ESSAYS ON PRODUCT INNOVATION AND FAILURES

by

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This dissertation is dedicated to my mentors and family.

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ABSTRACT

In this dissertation, I investigate how firms' various strategic decisions lead to innovation failures. Extant research in the strategic management field has suggested that a firms' strategic choices determine its innovation trajectories and outcomes. While previous studies predominantly have emphasized firms' successful innovation outcomes, very little research has been conducted on the antecedents of innovation failures. Although firms' successful innovation outcomes provide important implications in understanding the source of firms' competitive advantages, failed innovations would provide us with critical insight about firms' ability to survive and develop as they may result in unfavorable consequences, such as financial risks and negative impacts on firms' reputations In this light, I examine how various strategic choices – such as interorganizational relationships, acquisitions, and internal R&D – affect firm's innovation trajectories and failures.

In Essay 1, I explore how firms' decision to form interorganizational relationships can affect their innovation failures. In particular, I investigate how a venture's choice to form an investment relationship with a particular venture capitalist (VC) could determine the venture's innovation failures. I propose that the time pressure that VCs face may elicit negative consequences for their portfolio companies' innovation quality. In Essay 2, I examine how firms' efforts to acquire technology and knowledge from external markets through acquisitions could affect their innovation failure rates. I suggest and find that adverse selection and post-acquisition integration problems impose substantial costs on firms pursuing acquisitions leading them to experience high rate of innovation failures. In Essay 3, I examine how firms' efforts to develop new products incrementally affect their innovation failures. I suggest that, due to the path dependent nature of product development, when firms develop and introduce new products through an incremental approach, they may face the risk of their new products being exposed to

the failure associated with the products and underlying technologies upon which the new products

are built.

CHAPTER 1.   INTRODUCTION

Innovation is at the heart of the performance of many firms competing in high-technology industries and highly volatile environments. The ability to discover technological breakthroughs and translate them into commercial products is central to their survival and success. Furthermore, innovation allows firms to redefine the marketplace in their favor and achieve a sustainable competitive advantage. Accordingly, researchers examined various strategic choices that firms make to obtain the ability to achieve innovation, such as internal research and development (R&D) (Cassiman & Veugelers, 2006), interfirm relationships (Baum & Calabrese, 2000; Mowery, Oxley, & Silverman, 1996), and technology acquisitions (Ahuja & Katila, 2001; Rigby & Zook, 2002).

Acknowledging the importance of innovation, researchers have investigated different strategic choices that firms make to achieve innovation. Prior studies long have suggested that internal creation of resources and capabilities is a strong predictor of successful innovation outcomes. Internal development of knowledge and capabilities enables innovation by increasing embeddedness of routines and learning (Nelson & Winter, 1982). With greater exercise of routines and learning, the firm's employees may develop a deeper understanding of organizationally embedded knowledge, and the firm may achieve greater synergy from the resources (Cassiman & Veugelers, 2006; Karim & Mitchell, 2004). Furthermore, internal development of technological capabilities is suggested as a means to adapt radical technological innovation by building a firm's absorptive capacity (Cohen & Levinthal, 1990), which can help firms better identify, evaluate, and internalize external knowledge more easily – processes that often come through interorganizational relationships and acquisitions (Kogut & Zander, 1993).

A substantial body of research also has suggested that firms innovate by relying on knowledge residing external to focal firms' organizational boundaries. External knowledge is

critical for innovation in that it enables firms to overcome their limitations in internal development and create synergy with their existing knowledge (Katz & Allen, 1982; Hoang & Rothaermel, 2010). On the other hand, the absence of the acquisition of new knowledge may lead some organizations to fall into the trap of heavily relying on their preexisting knowledge base, making their innovation trajectory highly path-dependent (Helfat, 1994; Nelson & Winter, 1982). Firms utilize this channel to obtain technology and knowledge that cannot be obtained easily from the market or developed internally (Eisenhardt & Schoonhoven, 1996; Hamel, 1991) and to learn new capabilities from their partners (Doz, 1988; Khanna, Gulati, & Nohria, 1998; Mowery et al., 1996).

One way through which firms can obtain external knowledge is by establishing interorganizational relationships with other firms. Some known interorganizational arrangements that allow these functions are strategic alliances (Ozmel, Reuer, & Gulati, 2013a; Phelps, 2010; Rothaermel & Deeds, 2004), joint ventures (Inkpen, 2000), equity investments (Alvarez-Garrido & Dushnitsky, 2016; Dushnitsky & Lenox, 2005), venture capital investments (Hellmann & Puri, 2000; Ozmel, Robinson, & Stuart, 2013b; Pahnke, Katila, & Eisenhardt, 2015), and foreign direct investments (Monteiro, 2015). Furthermore, firms also may resort to mergers and acquisitions (M&As) to access new technology and knowledge for innovation. Compared with other interorganizational relationships, external technology acquisitions are characterized by transacting parties' strong commitment and substantial governance in controlling the acquisition process to help facilitate internalization of newly obtained technological resources (Villalonga & McGahn, 2005).

Although these studies provide interesting insights on the association between different strategic choices and successful innovation outcomes, I observed two important, but underexamined, research agendas. First, while previous studies predominantly have highlighted

successful innovation outcomes, very little research has been conducted on the different antecedents of innovation failures. When discussing firms' innovation outcomes, most studies examine the successful commercialization outcomes of innovation, such as the number of new products introduced into the market (Chatterji & Fabrizio, 2014; Katila & Ahuja, 2002; Pahnke et al., 2015) or the time required to introduce new products (Hellmann & Puri, 2000; Schoonhoven, Eisenhardt, & Lyman, 1990). Numerous others have examined firms' patenting behaviors to analyze their successful intermediary outcomes from innovation by examining the number of patent applications they have submitted (Ahuja & Katila, 2001; Arora, Belenzon, & Rios, 2014). Although firms' successful innovation outcomes provide important implications in understanding the source of firms' competitive advantages, failed innovations would provide us with critical insight about firms' ability to survive and develop as they may result in unfavorable consequences, such as financial risks and negative impacts on firms' reputations (Davidson III & Worrell, 1992; Rhee & Haunschild, 2006). Despite the impact of innovation failure on firms, shareholders, and consumers, management studies have shed little light on the issues surrounding innovation failures, which are a critical dimension when examining firms' innovation outcomes.

Second, while extant literature substantially has documented the positive effect of internal development and external knowledge acquisition on successful innovations, less emphasis has been placed on identifying the negative aspects of pursuing such strategic choices and how such choices result in innovation outcomes. Although interorganizational relationships, acquisitions, and internal R&D have been suggested as effective tools to help firms develop their capabilities to innovate, a growing body of literature points out that certain costs are associated with pursuing these strategies to achieve innovations. For instance, acquisitions can create organizational disruptions among R&D employees that often lead to the loss of specific human capital,

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subsequently harming post-acquisition innovation performance (He & Li, 2016; Kapoor & Lim, 2007). In interorganizational collaborations, a misalignment of interests between participating parties could arise and prevent firms from creating value through knowledge sharing (Diestre & Rajagopalan, 2012; Katila, Rosenberger, & Eisenhardt, 2008). Furthermore, firms that place a strong emphasis on internal research may be biased against acquiring and utilizing external knowledge (Katz & Allen, 1982); thus, these firms could resist making necessary changes to adapt to environmental shifts. Despite the importance of understanding the potential downside risk from innovations, it is surprising that little research has focused on examining causes of innovation failures, which are a critical dimension when examining firms' innovation outcomes (Thirumalai & Sinha, 2011).

To that end, the goal of this dissertation is to identify strategic factors that lead to innovation failures. Extant research in the strategic management field has suggested that a firm's strategic choices determine its innovation trajectories and outcomes. If we examine a firm's heterogenous strategic choices – such as interorganizational relationships, acquisitions, and internal R&D – we may be able to find new insights about why some firms experience innovation failures, while others do not for a long period of time. From this perspective, this dissertation's findings could have important implications for scholars and practitioners.

In this dissertation, I examine firms' failure to commercialize quality innovative products as a manifestation of innovation failure. As innovation concerns the process in which firms discover and transform new knowledge into commercialization (Rothaermel & Deeds, 2004; Madhaven & Grover, 1998), a commercialized product is the final outcome that firms can expect from their innovation efforts which brings them significant economic benefit. However, failure to deliver reliable, quality, and safe product to the general market could significantly impact current

and future competitiveness and development of firms. For instance, Boeing's recent innovation fiasco with its flagship aircraft, the 737 Max, reveals how detrimental a product failure can be to firms in terms of their financial returns and reputations.

My dissertation comprises three essays that incorporate the aforementioned underexplored inquiries from extant literature. In Chapter 2, I explore how firms' decision to form interorganizational relationships can affect their innovation failures. In particular, I investigate how a venture's choice to form an investment relationship with a particular venture capitalist (VC) could determine the venture's innovation failures. Previous studies have suggested that VCs often provide ventures with critical resources and guidance needed for commercializing the ventures' innovations, which are essential to their success (e.g., Kortum & Lerner, 2000; Stuart, Hoang, & Hybels, 1999). This largely positive view regarding VCs' effect on ventures' performance relies on the common assumption that VCs and ventures have an aligned interest in supporting ventures' success and exit (Graebner & Eisenhardt, 2004). I extend (but depart from) this literature by exploring the possibility that the time pressures that VCs face may elicit negative consequences for their portfolio companies' innovation quality. Whereas VCs with long investment horizons may adopt a long-term approach to nurturing their investees, VCs with short investment horizons may be under greater pressure to exit their investments (e.g., through IPOs or acquisitions) within a short period of time, which may result in undesirable consequences to ventures' development. Although time-pressured VCs' involvement may shorten ventures' time spent developing products before marketing them, I suggest the possibility that it could trigger unexpected consequences to marketed products' quality. In other words, time-constrained VCs may allow ventures to take shortcuts in developing new products and, consequently, create undesirable effects on product quality.

In Chapter 3, I examine how firms' efforts to acquire technology and knowledge from external markets through acquisitions could affect their innovation failure rates. Although pursuing acquisitions for external knowledge can be an effective way to speed up the innovation processes of firms competing in high-tech industries (Hagedoorn & Duysters, 2002), it also may raise other underexplored issues around the management of acquired resources or further organizations. Generally, searching for and coordinating new technologies require heavy investments of time and resources. Acquiring firms may not fully understand or may inaccurately evaluate external knowledge *ex ante*. Furthermore, organizational dissonance may be created, and the benefit of gaining new resources from acquisitions may decrease *ex post*. For instance, acquisitions create disruptions among R&D employees that often lead to the loss of specific human capital, subsequently harming post-acquisition innovation performance (He & Li, 2016; Kapoor & Lim, 2007). Given the complexity of managing the acquisition process and that understanding resources originating from other organizations may be more difficult than understanding resources from in-house R&D efforts (Lane & Lubatkin, 1998; Makri, Hitt, & Lane, 2010), managers may be challenged in trying to understand and manage the acquired organization and technology properly to achieve innovation. By incorporating research on value-destroying acquisitions, I propose and empirically test underlying mechanisms that explain the relationship between acquisitions and product failures. I suggest and find that adverse selection and post-acquisition integration problems impose substantial costs on firms pursuing acquisitions.

In the final chapter, I examine how firms' efforts to develop new products incrementally affect their innovation failures. Extant research across the strategic management and innovation fields has argued that firms achieve product innovation by introducing relatively incremental changes to existing products by exploiting established technology's potential (Helfat &

Raubitschek, 2000). Despite the benefits of utilizing a firm's existing knowledge base in new product development, extant literature sheds less light on the potential downside of firms relying on their existing knowledge base, especially when existing products' quality and the knowledge base surrounding them are questionable. I argue that, if existing products suffer from product failures (e.g., functional defects and unexpected side effects), failures may persist in products introduced subsequently, ultimately causing affected firms to suffer from such innovation failures. To that end, the primary goal of this chapter is to analyze whether the quality problems inherent in existing products affect the quality of new products that are built on existing ones. I further argue that the extent to which a new product's failure is affected by the questionable quality of the product built upon it is contingent upon the firm's willingness to change its current sets of actions. Furthermore, the firm's resistance to seeking solutions in external knowledge sources may exacerbate product failures.

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CHAPTER 2. EFFECT OF VENTURE CAPITAL INVESTMENTS ON PRODUCT FAILURES

2.1 Introduction

In the early stage of the corporate life cycle, a venture's interorganizational partnerships are important determinants of its growth and survival (Eisenhardt & Schoonhoven 1996; Gulati & Higgins, 2003; Hoehn-Weiss & Karim, 2014; Stuart, 2000). For example, previous studies have documented that ventures can overcome resource/knowledge constraints by forming a collaborative network with other market constituents (e.g., Baum, Calabrese, & Silverman, 2000; Kotabe & Swan, 1995; Schoonhoven, Eisenhardt, & Lyman, 1990; Shan, Walker, & Kogut, 1994). Among the different types of partnerships, venture capital investment relationships can be particularly important because venture capitalists (VCs) often provide ventures with the critical resources and guidance needed for commercializing ventures' innovations, which are essential for ventures' success (e.g., Hellmann & Puri, 2000; Kortum & Lerner, 2000; Stuart, Hoang, & Hybels, 1999).

