.12***	207.70***	227.49***
Hansen Test	p=0.17	p=0.17	p=0.19	p=0.31
AR1	p<0.01	p <0.01	p<0.01	p<0.01
AR2	p=0.23	p=0.25	p=0.24	p=0.25

Notes: *p<0.1, **p<0.05, and ***p<0.01 (one-tailed tests for hypothesized variables and two-tailed tests for control variables); Robust standard errors clustered by firms are in parentheses.

Table 7 Additional Test Results

Variables	Model 1 High labor intensity	Model 2 Low labor intensity	Model 3 High geographical diversity	Model 4 Low geographical diversity
Intercept	-0.979 (3.434)	-3.570 (2.940)	-5.730 (8.551)	1.492 (2.264)
Lagged Financial Returns	0.129** (0.062)	0.427*** (0.073)	0.298*** (0.085)	0.392*** (0.085)
Firm Size	-0.057 (0.063)	-0.034 (0.090)	-0.041 (0.084)	-0.032 (0.088)
Firm Age	-0.172 (0.387)	0.070 (0.232)	-0.465 (0.330)	-0.066 (0.266)
Firm Leverage	-0.669 (0.830)	-0.272 (0.520)	-0.640 (0.584)	-0.069 (0.689)
Marketing Expense	1.858* (1.067)	1.207*** (0.414)	0.966* (0.583)	0.386 (0.469)
Tangible Assets	0.318 (1.259)	1.072 (1.207)	1.395 (1.183)	-0.315 (1.532)
Industry Tobin's *q*	-0.197 (0.222)	0.110 (0.143)	0.181 (0.143)	-0.097 (0.188)
Industry Size	0.245 (0.153)	-0.018 (0.124)	-0.038 (0.159)	-0.154 (0.119)
Six Sigma Implementation	0.680* (0.383)	-0.137 (0.183)	0.434** (0.212)	-0.299 (0.204)
Operational Efficiency	1.512*** (0.472)	0.984** (0.403)	1.193*** (0.435)	1.046** (0.483)
R&D Investments	5.079* (3.000)	2.751* (1.495)	3.649** (1.456)	5.527** (2.591)
R&D Investments × Six Sigma Implementation	5.932* (4.605)	0.726 (2.493)	3.309** (1.773)	-2.608 (2.781)
R&D Investments × Operational Efficiency	10.576** (5.999)	4.719* (3.124)	5.763* (3.810)	-2.064 (3.251)
Year Dummies	Included	Included	Included	Included
Industry Dummies	Included	Included	Included	Included
Number of Observations	1124	1796	1302	1618
Wald Chi-squared	96.34***	298.38***	145.34***	215.33***
Hansen Test	p=0.68	p=0.56	p=0.98	p=0.97
AR1	p<0.01	p <0.01	p<0.01	p <0.01
AR2	p=0.55	p=0.28	p=0.48	p=0.49

Notes: *p<0.1, **p<0.05, and ***p<0.01 (one-tailed tests for hypothesized variables and two-tailed tests for control variables); Robust standard errors clustered by firms are in parentheses.

Table 8 Robustness Test Results

Variables	Model 1 Measure Operational Efficiency based on inventory turnover	Model 2 Compare different categories of Six Sigma implementation	Model 3 Replace Six Sigma Implementation with ISO 9000 Adoption
Intercept	-1.298 (2.937)	-0.585 (2.198)	-0.252 (3.190)
Lagged Financial Returns	0.419*** (0.059)	0.396*** (0.063)	0.388*** (0.063)
Firm Size	-0.050 (0.098)	-0.117 (0.113)	-0.116 (0.143)
Firm Age	-0.037 (0.252)	-0.036 (0.155)	-0.070 (0.170)
Firm Leverage	-0.469 (0.480)	0.018 (0.587)	0.137 (0.716)
Marketing Expense	1.208** (0.603)	0.546 (0.426)	1.241** (0.531)
Tangible Assets	-0.100 (1.077)	0.358 (0.867)	0.683 (0.927)
Industry Tobin's *q*	-0.004 (0.160)	0.003 (0.130)	0.031 (0.142)
Industry Size	0.129 (0.117)	-0.032 (0.113)	-0.070 (0.148)
Six Sigma Implementation	0.106 (0.223)		
Advanced Six Sigma Implementation		0.408 (0.440)	
General Six Sigma Implementation		0.236 (0.180)	
ISO 9000 Adoption			0.440 (0.339)
Operational Efficiency	1.191** (0.470)	1.151*** (0.359)	0.952** (0.369)
R&D Investments	4.673** (1.904)	5.501** (2.148)	5.997*** (2.117)
R&D Investments × Six Sigma Implementation	4.735** (2.482)		
R&D Investments × Advanced Six Sigma Implementation		8.010* (5.668)	
R&D Investments × General Six Sigma Implementation		2.814 (2.317)	
R&D Investments × ISO 9000 Adoption			4.947* (3.854)
R&D Investments × Operational Efficiency	9.800** (4.818)	5.243** (3.028)	6.702** (3.892)
Year Dummies	Included	Included	Included
Industry Dummies	Included	Included	Included
Number of Observations	2920	2920	2920
Wald Chi-squared	192.22***	242.58***	205.39***
Hansen Test	p=0.34	p=0.39	p=0.45
AR1	p<0.01	p<0.01	p <0.01
AR2	p=0.14	p=0.27	p=0.26