This largely positive view regarding the effect of VCs on ventures' performance relies on the common assumption that VCs and ventures have an aligned interest in supporting ventures' success and exit (Graebner & Eisenhardt, 2004). This assumption is plausible because VCs' ultimate investment returns are associated with their portfolio companies' timely exits and valuation in the exit market (Bottazzi, Da Rin, & Hellmann, 2008; Brander, Amit, & Antweiler, 2002). However, several studies hint that VCs' support in leading their portfolio companies to an exit event may not always confer advantages to the ventures but can instead affect the ventures negatively (Gompers, 1996; Gompers & Lerner, 2001b; Lee & Wahal, 2004; Pahnke, McDonald, Wang, & Hallen, 2015a).

Building on this literature, I aim to provide a more balanced perspective to the research on entrepreneurship and venture capital financing, which has predominantly suggested that ventures benefit from their VCs. I extend (but depart from) this literature by exploring the possibility that the time pressure faced by VCs may result in negative consequences for their portfolio companies. In so doing, I highlight that VCs' motivation to lead ventures to an exit in a timely manner can vary based upon their own time constraints (i.e., a finite investment horizon) to reap the investment returns. Whereas VCs with a long investment horizon may adopt a long-term approach to nurture their investees, VCs with short investment horizon may be under greater pressure to exit their investees within a short period of time, which may result in undesirable consequences on the ventures' development. Despite the heterogeneities in investment horizon among VCs and their associated motivation to orchestrate investee's development and exit strategies, previous studies to a large extent implicitly assumed that VCs' intention to exit their portfolio companies is beneficial for ventures, overlooking the implications of VCs' investment horizon and its impact on ventures' innovation outcomes. Given the importance of innovation and commercialization in entrepreneurial ventures' success (Gans, Hsu, & Stern, 2002), assessing the effect of VCs' incentives to exit can provide a better understanding of the nature of the relationships between VCs and their portfolio companies.

Specifically, to assess the effect of VCs' influence on their portfolio companies, I pay attention to the product failures of ventures, which is an important but underexplored dimension of product innovation (Haunschild & Rhee, 2004; Thirumalai & Sinha, 2011). I investigate that VCs may affect the rate of their portfolio companies' product failures depending on their investment horizons and under what conditions such effects are magnified or alleviated. The main

premise is that VCs[1] with a short investment horizon may lead their portfolio companies to expedite the product development process and rollouts to increase the chances of exiting the ventures. However, VCs' guidance to hasten ventures' product commercialization could inadvertently expose them to a greater probability of product quality problems (Cohen, Gompers, Kovner, & Lerner, 1996), particularly when the ventures are not completely ready to release their products to the market. Therefore, I suggest that the side effect of rushing ventures' product development to expedite an exit event may be that these ventures will experience a higher rate of unexpected product failures.

To delve into the mechanism underlying the main argument, I further examine the contingent effects of VCs' investment horizon on ventures' product failures. First, I propose that the above relationship is amplified when the VCs' fund performs poorly because these VCs are likely to be under greater pressure to exit the ventures. Second, I suggest that the predicted relationship in the main argument can be mitigated when VCs have limited influence to expedite the portfolio company's product development. In developing this hypothesis, I focus on the role of founders because they have been suggested to play a significant role in shaping a venture's development process, as well as future strategy, even after they depart (Beckman & Burton, 2008; Eesley, Hsu, & Roberts, 2014; Eisenhardt & Schoonhoven, 1990; Zuzul & Tripsas, 2020). That is, when the founders of portfolio companies have accumulated experience in product development and manufacturing, they may put the break on VCs' influence to control the product quality and manufacturing operation, thereby mitigating the proposed relationship in the main argument. To

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[1] In developing the arguments, I assume that VCs pursue financial returns that are constrained by an investment horizon; thus, I do not consider ventures solely invested in by corporate venture capitalists (CVCs). First, they are known to have strong strategic objectives, such as acquiring ventures' new technologies, other than the purely financial objective of investing in ventures (Benson & Ziedonis, 2009; Dushnitsky & Lenox, 2005). Second, they are not bound by the investment horizon because they invest corporate funds into ventures (Alvarez-Garrido & Dushnitsky, 2016). Third, there are very few ventures whose lead investor is a CVC.

test the predictions, I examine the product failures of VC-backed ventures in the U.S. medical device industry, a setting characterized by active VC investments (Ackerly et al., 2008) and strict regulation of product failures (Thirumalai & Sinha, 2011).

This research makes several important contributions through this study. First, this research suggests an alternative perspective to a stream of extant literature that has long discussed the role of interorganizational partners in helping ventures' survival and growth (e.g., Baum et al., 2000; Bottazzi et al. 2008; Hoehn-Weiss & Karim, 2014; Schoonhoven et al., 1990; Stuart et al., 1999). Previous studies in this area emphasize the positive aspects of interorganizational partnerships and focus on identifying the different types of benefits provided by external investors such as VCs. In this study, I highlight that VCs may not always confer benefits to ventures but in fact could even harm ventures, particularly when the VCs are under a great time pressure. In line with some recent studies that explore the potential negative effects of interorganizational partnerships (Dushnitsky & Shaver, 2009; Lee & Wahal, 2004; Joshi & Nerkar, 2011; Pahnke et al., 2015a; 2015b), I suggest that ventures' partners may operate under incentives that diverge from the wealth of ventures and may ultimately damage the ventures' performance.

Second, the findings of this study add to the literature on new product development. Many studies have focused on successful product developments by examining the frequency (e.g., Chatterji & Fabrizio, 2014; Katila & Ahuja, 2002), the sales (e.g., Leiponen & Helfat, 2010; Nerkar & Roberts, 2004), or the speed of new product introductions (e.g., Hellmann & Puri, 2000; Schoonhoven et al., 1990). However, research has paid little attention to the antecedents of firms' product development failures, which are a critical dimension when examining ventures' product innovation outcomes (Thirumalai & Sinha, 2011). In this paper, I aim to shed more light on the

above issue by analyzing the potential factors that lead to product failures associated with safety issues, which might have a significant ramification for firm performance and societal utilities.

Third, this research adds to the broad literature on the corporate governance of public and private firms. This literature pays substantial attention to understanding the heterogeneity of external investors, such as private funds, pension funds, angel investors, corporate investors, and VCs (e.g., Alvarez-Garrido & Dushnitsky, 2016; Bruton, Filatotchev, Chahine, & Wright, 2010; Hoskisson, Hitt, Johnson, & Grossman, 2002; Pahnke et al., 2015a; Tihanyi, Johson, Hoskisson, & Hitt, 2003). Although this stream of research provides insights into understanding the role of the governance structure depending on the type of investors, most studies in this area use a dichotomous or categorical proxy for how these investors differ from one another, overlooking the fact that a similar type of investors can diverge in their investment norms, values, and practices. I add to this literature by suggesting that even the same type of investors (VCs in this context) can adopt different investment strategies based on their interests, which, in turn, can affect their investees' performance.

2.2   Theoretical Background

VCs invest in entrepreneurial startups on behalf of limited partners (LPs).[2] Although it is important to note that VCs identify and select promising investment opportunities, they also need to coach and guide their portfolio companies to realize potential through successful exits (Baum & Silverman, 2004; Nahata, 2008). To achieve this aim, VCs have incentives to provide not only

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[2] Venture capital funds are organized as finite partnerships in which VCs act as the general partners and the outside investors that infuse capital to venture capital funds act as LPs (Sahlman, 1990). VCs have limited investment horizons because venture capital funds need to be liquidated to provide returns to limited partners at the end of the funds' life cycles (Gompers & Lerner, 1999). This is further articulated in the following paragraphs.

the necessary capital, but also other resources to help ventures pursue innovation and commercialization activities.

First, VCs offer financial capital to ventures to help execute the necessary strategies. The direct financial funding from VCs to ventures resolves ventures' financial constraints in pursuing innovation activities, thereby contributing to innovation outcomes (Hall & Lerner, 2010; Kortum & Lerner, 2000). Second, VCs actively interact with portfolio companies and engage in value-adding activities to promote the ventures' innovation. Some of the known value-adding activities and resources that VCs provide include recruiting key talent and managing human capital (Bottazzi et al., 2008; Hellmann & Puri, 2002); linking ventures to potential suppliers, customers, and alliance partners (Blevins & Ragozzino, 2018; Reuer & Devarakonda, 2017); and providing strategic counseling and advice (Bernstein, Giroud, & Townsend, 2016). It is worth noting that these resources and guidance provided by VCs typically focus on improving ventures' downstream activities, such as the commercialization (rather than development) of new innovations (Hellmann & Puri, 2000; Pahnke et al., 2015a). Third, VCs confer endorsement benefits on recipient ventures in that having a VC as a partner signals a positive assessment of the venture's prospects (Ozmel, Reuer, & Gulati, 2013a; Stuart et al., 1999). In particular, investments from reputable VCs may enable ventures to attract other investors, customers, and potential partners (Gulati & Higgins, 2003; Hall & Lerner, 2010).

The aforementioned benefits are based on the observation that VCs perceive themselves as the cocreators of ventures and align their own interests with those of ventures. In other words, previous studies predominantly assume that as much as ventures are eager to grow and prosper, VCs are motivated to be involved in portfolio companies' development paths (Graebner & Eisenhardt, 2004). For example, Hallen, Katila, and Rosenberger (2014) suggest that venture

capital investors frequently refer to themselves as members of the venture team and stake their professional identities on nurturing successful ventures.

The perspective that VCs are generally supportive of ventures' success is plausible given the fact that VCs' investment returns are closely aligned with the performance of their portfolio companies in the exit market (Gompers & Lerner, 2001a; Ozmel, Robinson, & Stuart, 2013b). Because venture capital deals are not structured in a way in which VCs can share ventures' profits or are paid off by dividends, VCs have a clear motivation to exit their portfolio companies, preferably through acquisitions or IPOs (Gaba & Meyer, 2008; Schwienbacher, 2008). Furthermore, in contrast to other financial intermediaries, venture capital funds have a predetermined lifetime of typically 10 years. During a venture capital fund's life cycle, the fund's managers, namely, the general partners, invest the capital collected from their LPs into several ventures. At the end of the funds' life cycle, the venture capital funds liquidate their investments in the ventures and return the profits to their LPs in exchange for management fees and carried interest (Gompers & Lerner, 2001a). Most of these funds are designed to be self-liquidating when the venture capital funds reach their maturity (Gompers & Lerner 2001a). As a result, VCs are primarily motivated to exert influence on ventures so that these ventures can exit in a timely manner, generating positive returns from their investments (Arthurs, Hoskisson, Busenitz, & Johnson, 2008; Bottazzi et al., 2008; Hellmann & Puri, 2000; Kaplan & Stromberg, 2001; Lerner, 1994).

Given these unique features of a predetermined lifetime and incentive structure of venture capital investment, VCs' motivation to exert influence in guiding ventures to exit may depend on VCs' investment horizon. The limited time frame of venture capital funds imposes pressure on VCs to secure returns on their investments by focusing on taking their ventures to timely exits. In

other words, VCs' predetermined lifetime of investment may create different incentives for their investees to make timely exits. In the following section, by building on this notion of heterogeneity associated with investment time horizons, I develop hypotheses about the effects of VCs' investment horizon on ventures' product quality problems (i.e., product failures) and two boundary conditions under which such effects are moderated.

2.3   Hypotheses Development

2.3.1   Effect of VCs' Investment Horizon on Ventures' Product Failures

VCs' investment horizon refers to the amount of time remaining until each fund reaches its maturity. With the given venture capital fund, VCs generally spend the first few years selecting investment targets and then spend the remaining period supporting the selected portfolio companies (Guler, 2007).[3] In the early years of venture capital funds, VCs have sufficient time to take their portfolio companies to an exit event. However, as venture capital funds approach the later stage of their life cycle, VCs have substantially less time remaining to exit the ventures in the funds' portfolio.

When VCs have a sufficiently long investment horizon (i.e., VCs investing with a venture capital fund in its early years), they may accommodate the long-term development of ventures. In this case, VCs can wait until ventures build up their capabilities sufficiently before exiting (Chemmanur & Fulghieri, 1999). In line with this reasoning, several studies (e.g., Ferreira, Manso, & Silva, 2014; Tian & Wang, 2012) suggest that investors (or shareholders) need to be patient for the firm to explore innovative ideas, which typically require a long time to produce observable payoffs.

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[3] Conditional on the consent of LPs, VCs are allowed to extend the fund's duration for up to three years (Barrot 2017).

However, when VCs have a relatively short investment horizon, VCs become increasingly bound to their investment horizons because of their distribution arrangements with LPs and, thus, focus on helping ventures reach milestones associated with progress toward the successful liquidation of venture capital funds (Cable & Shane, 1997; Sahlman, 1990). Otherwise, at the scheduled termination of their venture capital funds, VCs may have to painfully write off or hold a fire sale on the shares of their portfolio companies (Gompers & Lerner, 2001a). Therefore, to collect positive returns from their investments, VCs with shorter investment horizons may have greater incentives to engineer their portfolio companies to achieve significant milestones early than do VCs with longer investment horizons.

One of the significant milestones is the commercialization of innovations because marketable products can reduce the uncertainty regarding the ventures' prospect in the exit market and, hence, increase the chances of a successful exit (Park & Tzabbar, 2016; Wasserman, 2003). This is particularly relevant in high-technology industries where outsiders face substantial information asymmetry regarding the true value of ventures' resources and capabilities (Amit et al., 1990; Stuart et al., 1999). Moreover, VCs often gauge ventures' readiness for an exit event based on financial measures, such as revenues from marketed products (Gersick, 1994). Therefore, as ventures' innovation progresses, VCs are likely to emphasize product commercialization and the required activities, such as analyzing target markets, developing management systems, and providing expertise in downstream activities (e.g., marketing and distribution) (Park & Tzabbar, 2016). Supporting this view, several studies suggest and show that VCs' time-paced discipline leads ventures to advance the introduction of new products (Hellmann & Puri, 2000; Pahnke et al., 2015a).

Although time-pressured VCs' involvement may shorten ventures' time to market their products, I suggest the possibility that this could trigger an unexpected consequence to the quality of the marketed products. Major product quality problems associated with VCs' short investment horizon could occur in two consecutive value chain stages: the development (i.e., preproduction) and production stage (Hora, Bapuji, & Roth, 2011). First, I conjecture that time-constrained VCs may allow ventures to take shortcuts in developing new products and, consequently, create undesirable effects when it comes to the quality of the product. It has often been viewed that higher quality, in terms of unique features, innovativeness, and reliability, can be achieved at the expense of the longer time the product needs to stay in the development stage (Cohen, Eliashberg, & Ho, 1996; Kessler & Chakrabarti, 1996; Lilien & Yoon, 1990). In particular, structural problems in product design could arise when product developers are pressured to meet deadlines and take shortcuts in handling unexpected complications (Sheremata, 2000). Although such shortcuts are helpful in staying on schedule, they are not in the best interests of the project because developers interpret challenges in the development process conveniently and neglect potential sources of problems (Austin, 2001).

Second, product failures can be observed in the manufacturing process. The contamination of raw materials, incorrect machining, and faulty assembly are some examples of product failures during the manufacturing process. In this context, I propose that when VCs expedite product commercialization, their portfolio companies may underestimate the appropriate manufacturing capacity. This is because even when a venture has developed a successful prototype, it may lack sufficient experience and information to scale up production. Because VCs typically have little knowledge in technical aspects of manufacturing (Pahnke et al., 2015a), they may drive portfolio companies to squeeze the output from the manufacturing facilities to boost the companies' revenue.

However, in the manufacturing stage, the lack of slack capacity combined with the emphasis on efficiency often lead to deviation from standard operating procedures, overlooking potential operation problems (De Treville & Antonakis, 2006; Shah, Ball, & Netessine, 2017).

In sum, when VCs focus on accelerating their portfolio companies' product rollouts because of their short investment horizon, they are likely to mislead their portfolio companies, resulting in unexpected product failures. Therefore, I propose the following:

Hypothesis 1. VCs' investment horizon is negatively associated with their portfolio companies' product failure rates.

2.3.2 Contingent Effects of VCs' Investment Horizon on Ventures' Product Failures

To validate the theoretical arguments, it is critical to examine whether the suggested mechanism underlying VCs' investment horizon drives ventures' product failure rates. The approach hinges on the proposition that VCs lead their portfolio companies to exit early when they face a short investment horizon and that the degree of VCs' influence differs depending on the VCs' incentive and ability to do so. I identify two such factors: (*i*) venture capital funds' exit performance level and (*ii*) founders' expertise. I hypothesize that these factors can affect the magnitude of the influence that VCs impose on their portfolio companies, creating differential effects of VCs' investment horizon on the rate of product failures.

I expect that the extent to which ventures experience more product failures when they are invested in by VCs with a short investment horizon may be greater when the VCs' funds have poor prior performance. As described above, VCs collect capital from LPs to raise their venture capital funds. Although the successful exit of VC-backed ventures (i.e., acquisition and IPO) can generate returns for LPs, this type of successful exit is quite rare (Hochberg, Ljungqvist, & Lu, 2007; Ruhnka, Feldman, & Dean, 1992). Given this inherent risk in venture capital investments, LPs are

very cautious in making commitment to unproven, incapable VCs (Gompers & Lerner, 2001a). Therefore, when evaluating VCs, LPs often refer to signals that can convey reliable information about the VCs' capabilities, such as exit performance (Balboa & Marti 2007). Hence, when VCs' funds underperform, VCs have a clear motivation to improve their track records and reputation by exiting their portfolio companies (Gompers, 1996; Lee & Wahal, 2004). Building on this notion, I expect that when a venture capital fund experiences poor performance, VCs with a short investment horizon may face greater pressure to signal their capability by expediting their portfolio companies' commercialization process; otherwise, they may fail to raise the next funds. On the other hand, when VCs have a sufficiently long investment horizon, they may face little pressure to establish their track records within a short period of time and, thus, are likely to take a long-term approach in guiding their portfolio companies, thereby mitigating the effect of VCs' investment horizon on their portfolio companies' product failures.

Moreover, when a venture capital fund underperforms, its general partners, who work directly with ventures in the portfolio (Zider, 1998), may face greater pressure to exit them as the fund reaches maturity. This is because general managers' compensation is closely tied to the performance of the fund that they are responsible for. Along with management fees, which cover only the cost of managing the fund, carried interest, which is the share of the profits when the investments are liquidated, accounts for the primary source of general partners' compensation. Therefore, carried interest can work as a strong incentive for the general partners to improve the performance of the funds. Hence, when a venture capital fund underperforms, the general partners of funds with a short investment horizon will have even higher incentives to prompt ventures' exits by expediting the commercialization process. However, those facing a long investment horizon

may find the pressure associated with carried interest less real such that the effect of VCs' investment horizon on ventures' product failures can be reduced. Thus, I propose the following:

Hypothesis 2. The negative effect of VCs' investment horizon on ventures' product failures is mitigated (positively moderated) by the venture capital fund performance.

It has been well-established that founders' knowledge and experience determines not only the nature of entrepreneurial opportunities they pursue (Agarwal, Echambadi, Franco, & Sarkar, 2004; Shane, 2000) but also their ventures' behavior and performance (Beckman & Burton, 2008; Dencker & Gruber, 2015). Although founder experience may vary depending on their prior experience (e.g., education, work experience), previous literature has identified technical experience and expertise as one of the most important features in shaping ventures' innovation strategy (Eesley et al., 2014; Zuzul & Tripsas, 2020).

Building on this literature, I suggest that the negative relationship between VCs' investment horizon and their portfolio companies' product failures can also be mitigated when founders have expertise in the technical aspects of product development. Founders' technical expertise stemming from their experience as engineers or scientists can affect their ventures' long-term development paths in several ways. Specifically, founders rely on their own knowledge and experience in the domain of their expertise to identify the potential of new ideas that can be transformed into marketable products. Therefore, it is likely that founders with technical expertise may have a better understanding of the current and future technological landscape and, thus, have a better road map for product development and manufacturing (e.g., R&D, product design, production) in the commercialization process. Accordingly, these founders may be actively involved in the product development process and allocate more resources to promote product

quality, mitigating the risk of errors (Dencker & Gruber, 2015). Moreover, given that founders with a technical expertise or background are likely to have a wide range of connections with other experts in the technical community, they may be able to hire better human capital in the relevant labor market and receive prompt feedback from others, which can collectively improve the product development and manufacturing process (Eesley et al., 2014). In addition, technical expertise increases the absorptive capacity of the founder, enabling them to better utilize the feedback and suggestions provided by others, which would increase the quality of the product (Cohen & Levinthal, 1990; Lewin, Massini, & Peeters, 2011). However, founders without technical expertise may lack first-hand information and experience regarding the technologies and products and may pay attention to different functional activities, such as marketing and sales.

I propose that given the differences in the development paths depending on founders' experience, founders' technical expertise has significant ramifications for the relationship between VCs' investment horizon and portfolio companies' product failures. When investing in ventures, VCs rely on founders' deep insights into the anticipated technologies and products (Park & Tzabbar, 2016) because VCs have a limited understanding of the tacit nature of the knowledge underlying the innovations (Pahnke et al., 2015a). Therefore, even when VCs with a short investment horizon want to expedite the commercialization process, founders with technical expertise may put the break on VCs' influence. Moreover, founders with technical expertise tend to establish product development routines that focus on the quality (rather than speed), and other employee inventors share similar beliefs about the process (Beckman & Burton, 2008; Van den Steen, 2005). In this case, VCs with a short investment horizon may not be able to drive the commercialization process toward their own interests. In contrast, founders who lack technical expertise and focus on other functional domains are likely to agree with VCs' guidance to expedite

the commercialization process because these founders may believe that their products are reliable enough to be released in the market. It is important to note that the reasoning above should hold even when founders leave their ventures and new managers join the ventures. Founders' knowledge and experience determine the early choices and directions that can be deeply embedded in their ventures' organizational routines and structures (Boeker, 1989; Eisenhardt & Schoonhoven, 1990; Phillips, 2005). Hence, founders' characteristics can create a long-lasting imprint that can guide ventures' future strategy and actions (Beckman, 2006; Beckman & Burton, 2008; Eesley et al., 2014).

Taken together, I suggest that because founders with technical expertise and experience may develop long-lasting routines and structures that focus on the development of reliable products, ventures initiated by these founders are less likely to be influenced by VCs with a short investment horizon; however, those ventures initiated by founders who lack technical expertise are more likely to be driven by VCs' influence to expedite the commercialization process, which may result in more unexpected product failures. Therefore, I propose the following:

> *Hypothesis 3. The negative effect of VCs' investment horizon on ventures' product failures is mitigated (positively moderated) by the level of founders' technical expertise.*

2.4   Methodology

2.4.1   Sample and Data Sources

I selected VC-backed ventures in the medical device sector to test the proposed hypotheses. I chose VC-backed ventures because they are likely to have viable technologies that can be commercialized, which is the core of my arguments (Katila, Rosenberger, & Eisenhardt, 2008).

The medical device sector is appropriate for this study for several reasons. First, venture capital investments are active in the medical device industry. The medical device industry is one of the fastest growing industries in terms of venture capital investments, with a total of $4.1 billion invested in 2007, which is in the mid of the sample period (Ackerly et al., 2008). Second, product failures frequently occur and are observable in the medical device sector. Product failures in this industry refer to manufacturing defects, functional defects, and unexpected side effects that present a potential threat to patients' well-being. Firms experiencing product failures in this industry usually recall their defective products from the market in accordance with the Food and Drug Administration's (FDA) regulations.[4] As a result, the manufacturers of these recalled products suffer great financial and reputational losses (Chen, Ganesan, & Liu, 2009; Rhee & Haunchild, 2006), and physicians and patients suffer from adjusting to and/or replacing these defective products and experiencing unforeseen injuries or deaths (Thirumalai & Sinha, 2011). Therefore, I examined product recalls as an indicator of product failures because they are an apparent sign that a firm was unsuccessful in providing reliable, quality products and in meeting customers' needs and safety requirements (Thirumalai & Sinha, 2011; Liu & Shankar, 2015). The ventures in the sample faced similar regulatory environments but presented substantial variance in product recalls.

I constructed the sample by first collecting a list of U.S. medical device ventures[5] that received first venture capital investments from 1992 to 2015.[6] I obtained the list of ventures in

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[4] Product recall in the medical device industry occurs when a marketed device is defective and/or could be a risk to health. Recent studies show product recalls occur because of a firm's incapability to produce reliable products. For instance, Wowak et al. (2015) show that a lack of CEO caution results in a higher probability of product recalls, and Shah et al. (2017) argue that the overutilization of plants increases manufacturing recalls.

[5] These ventures are categorized into one of the following subsectors of the medical device industry: (1) surgical and medical instruments and apparatus (SIC 3841); (2) orthopedic, prosthetic, and surgical appliances and supplies (SIC 3842); (3) dental equipment and supplies (SIC 3843); (4) X-ray apparatus and tubes and related irradiation apparatus (SIC 3844); (5) electromedical and electrotherapeutic apparatus (SIC 3845); and (6) ophthalmic goods (SIC 3851) (De Vet & Scott 1992).

[6] I limited the sample to ventures that received their first venture capital investment between 1992 and 2015 because of data restrictions. Information on recalls is only available for recalls announced from 1989 to 2018. As I needed a

which VCs invested from Thompson One's VentureXpert. From VentureXpert, I also gathered

detailed information about the ventures, their VCs, and funding information, such as investment

dates and amounts. I cross-validated information on the fund names and vintage years with the

Pitchbook Platform, which documents detailed information on the venture capital investments, and

S-1 filings provided by the EDGAR database of the U.S. Securities and Exchange Commission. I

further restricted sample ventures to those that gained approval for at least one medical device to

examine the frequency of product failures. I used the FDA's Premarket Notification and Premarket

Approval databases to collect information about the ventures' FDA-approved medical device

products. These databases include the names of approved products, the applicants of these products,

and the dates when these products were approved, enabling me to identify the marketable products

that each venture developed and those that were recalled.

I tracked ventures' product recalls starting from the year after their first venture capital

investment until the end of the year 2018.[7] Information on recall incidents was collected from the

public product recall databases made available by the FDA. I obtained this information through

two different routes. Product recalls issued between 2003 and 2018 were directly obtained by

downloading the recall data from OpenFDA website, an FDA Office of Health Informatics

initiative providing FDA regulatory datasets. Because the product recall data provided by

OpenFDA starts from 2003, I manually collected information on recalls from Enforcement Reports

issued between 1989 and 2002 from the FDA website, which was accessed through the Wayback

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time window to account for ventures' prior recall trends in the empirical model, I selected the venture capital investment in 1992 as the earliest venture capital investment in the observation.