Table 8 Robustness Test Results (Continued)

Variables	Model 4 Include R&D Investments < 25%	Model 5 Include squared term of R&D Investments	Model 6 Include lagged R&D investments
Intercept	0.075 (2.155)	0.096 (2.526)	-0.953 (2.232)
Lagged Financial Returns	0.352*** (0.057)	0.399*** (0.065)	0.414*** (0.065)
Firm Size	-0.175** (0.082)	-0.195* (0.101)	-0.105 (0.094)
Firm Age	0.048 (0.166)	0.037 (0.190)	-0.008 (0.177)
Firm Leverage	-0.267 (0.422)	-0.118 (0.464)	-0.116 (0.433)
Marketing Expense	0.850** (0.375)	0.776* (0.423)	0.856** (0.407)
Tangible Assets	1.408 (0.928)	0.869 (1.189)	0.932 (1.054)
Industry Tobin's *q*	-0.025 (0.149)	-0.016 (0.145)	0.073 (0.130)
Industry Size	0.032 (0.097)	0.039 (0.109)	0.039 (0.096)
Six Sigma Implementation	0.079 (0.200)	0.159 (0.228)	0.108 (0.214)
Operational Efficiency	1.476*** (0.365)	1.201*** (0.404)	1.082*** (0.386)
R&D Investments	5.803*** (2.089)	6.498*** (2.296)	4.623** (2.347)
R&D Investments^2		-0.126 (1.218)	
One-year Lagged R&D Investments			2.169* (1.312)
Two-year Lagged R&D Investments			-0.485 (0.372)
R&D Investments × Six Sigma Implementation	3.266* (2.268)	4.420** (2.549)	3.761* (2.455)
R&D Investments × Operational Efficiency	5.946* (3.848)	5.601** (3.318)	5.352** (3.116)
Year Dummies	Included	Included	Included
Industry Dummies	Included	Included	Included
Number of Observations	2855	2920	2909
Wald Chi-squared	243.54***	228.38***	250.71***
Hansen Test	p=0.33	p=0.30	p=0.23
AR1	p <0.01	p <0.01	p <0.01
AR2	p=0.32	p=0.25	p=0.24

Table 8 Robustness Test Results (Continued)

Variables	Model 7 Include the two-year lag of dependent variable	Model 8 Use lagged values in t-2 to t-4 as instruments	Model 9 Perform random effect estimation
Intercept	0.986 (2.424)	0.067 (2.588)	-0.547*** (0.158)
Lagged Financial Returns	0.398*** (0.060)	0.411*** (0.068)	0.563*** (0.046)
Two-year Lagged Financial Returns	0.071 (0.056)		
Firm Size	-0.184 (0.136)	-0.185* (0.113)	-0.005 (0.011)
Firm Age	-0.006 (0.223)	0.018 (0.194)	-0.006 (0.020)
Firm Leverage	0.195 (0.717)	0.173 (0.527)	-0.071 (0.094)
Marketing Expense	0.411 (0.509)	0.779* (0.464)	0.449*** (0.120)
Tangible Assets	1.030 (1.006)	0.636 (1.277)	0.486*** (0.129)
Industry Tobin's *q*	-0.003 (0.138)	-0.007 (0.190)	-0.007 (0.044)
Industry Size	-0.053 (0.116)	0.022 (0.111)	0.011 (0.011)
Six Sigma Implementation	0.166 (0.210)	0.188 (0.248)	0.075** (0.032)
Operational Efficiency	1.077*** (0.353)	1.391*** (0.482)	0.683*** (0.177)
R&D Investments	5.703*** (2.084)	7.094*** (2.472)	1.034*** (0.387)
R&D Investments × Six Sigma Implementation	3.552* (2.401)	4.510* (2.885)	1.070*** (0.354)
R&D Investments × Operational Efficiency	6.448** (3.298)	6.805** (4.095)	3.300* (2.438)
Year Dummies	Included	Included	Included
Industry Dummies	Included	Included	Included
Number of Observations	2909	2920	2920
Wald Chi-squared	272.66***	212.92***	704.26***
Hansen Test	p=0.14	p=0.26	
AR1	p <0.01	p <0.01	
AR2	p=0.96	p=0.27	
R-squared			0.60

Notes: *p<0.1, **p<0.05, and ***p<0.01 (one-tailed tests for hypothesized variables and two-tailed tests for control variables); Robust standard errors clustered by firms are in parentheses.