[7] I limited the sample to include ventures that had at least one FDA-approved medical device (i.e., devices approved through the Premarket Notification [also known as 510k] and Premarket Approval processes) after they are invested in by VCs. Many ventures do not have any products upon receiving venture capital. Therefore, when ventures do not have any products at the time of the first venture capital investment, I included those ventures in the sample starting from the year in which they first introduced their products so that I could examine these ventures' product failures after they receive venture capital.

Machine, an online digital archive. From each recall announcement, I identified the name of the product being recalled, the recalling venture, and the recall initiation date, which enabled me to examine the annual number of product recalls in which the sample ventures were involved.

Next, I hand-collected information about the sample ventures' founders and their career histories by implementing a rigorous web search using data sources such as Bloomberg Businessweek's executive profile, Capital IQ, Crunchbase, Factiva, Relationship Science, LinkedIn, SEC filings, and company websites. I first searched for each founder's (or cofounder's) prior employers, job titles, and the years in which he or she worked. I traced the founders' most recent jobs within 10 years before founding the sample venture because reliable information on founders' jobs in their earlier careers is difficult to find. Although a 10-year window could be somewhat arbitrary, I conjecture that a 10-year period is adequate to capture the most recent and sufficient industry-specific knowledge that founders have obtained from their job experiences before they started their own ventures. The dataset further includes information collected from various other sources. I used Thompson One's companion database of VC-backed IPOs and acquisitions to identify the performance level of each VC and venture capital fund. I collected U.S. patent data from PatentsView, an online patent data platform supported by the U.S. Patent and Trademark Office. For ventures' alliance information, I used the alliance module of Security Data Corporation.

With the baseline sample, I traced the product recalls of all ventures for a period of up to 10 years from the year of their first venture capital investment.[8] In cases where the sample ventures were acquired or went bankrupt prior to reaching to the tenth year, I stopped tracking ventures

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[8] I tracked each venture up to 10 years because VCs typically want to sell their position within 10 years (Hochberg et al., 2007). To ensure robustness, I examined each venture up to 8 and 12 years, respectively, and find similar results to the main results, as described below.

after they were acquired or went bankrupt. The final sample comprises an unbalanced panel of 2,147 venture-year-level observations across 345 VC-backed ventures.

2.4.2 Measures

Dependent Variable. Following extant studies (Liu & Shankar, 2015; Thirumalai & Sinha, 2011; Wowak, Mannor, & Wowak, 2015), I selected the number of product recalls as a measure for product failures. *Product failure count$_{it}$* is a count variable indicating the number of recalls that venture *i* initiated in year *t* after the venture capital investment. Because I only consider products applied after the venture capital investments and the extent to which these products are recalled, the recalls of products that are approved prior to venture capital investments are not included in the sample.

Independent Variables. Following previous studies on VCs (e.g., Hochberg et al., 2007; Ozmel & Guler, 2015), I used the lead VCs' characteristics as the main measure for all VC-related variables. Given that lead VCs invest the most amount of capital and play the most important role in overseeing ventures (Wright & Lockett, 2003), their interests generally matter the most to a venture's product development (Bernstein et al., 2016). As per convention, I defined a lead venture capital investor as an independent VC investing in the venture's first investment round with the largest total investment in the company (Hsu & Ziedonis, 2013; Ozmel & Guler, 2015; Sørenson, 2007).

VCs' investment horizon is measured based on the age of the venture capital fund at the time a lead VC made the first investment in a venture. I calculated the venture capital fund age by taking the difference between the year that the lead VC made its first investment in a given venture and the fund vintage year (i.e., the fund's launch year). To make the interpretation of the results more intuitive, I then used a negative value of fund age in the analysis such that a higher value of

this variable indicates a longer investment horizon. If more than one fund is involved in the lead VC's earliest investment round in a venture, following extant research, I used the age of the oldest fund to calculate the VCs' investment horizon because the oldest fund is the closest one to the liquidation (Guler, 2007).

Fund performance is measured by the cumulative ratio of the number of successful exits (i.e., IPOs and acquisitions) to the number of ventures invested in by each fund investing in venture *i* in a given year. For instance, if a venture *i*'s venture capital fund has exited (either through IPO or acquisition) three ventures out of its 10 portfolio companies in a given year, the *fund performance* has the value of 0.3. To reduce the potential multicollinearity, I mean-centered the continuous independent and moderating variables (Aiken & West, 1991).

Founders' expertise is a dummy variable measuring venture founders' prior experience in engineering and science associated with product development. To identify the founders' technical expertise/experience, I identified their employers, job titles/functions, and the years prior to founding their ventures. If the founders' prior job titles include any of the following functions, I gave a value of 1 and 0 if otherwise: research and development, technology, manufacturing, and product design (e.g., chief technology officer, chief medical officer, chief scientist officer, manager/director/engineer/vice president in product development, product designer) (Beckman & Burton, 2008; Eesley et al., 2014).

I lagged the independent variables and control variables described below by two years with respect to the product recalls throughout the empirical models (i.e., $t - 2$). The empirical model is designed to capture the variations in ventures' product recalls at time *t* that are driven by various VC- and venture-specific factors. Because product recalls are not initiated immediately after the products are introduced to the market (i.e., there is a time gap between the product introduction

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and the first time there is a recall), the covariates measured at year t may not properly capture the causal relationships between VC- and venture-specific factors on ventures' product development behaviors. To account for such a time gap, I took the average time lag between the product application and first product recall in the sample, which is 2.1 years.[9]

Control Variables. I included several control variables to demonstrate other potential factors that may determine ventures' product failures. First, I controlled for ventures' prior recalls by including the variable *prior product failure count* in the past three years in all models to consider a possibility that companies with a history of product recalls are more likely to experience the same problems subsequently (Rhee, 2009; Wowak et al., 2015). I controlled for ventures' *product count* by counting the number of medical devices approved by the FDA in the past three years, as ventures with a greater number of products may be more susceptible to facing a higher chance of product recalls. I further included ventures' *patent count,* which is measured by counting the number of patents a venture applied for (and granted in later years) in the past three years to account for the ventures' technological capabilities (Hagedoorn & Cloodt, 2003). I used natural log-transformed values because of the skewedness in these two count variables. I also controlled for the number of alliances (*alliance count*) that the venture formed in the past three years, as collaboration with external partners affects ventures' innovation outcomes (Sampson, 2007). I included *venture age,* measured by counting the number of years that have elapsed since the venture's founding year, and *investment amount*, measured by the natural logarithm of the dollar amount of venture capital received until the given year. I controlled for the number of years elapsed since the venture received its first venture capital funding (*time since investment*).

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[9] To ensure robustness, I used a different time lag $t - 1$, and the results are similar to the main analysis, as described below.

I also included VC- and fund-specific covariates to account for the effect of VCs' specific characteristics on ventures' product failures. At the fund level, I included a dummy variable indicating whether the fund investing in a venture is the *first-time fund* raised by the VC because a VC investing with the initial fund may be less experienced than VCs that have raised multiple funds (Gompers & Lerner, 2001a). At the VC level, I controlled for various factors that may represent VCs' experience and capability. I controlled for VCs' total number of investments in the medical device sector in the past three years (*VCs' prior investment experience*). The estimation model also included *VCs' performance* as measured by VCs' ratio of successful exits (i.e., acquisitions and IPOs) to the total number of ventures invested in. *VCs' product failure count* is the total number of recalls that VCs' portfolio companies announced in the past three years; this measure accounts for the VCs' tendency of investing in ventures with the high risk of product failures. I controlled for the natural log of *VCs' age*. Finally, to control for geographic proximity between ventures and VCs, I included a dummy variable with the value of 1 if they are located in a same state and 0 if otherwise.[10]

2.4.3 Empirical Strategy

The dependent variable of the study is a count variable with overdispersion in repeated observations. Because of the nature of the data structure, I used the generalized estimating equation (GEE) model in the main empirical analysis (Ballinger, 2004). This estimation uses a quasi-likelihood estimation approach to estimate the parameters of panel data. Although GEE is an extension of generalized linear model (GLM), unlike GLM, GEE does not assume that the response variable is normally distributed and independent over time. For these reasons, prior

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[10] Instead of a three-year window, I used a five-year window for all of the covariates, and the results remained consistent.

studies have used GEE to examine product recalls over time (e.g., Rhee, 2009; Shah et al., 2017; Wowak et al., 2015). I used a GEE model with a negative binomial distribution and a log linear-link function. I selected an exchangeable correlation structure with robust standard errors clustered at the venture level to correct potential serial correlations in the correlation structure.

One concern with this empirical approach is that the selection effects of venture capital investment may drive the results, as the match between a particular VC and a particular venture may not be random (Bottazzi et al., 2008; Sørensen, 2007). However, theoretically, VCs would not intentionally choose to invest in ventures with a high potential for product failures, as product failures may significantly damage a VC's reputation and venture's market value (Rhee & Haunschild, 2006; Thirumalai & Singh, 2011). Nonetheless, it could be possible that VCs with short investment horizons might prefer to invest in more mature ventures with a higher chance of exit that are more susceptible to product failures. Furthermore, from the perspective of ventures, ventures taking a more cautious and discreet approach in developing products may foresee VCs' pressure to expedite the commercialization processes and, thus, choose not to be invested by VCs with short investment horizons in the first place. In either of these cases, the investment decisions made by VCs and ventures *ex ante* may drive the proposed results of this study.

In order to distinguish the treatment effect of investment horizon, following prior studies, I controlled for potential selection bias in the analyses using a two-stage model (Bottazzi et al., 2008; Heckman, 1979; Ozmel & Guler, 2015). In the first stage, I predicted the probability that a particular venture receives investments from a particular venture capital fund (*likelihood of investment tie*) using a probit regression and computed the inverse Mills ratio based on the estimation. Following Sørensen (2007), I included both realized and unrealized investment pairs between all U.S. medical device venture and venture capital funds between 1992 and 2015. A

realized investment pair occurs when a venture is invested in by a particular venture capital fund in its first investment round as a lead investor. In the selection model, a realized pair has a value of 1, and a non-realized pair has a value of 0. For an exclusion restriction, following prior studies, I used *availability of venture capital funds* in the ventures' local geographic markets to address the non-random nature of the formation of investment relationships between ventures and VCs (Ozmel & Guler, 2015; Park & Tzabbar, 2016). The availability of venture capital funds in a certain geographic market affects a venture's likelihood of receiving venture capital funding from a particular investor, but it is unlikely that the availability of venture capital funds directly influences the venture's product failures.

I measured the *availability of venture capital funds* in the local geographic market by counting the total number of venture capital funds invested in the state in which the venture is located in each quarter when the venture seeks venture capital funding (i.e., its first venture capital investment) (Ozmel & Guler, 2015; Sørenson, 2007). In the first stage model, in addition to the exclusion restriction variable, I controlled for other covariates that could affect the match between a venture and venture capital fund, including *VC's investment horizon, fund performance, founder's experience, prior product failure count, product count*, *patent count*, *alliance count*, *venture age, first-time fund, VC's prior investment experience, VC's performance, VC's product failure count, VC's age,* and *same state*. After running the probit model, I calculated the inverse Mills ratio and used it as a control variable in the second stage model using a GEE model.

2.5 Results

2.5.1 Main Results

Table 1 reports the descriptive statistics and correlations for the variables used in the analysis. I report the results of the selection model in Table 2, in which I estimate the likelihood that a particular venture receives investments from a particular venture capital fund using a probit regression. As I predicted, the coefficient for *availability of venture capital funds*, the exclusion restriction, is negative and statistically significant ($\beta = -0.001$, $p < 0.001$). I calculated the inverse Mills ratio using this estimation and included it in all of the second stage models presented in Table 3 to control for the selection effect.

Table 2.1 Descriptive Statistics and Correlations

		Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1.	Product failure count	0.09	0.45																
2.	VC's investment horizon	3.39	2.20	**0.13**															
3.	Fund performance	0.20	0.18	0.02	**0.26**														
4.	Founder's expertise	0.30	0.46	-0.03	**0.11**	**0.09**													
5.	Prior product failure count	0.18	0.76	**0.24**	**0.16**	0.04	-0.04												
6.	Product count (log)	0.94	0.75	**0.13**	0.05	0.08	0.05	**0.15**											
7.	Patent count (log)	1.59	1.12	**0.08**	-0.06	**0.14**	**0.12**	0.06	**0.34**										
8.	Alliance count	0.08	0.39	0.00	0.04	**0.12**	0.02	-0.01	**0.08**	**0.13**									
9.	Venture age	8.22	4.61	**0.06**	**0.06**	**0.25**	-0.09	**0.15**	0.04	**-0.13**	0.02								
10.	Investment received (log)	2.31	1.23	**0.13**	-0.07	**0.36**	**0.13**	**0.15**	**0.22**	**0.31**	0.03	**0.19**							
11.	Time since investment	5.54	2.65	**0.07**	**-0.09**	**0.54**	0.01	**0.12**	0.03	0.01	**0.07**	**0.53**	**0.54**						
12.	First-time fund	0.17	0.37	-0.04	**0.08**	-0.04	**-0.05**	-0.02	**0.06**	-0.03	-0.01	**0.06**	**-0.11**	-0.03					
13.	VC's prior investment experience	6.24	6.18	**-0.07**	**-0.15**	0.00	**0.08**	**-0.11**	0.03	**0.12**	-0.03	**-0.13**	**0.27**	0.01	**-0.18**				
14.	VC's performance	0.29	0.61	0.01	**0.06**	**0.21**	-0.01	**0.06**	-0.02	0.01	0.01	**0.09**	**0.08**	**0.17**	**-0.09**	**-0.10**			
15.	VC's product failure count	0.85	1.52	0.03	0.00	**0.13**	0.02	**0.18**	0.04	0.02	-0.03	**0.10**	**0.25**	**0.17**	**-0.11**	**0.28**	0.01		
16.	VC's age (log)	2.76	0.59	**0.04**	**0.06**	**0.35**	**0.11**	0.04	0.02	**0.13**	0.04	**0.15**	**0.35**	**0.36**	**-0.46**	**0.18**	**0.14**	**0.13**	
17.	Same state	0.48	0.50	**-0.07**	**-0.22**	**-0.09**	-0.01	**-0.11**	**-0.05**	**0.07**	-0.04	**-0.14**	-0.02	-0.04	**-0.08**	**0.12**	**-0.05**	**-0.05**	**0.08**

Bolded pairwise correlations are significant at least at the 0.05 level. n=2,147.

Table 2.2 Selection Model Using Probit Regression

Variables	Model 1
Availability of venture capital	-0.001***
	[0.000]
VC's investment horizon	0.081***
	[0.007]
Fund performance	-0.875***
	[0.183]
Founder's expertise	0.012
	[0.030]
Prior product failure count	0.017
	[0.101]
Product count (log)	0.006
	[0.032]
Patent count (log)	-0.000
	[0.016]
Alliance count	-0.029
	[0.079]
Venture age	0.002
	[0.003]
First-time fund	0.073+
	[0.039]
VC's prior investment experience	0.038***
	[0.002]
VC's performance	-0.090
	[0.087]
VC's product failure count	0.028*
	[0.013]
VC's age (log)	-0.014
	[0.021]
Same state	0.626***
	[0.033]
Constant	-2.563***
	[0.103]
Log pseudolikelihood	-4342.296
Wald chi-squared	1340.76***
Observations	775,377

Standard errors in brackets
*** $p<0.001$, ** $p<0.01$, * $p<0.05$, + $p<0.1$

Table 3 reports the results of the second stage regression using the GEE model, predicting

VC-backed ventures' product failures. In the second stage model, after incorporating the selection

effect in venture capital investments by including the inverse Mills ratio calculated from the first

stage, the association between the ventures' product failures and VCs' investment horizon can be

attributed to the VCs' influence. Model 1 shows the results of the GEE model, including only the baseline control variables. Model 2 indicates that the coefficient for *VC's investment horizon* is negative and significant ($\beta = -0.139$, $p = 0.002$), suggesting that VC-backed ventures are associated with a greater number of product failures when they are invested in by VCs with short investment horizons. This result provides strong support for Hypothesis 1. The significance level holds in other specification where I included interaction terms (Models 3–5). The marginal effect of VCs' investment horizon is material: a decrease in VCs' investment horizon by one standard deviation from its mean value results in an increase in the number of annual product failures by 35.6%.

Table 2.3 Second Stage GEE Regression of Product Failures (Product Failure Count)

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
			DV: Product failure count		
VC's investment horizon			-0.139**	-0.157***	-0.206***	-0.221***
			[0.046]	[0.044]	[0.053]	[0.051]
VC's investment horizon x Fund performance			0.467*		0.439*
			[0.182]		[0.176]
VC's investment horizon x Founder's expertise				0.258**	0.254**
				[0.090]	[0.090]
Fund performance			-1.614*	-1.339+	-1.772*	-1.499+
			[0.776]	[0.792]	[0.752]	[0.766]
Founder's expertise			-0.453	-0.500+	-0.355	-0.396
			[0.290]	[0.293]	[0.286]	[0.290]
Prior product failure count	0.096	0.077	0.094	0.049	0.062
	[0.075]	[0.069]	[0.066]	[0.071]	[0.068]
Product count (log)	0.522***	0.498**	0.480**	0.509**	0.490**
	[0.152]	[0.157]	[0.155]	[0.161]	[0.159]
Patent count (log)	0.134	0.160	0.154	0.121	0.115
	[0.121]	[0.126]	[0.123]	[0.129]	[0.127]
Alliance count	-0.142	-0.199	-0.182	-0.245	-0.222
	[0.203]	[0.211]	[0.211]	[0.216]	[0.216]
Venture age	0.038*	0.024	0.019	0.016	0.012
	[0.017]	[0.017]	[0.018]	[0.018]	[0.019]
Investment received (log)	0.470**	0.450**	0.453**	0.463**	0.462**
	[0.154]	[0.143]	[0.142]	[0.148]	[0.147]
Time since investment	0.025	0.136*	0.127+	0.148*	0.138*
	[0.059]	[0.067]	[0.069]	[0.068]	[0.070]
First-time fund	-1.087*	-0.983*	-0.925*	-0.881*	-0.830+
	[0.437]	[0.414]	[0.415]	[0.426]	[0.426]
VC's prior investment experience	-0.089**	-0.073*	-0.071*	-0.071*	-0.068*
	[0.031]	[0.030]	[0.029]	[0.030]	[0.029]
VC's performance	-0.100	-0.048	-0.047	-0.034	-0.034
	[0.119]	[0.089]	[0.085]	[0.087]	[0.083]
VC's product failure count	-0.086	-0.052	-0.049	-0.057	-0.056
	[0.091]	[0.090]	[0.088]	[0.092]	[0.091]
VC's age (log)	-0.156	-0.228	-0.256	-0.241	-0.265
	[0.243]	[0.269]	[0.273]	[0.276]	[0.280]
Same state	-0.502+	-0.360	-0.376	-0.382	-0.404
	[0.290]	[0.293]	[0.284]	[0.280]	[0.273]
Inverse Mills ratio	-0.128	-0.087	-0.112	-0.165	-0.189
	[0.231]	[0.221]	[0.224]	[0.228]	[0.232]
Constant	-2.935*	-3.122**	-2.818**	-2.925**	-2.623*
	[1.261]	[1.050]	[1.042]	[1.081]	[1.072]
Year fixed effects	Included	Included	Included	Included	Included
Wald chi-squared	360.25***	414.26***	431.01***	316.33***	333.03***
Observations	2,147	2,147	2,147	2,147	2,147
Number of ventures	345	345	345	345	345

Robust standard errors clustered at the venture-level are in brackets.

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Model 3 shows the evidence for Hypothesis 2. As predicted, the coefficient of the interaction term between *VC's investment horizon* and *fund performance* is positive and significant ($\beta = 0.467$, $p = 0.009$). This result indicates that the negative effect of VCs' investment horizon on the rate of product failures decreases as VCs' fund performance increases, providing strong support for Hypothesis 2. The economic significance of this result shows that at the mean level of fund performance, one standard deviation decrease in VCs' investment horizon from its mean increases product failures by 41.1%. However, when the fund performance variable is one standard deviation above its mean, product failures increase only by 17.4%. Model 4 includes an interaction term between *VC's investment horizon* and *founder's experience*. The coefficient of this interaction term is positive and statistically significant ($\beta = 0.258$, $p = 0.004$), suggesting strong support for Hypothesis 3. This result indicates that when ventures' founders lack technical expertise, one standard deviation decrease in VCs' investment horizon increases product failures by 57.1%. However, when founders have technical expertise, one standard deviation decrease in VCs' investment horizon increases product failures only by 10.9%. The statistical significance of the interaction terms remains consistent in Model 5, which includes both interaction terms.

2.5.2   Robustness Checks

To validate the main results, I performed several additional analyses. To ensure robustness, I ran the analysis using an alternative dependent variable, a binary measure of whether a venture experienced a recall in a given year (*product failure dummy*). As presented in Table 4, after controlling for the selection effect, I find results consistent with the arguments.

Table 2.4 Second Stage GEE Regression of Product Failures (Product Failure Dummy)

	Model 1	Model 2	Model 3	Model 4	Model 5
		DV: Product failure dummy			
VC's investment horizon			-0.155**	-0.169***	-0.234***	-0.245***
			[0.050]	[0.050]	[0.052]	[0.051]
VC's investment horizon x Fund performance			0.429*		0.398*
			[0.199]		[0.198]
VC's investment horizon x Founder's expertise				0.263*	0.259*
				[0.120]	[0.123]
Fund performance			-1.383+	-1.108	-1.600*	-1.309
			[0.833]	[0.841]	[0.805]	[0.813]
Founder's expertise			-0.610*	-0.645*	-0.504+	-0.538+
			[0.279]	[0.283]	[0.278]	[0.281]
Prior product failure count	0.178+	0.164+	0.173+	0.127	0.136
	[0.093]	[0.091]	[0.091]	[0.092]	[0.092]
Product count (log)	0.599***	0.597***	0.580***	0.605***	0.588***
	[0.153]	[0.152]	[0.152]	[0.154]	[0.154]
Patent count (log)	0.200+	0.233*	0.232*	0.202+	0.201+
	[0.106]	[0.110]	[0.110]	[0.112]	[0.112]
Alliance count	-0.213	-0.243	-0.237	-0.290	-0.277
	[0.247]	[0.237]	[0.241]	[0.234]	[0.236]
Venture age	0.040+	0.029	0.026	0.023	0.020
	[0.022]	[0.020]	[0.020]	[0.019]	[0.020]
Investment received (log)	0.316*	0.335**	0.339**	0.364**	0.364**
	[0.135]	[0.126]	[0.126]	[0.132]	[0.131]
Time since investment	0.012	0.104	0.093	0.117+	0.105
	[0.063]	[0.071]	[0.072]	[0.071]	[0.072]
First-time fund	-0.904+	-0.805+	-0.768+	-0.716+	-0.685
	[0.464]	[0.426]	[0.430]	[0.435]	[0.437]
VC's prior investment experience	-0.054*	-0.043*	-0.043+	-0.042+	-0.041+
	[0.024]	[0.022]	[0.022]	[0.022]	[0.022]
VC's performance	-0.005	0.023	0.019	0.031	0.027
	[0.088]	[0.079]	[0.079]	[0.077]	[0.077]
VC's product failure count	-0.026	0.006	0.006	0.002	0.001
	[0.072]	[0.071]	[0.070]	[0.072]	[0.071]
VC's age (log)	-0.164	-0.215	-0.240	-0.225	-0.248
	[0.297]	[0.304]	[0.309]	[0.308]	[0.313]
Same state	-0.275	-0.158	-0.173	-0.167	-0.186
	[0.262]	[0.261]	[0.256]	[0.252]	[0.249]
Inverse Mills ratio	-0.101	-0.058	-0.081	-0.122	-0.145
	[0.243]	[0.229]	[0.231]	[0.232]	[0.234]
Constant	-4.062**	-4.054**	-4.074**	-4.244**	-3.981**
	[1.536]	[1.356]	[1.331]	[1.358]	[1.350]
Year fixed effects	Included	Included	Included	Included	Included
Wald chi-squared	144.01***	203.24***	203.24***	218.85***	225.28***
Observations	2,147	2,147	2,147	2,147	2,147
Number of ventures	345	345	345	345	345

Robust standard errors clustered at the venture-level are in brackets.

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

In Table 5, I estimated the *product failure hazard* at the product level using an event history analysis. As the main empirical approach adopts a firm-level unit of analysis, it does not control for heterogeneity in the risks of product failure across different product types, which may create bias in the main results. For instance, compared with ventures invested in by VCs with long investment horizons, ventures invested by VCs with short investment horizons may develop certain types of products that are systematically more prone to suffer from product failures. To address this concern, I used an event history analysis to estimate the hazard of product failure of each product with product class- and type-fixed effects to control for heterogeneity across different product categories. The FDA classifies approved medical devices into Class I, II, or III depending on the level of risk that the device poses to patients: Class III being the riskiest and Class I being the least risky. To control for this classification-specific effect, I included dummy variables for each product class (*product class fixed effects*). Furthermore, I included dummy variables for each product based on their therapeutic areas, as designated by the FDA (*product therapeutic area fixed effects*), because the hazard of product failure may vary depending on the characteristics of the devices' medical specialties (e.g., Zuckerman et al., 2011).[11] I also included a control variable *product review time,* which is the time difference between FDA approval and application dates. A longer review time could mean that the product's underlying technology is novel (Stern, 2014) and that the product could be more susceptible to failures. Because product recall events can occur more than once for each product, I used an extension of the Cox model, which can accommodate for multiple failure events. To account for the time between multiple failure events, I employed a common gap method, which resets the clock after each failure event. To take the lack of

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[11] The FDA uses 19 medical specialties to classify medical devices (i.e., anesthesiology, cardiovascular, dental, etc.). Zuckerman et al. (2011) show the variations in recall rates among the medical devices categorized in different medical specialties.

independence between failure events into account, I used the Andersen-Gill model, a commonly used correction method using robust standard errors to account for correlation (Anderson & Gill, 1982; Furr, 2019). In this analysis, I examined a time to recall for the sample ventures' products since the products were first introduced in the market.[12] I also included all control variables used in the main model. The results presented in Table 5 demonstrate that the product-level analysis produced consistent results with the firm-level analysis.

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[12] To be consistent with the main analysis, I tracked whether each product was recalled up to 10 years since it had been first marketed. I shortened the time period to five and seven years, and the results are similar to the main results.

Table 2.5 Product Level Analysis Using Multievent Cox Regression

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
VC's investment horizon		-0.102*	-0.113**	-0.163***	-0.161***
		[0.040]	[0.039]	[0.046]	[0.046]
VC's investment horizon x Fund performance			0.827**		0.678**
			[0.284]		[0.252]
VC's investment horizon x Founder's expertise				0.308*	0.250*
				[0.123]	[0.101]
Fund performance		-0.312	-0.301	-0.576	-0.513
		[0.857]	[0.827]	[0.789]	[0.798]
Founder's expertise		-0.201	-0.296	-0.239	-0.297
		[0.207]	[0.209]	[0.210]	[0.214]
Product review time	0.182	0.220+	0.180	0.195+	0.163
	[0.128]	[0.126]	[0.118]	[0.117]	[0.114]
Prior product failure count	0.065	-0.056	0.002	-0.118	-0.051
	[0.103]	[0.129]	[0.122]	[0.145]	[0.139]
Product count (log)	-0.330*	-0.369*	-0.434**	-0.344*	-0.403*
	[0.156]	[0.161]	[0.159]	[0.165]	[0.162]
Patent count (log)	0.276*	0.276*	0.257*	0.211*	0.199+
	[0.123]	[0.120]	[0.111]	[0.104]	[0.104]
Alliance count	-0.272	-0.282	-0.234	-0.278	-0.231
	[0.211]	[0.227]	[0.200]	[0.210]	[0.196]
Venture age	0.009	0.007	-0.007	-0.003	-0.014
	[0.016]	[0.016]	[0.017]	[0.016]	[0.018]
Investment received (log)	0.297**	0.270**	0.275**	0.224*	0.236*
	[0.099]	[0.091]	[0.092]	[0.090]	[0.092]
Time since investment	-0.006	0.072	0.055	0.095	0.076
	[0.059]	[0.060]	[0.064]	[0.063]	[0.066]
First-time fund	-0.981**	-0.954**	-0.821*	-0.805*	-0.719*
	[0.373]	[0.355]	[0.333]	[0.336]	[0.329]
VC's prior investment experience	-0.101***	-0.087**	-0.078**	-0.083**	-0.075**
	[0.031]	[0.029]	[0.025]	[0.027]	[0.025]
VC's performance	-0.001	0.006	0.013	0.003	0.011
	[0.107]	[0.109]	[0.097]	[0.109]	[0.098]
VC's product failure count	0.076	0.091	0.081	0.094	0.082
	[0.067]	[0.070]	[0.070]	[0.072]	[0.072]
VC's age (log)	-0.238	-0.393	-0.413	-0.381	-0.398
	[0.217]	[0.250]	[0.265]	[0.252]	[0.264]
Same state	-0.242	-0.138	-0.158	-0.106	-0.135
	[0.204]	[0.215]	[0.213]	[0.221]	[0.217]
Product class fixed effects	Included	Included	Included	Included	Included
Product therapeutic area fixed effects	Included	Included	Included	Included	Included
Year fixed effects	Included	Included	Included	Included	Included
Log pseudolikelihood	-1802.01	-1795.55	-1784.42	-1785.56	-1778.04
Observations	2,650	2,650	2,650	2,650	2,650

Robust standard errors clustered at product-level are in brackets

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

2.6 Conclusion and Discussion

Previous studies have widely documented the positive effects of interorganizational collaborations and, relatedly, venture capital investments on ventures' survival and performance (Eisenhardt & Schoonhoven, 1996; Gulati & Higgins 2003; Hoehn-Weiss & Karim 2014; Ozmel et al., 2013b; Stuart, 2000). In this paper, I aim at providing a more balanced perspective to the above studies by shedding more light on the (unexpected) negative effects of interorganizational partnerships on ventures' innovation outcomes. I am particularly interested in the potential side effects of venture capital investments on the rate of ventures' product failures as product failures are important indicators of the issues associated with the ventures' underlying capabilities and prospects (Thirumalai & Sinha, 2011).

My main argument is that VCs with a short investment horizon may have high incentives to direct their portfolio companies to expedite their product development process and rollouts in order to increase the portfolio companies' likelihood of exit events. In other words, I suggest that even though VCs engage in various value-enhancing activities that will help ventures achieve higher performance, under certain circumstances, the VCs' heavy focus on taking their portfolio companies to successful exit events might generate unwanted consequences, such as problems associated with the ventures' innovative quality. The empirical evidence shows that as the VCs' investment horizon decreases, the portfolio companies are more likely to experience product failures.

Furthermore, I took a contingency perspective to show that the negative association between VCs' investment horizon and ventures' product failures is amplified when VCs' funds perform poorly because such VCs are likely to be under greater pressure to exit their portfolio companies. In addition, I also show that the negative association between VCs' investment horizon and ventures' product failures is decreased when the VC has a limited influence to affect the

venture's product development process. I show that if the venture's founders have expertise in product development and manufacturing process, the VCs have marginally less impact on the pace of the product development process and, in turn, product quality.

In this paper, I also exerted much effort to address potential endogeneity issues. For instance, if the VCs' investment horizon is somehow related to the ventures' innovative path and direction, then it is possible that the results would be generated by endogenous process. To address this issue, I have used a two-stage model with various control variables, such as ventures' previous product failure history and product introduction rates. Furthermore, I have repeated the analyses at the product level, which enables me to further control for the product's technological category and other product characteristics. Hence, I am confident that the results indeed reflect a positive association between VCs' short investment horizon and ventures' product recall.

I contribute to previous studies in many dimensions. First, I complement previous research on interorganizational ties in general and on VCs' investments in particular by highlighting the cost of forming interorganizational ties (i.e., forming investment ties with VCs in this context) (Hsu, 2004; Joshi & Nerkar, 2011; Lee & Wahal, 2004; Ozmel & Guler, 2015; Pahnke et al., 2015b). Given that most studies on venture capital investment are heavily focused on the value-adding effects of forming interorganizational collaborations with VCs (e.g., Stuart et al., 1999; Bottazzi et al., 2008), this paper extends these studies by identifying the costs of receiving venture capital investments. Second, I contribute to the studies on innovation and new product development. Surprisingly, even though the studies on product development put a heavy emphasis on successful product developments, the flip side, which is the negative outcomes associated with product development, is largely neglected (e.g., Thirumalai & Sinha, 2011). In this paper, I aim to shed more light on the negative outcomes of product development and analyze potential factors

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that lead to product failures associated with safety issues that might have a significant ramification for firm performance and innovation. Third, I add to the broad literature on corporate governance of public and private firms by showing that even the same type of investors (such as VCs in this context) can adopt different investment strategies based on their incentives, which, in turn, affect their investees' strategies and performance.

This study has several limitations that offer opportunities for future research. First, although this study provides empirical evidence using detailed information on ventures and carefully designed empirical strategies, it does not directly show whether the suggested mechanisms actually explain the hypothesized outcomes. Therefore, qualitative information gathered through surveys and interviews can be helpful in understanding whether VCs' short time horizon drives VCs to pressure ventures to hasten ventures' product innovation. With this approach, future studies can help deepen our understanding of VCs' incentive to exit their portfolio companies early and how such an incentive could negatively influence ventures' development and viability. For example, researchers may be able to examine how a VC's incentive can affect the other aspects of ventures' other corporate development activities (e.g., alliances and development of human capital).

To provide empirical support for the hypotheses, I analyzed the product failures of VC-backed ventures in the U.S. medical device industry. Future studies can incorporate other industries into research settings where ventures' innovative products are important quality signals in the exit markets because VCs' main goal is to take their portfolio companies to exit events, which is a well-established phenomenon (e.g., Gompers & Lerner, 2000a). Furthermore, future studies can analyze the effects of VCs' investment horizons on ventures' other dimensions of innovation, such as the ventures' propensity to pursue explorative versus exploitative innovation

paths. Exploration is a risky activity that might lead to novel innovations yet entail high uncertainty. On the other hand, exploitation is about the marginal improvement of the existing technology. Hence, it would be interesting to see the role of VCs' investment horizon on the VCs' incentives and preferences to guide ventures to pursue different innovation paths.

Moreover, future studies can extend this paper by further analyzing the conditions under which venture capital investments might have side effects on a venture's innovation. In this paper, I suggested that the technological experience of ventures' founders can help the venture resist VCs' incentives to accelerate the product rollout process. Future studies can further investigate what other kinds of venture characteristics can curb VCs' incentives to do so.

Future studies may extend this study by exploring how other types of interorganizational relationships guide a focal firm to modify its innovation process and pace. The venture capital investment relationship provides an ideal setting to examine the suggested mechanisms in which partners have different incentives (Arthurs et al., 2008; Ozmel & Guler 2015; Pahnke et al., 2015b). However, ventures also rely on other types of interorganizational relationships, such as R&D alliances, in which partners may have divergent interests (e.g., Diestre & Rajagopalan, 2012; Khanna, Gulati, & Nohria, 1998). Therefore, future studies can examine how the diverging interests between a focal venture and its other types of interorganizational partners may influence a venture's innovation.

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CHAPTER 3.   EFFECT OF ACQUISITIONS ON PRODUCT FAILURES

3.1   Introduction

Mergers and acquisitions (M&As) play an important role in a firm's innovation and new product development. Particularly in industries in which the ability to generate new technologies and introduce innovative products continuously is a crucial factor for a firm's competitive advantage, many firms choose to extend their technological resources and capabilities through acquisitions (Ahuja & Katila, 2001; Cloodt, Hagedoorn, & Van Kranenburg, 2006). A substantial body of work in strategic management and innovation has advanced our understanding of how firms make use of acquisitions to obtain external resources to innovate. For instance, prior studies have asserted that through acquisitions, firms enjoy opportunities for organizational learning by obtaining highly developed technical expertise, research and development (R&D) know-how, and a specific new technological domain (e.g., Arora, Belenzon, & Rios, 2014; Arora & Gambardella, 1990; Hitt, Hoskisson, & Ireland, 1990). Furthermore, studies suggest that access to external know-how through acquisitions helps a firm reconfigure the efficiency of internal efforts to seek innovations in a complementary manner (Cassiman & Veugelers, 2006). At the intersection of acquisitions and innovation, extant literature has been identifying the benefits of acquiring new technology and how such acquisitions help firms achieve greater innovation outcomes (e.g., Ahuja & Katila, 2001; Colombo & Rabiosi, 2014; Makri, Hitt, & Lane, 2010; Ransbotham & Mitra, 2010).

Although acquisitions can be an effective way to enhance firms' innovation outcomes for those competing in the high-tech sector, they may raise other underexplored issues related to selecting and managing acquired resources and organizations. Research in strategic management and finance has suggested that M&As often do not create, but rather destroy, firm value (Berger

& Ofek, 1996; Lys & Vincent, 1995; Seth, Song, & Pettit, 2002). On one hand, unsuccessful acquisitions are attributed to information asymmetry between acquirers and potential targets, in which targets may attempt to disguise information regarding their prospective resources that would lower their perceived value to acquirers (Balakrishnan & Koza, 1993; Coff, 1999; Cuypers, Cuypers, & Martin, 2017; Reuer & Ragozzino, 2012; Reuer, Tong, & Wu, 2012). Such information asymmetries may lead to acquirers overbidding for targets or selecting the wrong targets in the first place (Reuer & Ragozzino, 2008; Shen & Reuer, 2005). On the other hand, organizational dissonance between acquirers and acquired firms may arise during the acquisition process, and the expected value creation from acquisitions may not be realized post-acquisition (Haspeslagh & Jemison, 1991; Jemison & Sitkin, 1986; Puranam, Singh, & Zollo, 2006).

Despite the known downsides of acquisition, existing literature on acquisition has paid less attention to the costs of acquisition and its impact on acquiring firms' innovation and new product development. Therefore, in this paper, I investigate how acquisitions can influence acquiring firms' innovation outcomes negatively and examine underlying mechanisms that explain the phenomenon. In doing so, I investigate whether firms' product failure rates are contingent on their engagements in acquisitions. Furthermore, by incorporating research on value-destroying acquisitions, I propose and empirically test underlying mechanisms that explain the relationship between acquisitions and product failures. I suggest and find that adverse selection and post-acquisition integration problems impose substantial costs on firms pursuing acquisitions.

I examined product failures among U.S. medical device manufacturers during the 2003–2016 period, a setting characterized by active M&As (International Trade Administration, 2016) and strict regulation of product failures (Ball, Macher, & Stern, 2019; Thirumalai & Sinha, 2011). In the empirical analysis, I performed two sets of analyses at both firm- and product-levels. In the

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firm-level analysis, I sought to establish an association between acquisitions and product failures. I found a positive association between acquisition activities and product-failure rates, measured by product recall volume. I also found that firms pursuing related acquisitions in terms of product portfolios experience fewer recalls. Product-level analysis enables me to pinpoint products directly associated with acquisitions (i.e., products that acquired firms developed after being acquired) and identify the characteristics of acquired firms that developed the product so that I could test the proposed mechanisms underlying the relationship between acquisition and product failure. In the product-level analysis, I found evidence that both information asymmetry and integration problems lead to firms experiencing increases in the risk of product failures.

I attempt to make several contributions with this study. First, previous studies have argued that acquisition is an effective means through which firms can obtain external resources and technologies to enhance their capabilities (e.g., Ahuja & Katila, 2001; Cassiman & Veugelers, 2006; Makri et al., 2010). However, this stream of literature has paid less attention to the downsides of firms' efforts to obtain external resources and technologies through acquisitions. Therefore, in this study, I attempt to fill this literature gap in corporate strategy and innovation by highlighting the trade-off between resource acquisition and product failure. Second, the proposition in this study resonates with diseconomies of time compression (Dierickx & Cool, 1989) in that acquisitions may be one of the fastest ways to acquire established products or develop innovative products, yet simultaneously can include a high risk of product failure. Thus, the results provide new evidence of acquisitions' "dark side." Finally, the literature on new product development highlights successful product development by examining the frequency or speed of new product introductions (Huang, Vir Singh, & Srinivasan, 2014; Kremer, 1998; Schoonhoven, Eisenhardt, & Lyman, 1990). Despite product failures' impacts on firms, shareholders, and consumers, it is surprising that so

little research has examined causes of product failures. The present study highlights that product failures are a critical dimension when examining ventures' product innovation outcomes.

3.2 Theory and Hypotheses Development

3.2.1 Effect of Acquisitions on Product Failures

The creation of novel knowledge is a critical purpose of innovative organizations. Particularly in high-tech industries, new capabilities and technologies acquired externally are important resources in the innovation and new product development process (Hitt et al., 1990). Firms complement internal research and development (R&D) efforts with acquisitions that enable the development of new knowledge and technology by combining existing resources with newly added ones (Arora et al., 2014; Cassiman & Veugelers, 2006). This matters because relying solely on in-house R&D may not be sufficient to develop new products effectively, and firms may search for and integrate appropriate external resources. For instance, Laursen and Salter (2006) show that acquiring knowledge in the external market facilitates the absorption of critical knowledge. Similarly, Zhou and Li (2012) suggest that high-tech firms with a deep knowledge base may rely more on external market options than internal knowledge development to obtain new knowledge. Grigoriou and Rothaermel (2017) argue that a firm's success in developing new products using external knowledge sourcing is dependent on the firm's internal knowledge properties (e.g., re-combinatory potentials). Generally, prior studies have suggested that benefits can be reaped from potential synergies between internal and external resources.

To acquire external resources, firms implement distinct corporate-level strategies, such as R&D outsourcing (e.g., Grimpe & Kaiser, 2010), strategic alliances (e.g., Inkpen, 2000; Kogut & Zander, 1993), and acquisitions (e.g., Ahuja & Katila, 2001; Steensma & Corley, 2000). Each

external resource acquisition mode has its own characteristics. For instance, firms in non-equity alliances, such as licensing and R&D collaborations, do not have much control over their counterparts and the outcome of collaboration process (Chiesa & Manzini, 1998). On the other hand, equity modes (i.e., M&As) for external resource acquisition are characterized by transacting parties' strong commitment and substantial governance controlling the acquisition process and facilitating the internalization of newly obtained technological resources (Villalonga & McGahn, 2005). Furthermore, equity acquisitions enable firms to obtain organizational knowledge quickly and access deeper and broader levels of knowledge (Auster, 1992; Jones, Lanctot Jr., & Teegen, 2001).

However, obtaining new resources through acquisitions often can be challenging. The acquisition literature demonstrates that high information asymmetry exists between acquirers and potential targets that could lead to adverse selection problems (Reuer & Ragozzino, 2008; Shen & Reuer, 2005). Particularly in knowledge-intensive industries, technology-based resources generally are more costly and difficult to evaluate than tangible resources (Higgins & Rodriguez, 2006). Furthermore, potential targets may attempt to disguise information that would lower their perceived value, thereby hiding it from potential acquirers and making it even more difficult for acquirers to assess the value of targets' resources (Balakrishnan & Koza, 1993; Reuer & Ragozzino, 2012: Reuer, Tong, & Wu, 2012). As a consequence, when potential target firms have superior information advantages over acquiring firms in terms of the true value of their resources over acquiring firms, acquiring firms tend to become the victim of the winner's curse and overpay for the target (Chatterjee & Wernerfelt, 1991; Coff, 1999; Higgins & Rodriguez, 2006). Furthermore, acquirers with information disadvantages might not appraise the potential value of target firms' resources properly, leading to suboptimal choices in selecting target firms.

Another difficulty with acquisitions is that firms may integrate target firms ineffectively. Extant research has emphasized that the extent to which the potential for synergies from acquisitions can be realized depends on acquiring firms' ability to coordinate and integrate acquired firms during the post-acquisition process (Haspeslagh & Jemison, 1991; Jemison & Sitkin, 1986). However, on many occasions, incongruence in acquiring and acquired firms' administrative practices, cultural practices, and personnel characteristics lowers the degree to which merged firms are integrated with regard to routine operations in the post-acquisition process (Jemison & Sitkin, 1986). Such organizational dissonance between acquiring and acquired firms is particularly problematic in the technology acquisition context because the advantages of gaining new knowledge and capabilities from acquisitions may decrease as dissonance intensifies. In the absence of smooth organizational integration, acquiring and acquired firms may experience a lack of group conventions, common language, information communication channels, and group identity (Ibarra, 1993), limiting acquiring firms from exploiting acquired firms' knowledge (Ambos & Ambos, 2009). Furthermore, organizational integration often requires that newly combined firms be reorganized, which entails organizational adjustments that change routines of previously separate firms (Colombo & Rabiosi, 2014; Zollo & Singh, 2004). However, such reorganization occasionally elicits conflicts among firms' employees, destroying potential benefits from the acquisition (Puranam et al., 2006). In this context, prior studies have documented that acquisitions create disruptions among R&D personnel that often lead to the loss of specific human capital and, subsequently, harm post-acquisition innovation performance (Colombo & Rabiosi, 2016; Kapoor & Lim, 2007).

Taken together, I argue that firms pursuing acquisitions will be exposed to these critical challenges, which will be reflected in their innovation outcomes. Specifically, I expect that firms

involved with greater acquisition activities will experience higher product failure rates. Thus, I propose:

Hypothesis 1. Acquisition activity is positively associated with product failures.

If firms' increase in acquisitions is, indeed, associated with a greater number of product failures, I expect that the effect of acquisitions on product failures is more prevalent when information asymmetry and post-acquisition coordination problems are more severe. In the following hypothesis, I propose that the relatedness between acquiring and acquired firms in terms of their product portfolios may likely decrease the impact of acquisition on product failures.

First, relatedness between acquiring and target firms may be important in lowering information asymmetry between both groups of firms and, thus, may help acquiring firms experience fewer product failures post-acquisition. In the case of tech-focused acquisitions, target firms' knowledge and technology-based assets are difficult to evaluate (Higgins & Rodriguez, 2006). However, when acquiring firms have substantial knowledge and familiarity with the underlying technology in target firms' products prior to acquisitions, they may be able to lower their potential information disadvantage before they acquire them. In particular, when acquiring and acquired firms' resources are similar, acquiring firms may be able to assess target firms' resources more effectively because acquirers may have a decent understanding of these resources (Coff, 1999). For instance, Stuart (1998) argues that firms possessing similar technological knowledge make the requirement for costly investments in understanding transaction partners' technologies unnecessary. Furthermore, engaging in similar research with potential targets enables acquirers to evaluate targets' research more effectively (McCann, Reuer, & Lahiri, 2016; Rosenkopf & Nerkar, 2001). Therefore, similarities in technological resources between acquiring and acquired firms are a critical factor for information and adverse selection risk (McCann et al.,

2016). Acquiring a target firm with a related portfolio of products may help firms identify potential targets that have inferior products or underlying technologies that could lead to product failures before they select the target.

Second, relatedness between acquiring and target firms may be critical in mitigating the risk of coordination problems that acquiring and acquired firms experience post-acquisition and, thus, may help acquiring firms experience fewer product failures. In particular, relatedness in acquiring and acquired firms' product portfolios is critical for lowering post-acquisition integration problems, as underlying knowledge in developing products is related. Similarities between the acquiring firm's existing knowledge and newly acquired knowledge may help the acquiring firm understand, assimilate, and apply acquired knowledge due to the acquiring firm's absorptive capacity (Cohen & Levinthal, 1990). If knowledge similarities between acquiring and target firms increases, the extent to which acquiring firms can combine resources may become greater. Furthermore, synergy potentials in shortening the innovation process, sharing technological expertise, and engaging in collaborative projects also can be expected from acquiring related knowledge through acquisitions (Hagedoorn & Duyster, 2002). On the other hand, acquiring knowledge distant from the acquiring firm's knowledge base may incur high integration costs (Argyres, 1996; Huang & Chen, 2010; Katila & Ahuja, 2002). Integrating distant knowledge requires significant time and effort because such knowledge is more intricate and demanding to integrate than similar knowledge (Grant, 1996). As the knowledge portfolio becomes more diversified after acquiring distant knowledge, acquisition of distant knowledge may lead to firms falling into an overdiversification trap, in which excessive coordination and integration costs from newly acquired knowledge may be needed (Lin, Chen, & Wu, 2006). Subsequently, when acquiring overly distant knowledge, internal efforts to integrate the newly acquired knowledge

may surpass the advantages from synergy potentials and negatively affect the firm's innovation performance (Huang & Chen, 2010). Therefore, acquiring a target firm with a related portfolio of products may help firms lower the risk of integrating newly acquired resources and technologies that potentially could lead to product failures. Taking these arguments together, I propose the following hypothesis:

Hypothesis 2. The number of related acquisitions is negatively associated with product failures.

Note that a positive association between acquisition and product failure could be the result of firms adversely selecting target firms due to information asymmetry pre-acquisition or firms having a problem integrating newly acquired target firms post-acquisition. The main empirical model that used a firm-level analysis does not distinguish between these two possibilities. I am only claiming that a relationship between acquisitions (and related acquisitions) and product failures exists without separating the effects of two possible mechanisms. However, in the supplementary analyses section, I attempt to test whether these two underlying mechanisms explain how acquisitions may lead firms to experience greater rates of product failures.

3.3   Methodology

3.3.1   Empirical Setting

In this paper, I investigate how external knowledge acquisition can influence firms' product failures. In doing so, I examine product recalls as a proxy for product failures experienced by acquiring firms competing in high-tech industries. I believe that product recalls reasonably represent failures in developing new products because they are an apparent sign that a firm was unsuccessful in providing reliable, quality products and meeting customers' needs and safety

requirements (Liu & Shankar, 2015), thereby incurring substantial financial, legal, and reputational costs to the firm (Davidson III & Worrell, 1992; Mashaw & Harfst, 1990; Thirumalai & Sinha, 2011). For instance, Bromiley and Marcus (1989) find that financial markets react negatively to firms' product recalls immediately around the announcement day. Similarly, Rhee and Haunschild (2006) find that firms experiencing product recalls lose market share during the following period. Furthermore, firms' product recalls also may deteriorate their competitiveness in a given product market, as they are forced to pull out their products from the market, providing an opportunity for competitors to capitalize on such events (Ball et al., 2019).

To construct the sample, I selected U.S. public firms in the medical device industry to examine the relationship between acquisitions and product failures. I believe that the medical device industry is an appropriate empirical setting for this study for several reasons. First, M&A deals are common in the medical device sector. The industry's highly competitive nature often motivates firms, especially large players, to enter M&A deals with smaller counterparts (notably innovative startups) to increase their product offerings and learn innovative technologies (International Trade Administration, 2016).

Second, product recalls frequently occur and are observable in this sector. The FDA's Center for Devices and Radiological Health (CDRH) regulates medical devices, both as a pre-market gatekeeper and as a post-market regulator. First, the CDRH oversees the new product submission process by reviewing whether the products are safe and effective for patients before they reach the commercial market. After the devices are released into the market, the CDRH monitors the safety and effectiveness of the approved devices. One of the ways in which the CDRH ensures patient safety is by demanding that medical device manufacturers and hospitals report any malfunctions in medical devices to CDRH. When such defects are found to be systematic, the

medical device firms voluntarily recall their products overseen by the CDRH (Ball et al., 2019). Therefore, medical device manufacturers recall their products when manufacturing defects, functional defects, and unexpected side effects that present a potential threat to patients' well-being are identified. As a result, manufacturers of such recalled products suffer great financial and reputational losses (Chen, Ganesan, & Liu, 2009; Rhee & Haunschild, 2006), and physicians and patients suffer as they must adjust to and/or replace these defective products and possibly experience unforeseen injuries or deaths (Thirumalai & Sinha, 2011).

3.3.2   Data and Sample

Testing the hypotheses of this study required information on medical device recalls, acquisitions, parent-subsidiary links, market performance of firms recalling devices, and firm characteristics. I collected this information from several key sources: the FDA's medical device recall database; the FDA's premarket notification and approval databases; Thomson Financial SDC; the Compustat database via Wharton Research Data Services; 10-K documents; and the Crunchbase database.

I constructed the sample by first identifying U.S. public firms with at least one FDA-approved medical device using the FDA's premarket notification and approval databases. I then assigned each approved product to public firms and their subsidiaries as identified in the firms' 10-K reports. Using the recall database, I identified whether and when each product was recalled. The database includes the name of the product being recalled, its unique product identifier, the recalling firm names, the first recall date, and the reason for the recall. Although the FDA provides product recall data from 2003 to 2019, I set the sample from 2003 to 2016 because I conjectured that the number of new products that the FDA listed would affect the probability of product recall and because many recall cases initiated after 2016 are still ongoing. I traced prior product recall

cases and the filing of new products, and I focused on the recall cases that have been completed. In the sample, out of 392 firms, 296 experienced at least one product recall incident. I drew on the Thomson Financial SDC database to obtain information on firms' acquisition deals.

3.3.3   Measures

Dependent variable. Following extant studies (Liu & Shankar, 2015; Thirumalai & Sinha, 2011; Wowak, Manor, & Wowak, 2015), I selected the number of product recalls as a measure for product failures. *Product failure count$_{it}$* is a count variable indicating the number of recalls that firm *i* initiated in a given year *t*.

Independent variables. The first independent variable is a firm's acquisition activity in a given year *t* – 1 (*acquisition intensity*). The variable represents cost outflow or equivalent values used for corporate acquisitions, such as the acquisition of additional ownership, assets regarding M&A, additional costs of an acquisition, net assets of acquired businesses, and acquired companies' property, plants, and equipment.[13] I obtained the information from Compustat and cross-validated it with the firm's 10-K document. To capture acquisition intensity, I scaled the sum of the values by a firm's total assets. As an alternative to acquisition intensity, I also used the *number of acquisitions* that a firm made in the past five years.

The second variable is the *number of related acquisitions* in the past five years. To operationalize this variable, I first measured product portfolio distance between acquirer-acquired firm pairs previous to year *t*. The product portfolio distance was calculated first by aggregating products by each firm and tabulating the percentage of assignments in each product's therapeutic

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[13] Each transaction's payment method can be cash-only, stock-only, or both cash and stock. Public companies should report the total value of each acquisition in their quarterly or annual reports. The variable captures the total paid value for acquisitions in a given year.

area. I then calculated the Euclidean distances between two vectors representing the product's therapeutic areas to which each firm's product is assigned.[14] The product portfolio distance between the acquiring firm i and the target firm j is defined as:

$$\sqrt{\sum_{k=1}^{N}\left(p_i^k - p_j^k\right)^2}$$

N is the number of therapeutic area dimensions represented by all products used in this study (19 therapeutic areas). Ratio p_i^k represents the ratio of the number of products in product therapeutic area k assigned to acquiring firm i to the total number of products assigned to firm i. If acquirer-acquired firms have similar product portfolios, this variable would have a relatively low value. Among acquisitions with different distance values, I split the product portfolio similarity into quartiles, from lowest to highest, and I coded these acquisitions in the first quartile as the related acquisitions and counted the related acquisitions that an acquiring firm i implemented in the past five years.

Control variables. I incorporated several control variables in the firm-level analysis to capture the effects from other possible product recall determinants and ruled out alternative explanations. I controlled for *advertisement intensity*, measured by a firm's advertisement expenditures, scaled by its total assets, to account for the fact that a firm that engages in more advertising is likely to be more sensitive to product recalls (Chen et al., 2009). I controlled for a set of financial status variables that might affect a firm's recall behaviors: *cash*, *debt to equity*, and operating performance measured as *ROA*. I also included the *number of prior product failures* in the past five years, considering that a firm that previously experienced product failures may be

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[14] Measuring product portfolio similarity between two companies using Euclidean distances is analogous to the way previous studies operationalized technological similarities between firms using patents (e.g., Ahuja, 2000; Rosenkopf & Almeida, 2003).

more likely to exhibit the same problems subsequently (Wowak et al., 2015). I controlled for a firm's *product count* by counting the number of products that the FDA approved in the past five years because a firm with a greater number of recalls may have a higher likelihood of experiencing product failures. I further accounted for a firm being a large conglomerate in the medical device industry. Previous literature suggests that some industry giants are highly involved in acquisitions, new product introductions, and product recalls and, thus, could act as outliers in the sample (Chatterji, 2009). Therefore, I created a dummy variable, *big conglomerate*, and assigned a value of 1 if the firm is one of the top five conglomerates in the sample (i.e., Johnson & Johnson, Medtronic, Boston Scientific, 3M, Abbott Laboratories), and 0 otherwise.

3.3.4   Estimation

In the firm-level analysis, considering that the dependent variable is a count variable (i.e., the number of product recall incidents in a given year), I estimated all models using a panel Poisson model with conditional firm-fixed effects to capture time-invariant, unobserved heterogeneity at the firm level (e.g., Chatterji & Fabrizio, 2014; Frankort, 2016; Wooldridge, 2012), as well as a panel Poisson model with random effects to capture variations among other firms (e.g., Katila & Ahuja, 2002).[15] I included industry-fixed effects using a set of binary variables based on the venture's first two-digit SIC codes to account for industry-specific influences. I also included year-fixed effects to control for macro-level technological regulations and temporal trends during the sample period. Robust standard errors clustered at the firm level are used to account for the observations' non-independence (Petersen, 2009).

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[15] In the Poisson model with conditional firm-fixed effects, because some sample firms without temporal variation on the dependent variable were dropped, the sample size was affected.

3.4   Results

3.4.1   Main Results

Table 1 presents a correlation matrix and descriptive statistics for the variables used to estimate the relationship between acquisition and product failures at the firm level. In Table 2, I report the results of the relationship between a firm's acquisition implementations and number of product failures. Results in Models 1, 3, and 5 are from the panel Poisson regressions with conditional firm-fixed effects, and those in Models 2, 4, and 6 are from panel Poisson regressions with random effects. As shown in Models 1 and 2, the coefficients of *acquisition intensity* are positive and significant ($\beta_{RE} = 0.148$, $p < 0.05$; $\beta_{FE} = 0.165$, $p < 0.05$), which is consistent with my argument that acquisitions are associated with a greater number of product failures. In Models 3 and 4, instead of *acquisition intensity*, I used the *number of acquisitions* to test whether firms with a large absolute number of acquisitions experience a high rate of product failures. The positive and significant coefficients that these two models indicate that firms with a high number of acquisitions experience more product failures ($\beta_{RE} = 0.025$, $p < 0.05$; $\beta_{FE} = 0.024$, $p < 0.05$). These two sets of results suggest that firms engaging in more acquisitions experience a greater number of product failures.

Table 3.1 Descriptive Statistics and Correlations (Firm-Level Analysis)

		Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12
1.	Product failure count	2.72	8.39												
2.	Acquisition intensity	0.68	0.25	0.52											
3.	Number of acquisitions	2.60	5.03	0.22	0.36										
4.	Number of related acquisitions	0.10	0.33	0.03	0.00	0.09									
5.	Firm size	1.32	1.52	0.43	0.50	0.52	0.06								
6.	R&D expenditure	-0.13	0.44	0.46	0.55	0.39	-0.01	0.80							
7.	Advertise expenditure	0.05	1.05	0.04	0.21	0.28	0.00	0.46	0.46						
8.	Firm cash	4.04	2.36	0.37	0.43	0.47	0.06	0.83	0.68	0.42					
9.	Debt to equity	0.08	0.72	0.08	0.09	0.04	-0.01	0.06	0.08	0.01	0.07				
10.	ROA	-0.09	0.32	0.12	0.12	0.23	0.09	0.37	0.21	0.19	0.41	-0.02			
11.	Prior product failure count	0.89	1.24	0.53	0.37	0.30	0.17	0.51	0.40	0.04	0.48	0.06	0.24		
12.	Product count	1.99	1.58	0.38	0.33	0.33	0.19	0.52	0.37	0.12	0.54	0.03	0.30	0.81	
13.	Big conglomerate	0.05	0.21	0.20	0.24	0.41	-0.03	0.40	0.47	0.21	0.35	0.01	0.12	0.31	0.31

Coefficients greater than 0.04 are significant at the 0.05 level.

Table 3.2 Effect of Acquisition on Product Failure (Firm-Level Analysis)[16]

Variables	Model 1 RE (Between)	Model 2 FE (Within)	Model 3 RE (Between)	Model 4 FE (Within)	Model 5 RE (Between)	Model 6 FE (Within)
			DV: Product failure count			
Acquisition intensity	0.148*	0.165*				
	[0.072]	[0.076]				
Number of acquisitions			0.025*	0.024*	0.027**	0.026**
			[0.010]	[0.011]	[0.009]	[0.010]
Number of related acquisitions					-0.332*	-0.351*
					[0.159]	[0.165]
Firm size	0.380*	0.173	0.419**	0.259	0.481**	0.369+
	[0.148]	[0.236]	[0.134]	[0.224]	[0.123]	[0.204]
R&D expenditure	-0.358	-0.283	-0.442	-0.378	-0.368	-0.276
	[0.383]	[0.421]	[0.394]	[0.453]	[0.313]	[0.344]
Advertise expenditure	0.159*	0.202**	0.154*	0.194**	0.157*	0.200**
	[0.066]	[0.057]	[0.062]	[0.055]	[0.068]	[0.059]
Firm cash	-0.017	-0.034	-0.040	-0.057	-0.035	-0.053
	[0.053]	[0.052]	[0.055]	[0.056]	[0.055]	[0.056]
Debt to equity	-0.014	-0.002	0.024	0.030	0.027	0.033
	[0.080]	[0.060]	[0.023)	[0.023)	[0.021)	[0.020)
ROA	0.588+	0.603+	0.548+	0.589	0.496+	0.537
	[0.318)	[0.362)	[0.311]	[0.364)	[0.292]	[0.350]
Prior product failure count	-0.011	-0.015	-0.025	-0.036	-0.039	-0.051
	[0.115]	[0.114]	[0.110]	[0.106]	[0.108]	[0.104]
Product count	0.148	0.067	0.186*	0.120	0.181+	0.115
	[0.098]	[0.107]	[0.094]	[0.102]	[0.094]	[0.102]
Big Conglomerate	1.159+		0.996		0.731	
	[0.642]		[0.618]		[0.475]	
Year fixed effects	Included	Included	Included	Included	Included	Included
Industry fixed effects	Included		Included		Included	
Constant	-2.463***		-2.523***		-4.575***	
	[0.658]		[0.714]		[0.799]	
Observations	1,817	1,330	1,817	1,330	1,817	1,330
Number of Firms	392	182	392	182	392	182
Log Pseudo Likelihood	-3101.84	-2297.63	-3097.73	-2296.66	-3078.43	-2275.98

Robust standard errors clustered at the firm-level are in brackets.

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

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[16] 114 firms that have only one observation per year (i.e., only single year observation) and 96 firms that have all zero product failure counts (total 373 observations) have been dropped from the sample in the FE model. Thus, the sample size between FE Poisson and RE Poisson is different (1817=1330+114+373). In addition to this, in the FE Poisson model, the variable has no variation over the years is dropped (i.e., *Big Conglomerate*). I acknowledge that industry dummies are subsumed in FE model since there is no variation over the sample period.

In Models 5 and 6, I tested whether firms pursuing related acquisitions in terms of their product portfolios mitigate the risk of experiencing product failures. The coefficients of *related acquisitions* are negative and significant ($\beta_{RE} = -0.332$, p < 0.05; $\beta_{FE} = -0.351$, p < 0.05), suggesting that related acquisitions are associated with fewer product failures.

3.4.2 Understanding Mechanisms: Information Asymmetry and Coordination Problems

The empirical results above suggest that acquisitions lead to an increase in product failures. My argument asserts that a positive association between acquisition and product failure is attributed to information asymmetry between acquirer and target pre-acquisition and integration problem post-acquisition. However, the firm-level empirical design does not enable me to claim that the suggested underlying mechanisms drive the results. In the firm-level analysis, I aggregated the intensity and number of acquisitions at the firm-year level and assessed the number of product failures that each acquiring firm (and their acquired firms) experienced in a given post-acquisition year. A primary disadvantage associated with such an analysis is that I cannot specify the effect of acquiring a particular target on product failure after the acquisition because many firms pursue multiple acquisitions during a given period of time. Therefore, firm-level analysis limits me from disentangling the effect of acquiring targets with particular characteristics – which can affect the degree of information asymmetry and integration problems – on acquiring firms' product failures. Another drawback from applying firm-level analysis is that the empirical approach also takes products that are not directly associated with the acquisitions into account. It could be possible that these products, unaffected by firms' acquisitions, are more susceptible to failures and, consequently, lead to overestimations in the main empirical findings.

To complement the main empirical results, I performed product-level analysis, which is useful in that it distinguishes products directly associated with the acquisition (i.e., products

developed by acquired firms after being acquired) and identifies the characteristics of acquired firms that developed the products. Such an approach enables me to perform additional analyses to test the proposed mechanisms underlying the relationship between acquisitions and product failures. In this set of analyses, I compared the product-failure likelihood of each product developed by acquired firms with different characteristics, with the product-failure likelihood of products developed by acquiring firms to understand whether information asymmetry and integration problems explain the main findings. As such, I made the following five predictions in product-level analyses: (1) The likelihood that products developed by acquired firms post-acquisition will fail is greater than the likelihood that products developed by acquiring firms (i.e., developed in-house) will fail; (2) among those products developed by acquired firms post-acquisition, products that older firms develop are less likely to fail than those developed by younger firms; (3) among products developed by acquired firms post-acquisition, products that public firms develop are less likely to fail than those developed by private firms; (4) among those products developed by acquired firms post-acquisition, products developed by firms whose CEOs remain post-acquisition are less likely to fail than those developed by firms whose CEOs leave post-acquisition; (5) among those products developed by acquired firms post-acquisition, products developed by firms acquired through partial acquisitions are less likely to fail than those developed by firms acquired through full acquisitions.

Acquired Products vs. In-House Products. One of the limitations of the firm-level analysis is that it does not enable me to distinguish likelihood of failure between products affected by acquisitions and those unaffected by acquisitions. If newly acquired firms experience organizational dissonance after being acquired or adversely selected by acquiring firms due to information asymmetry pre-acquisition, their products may be at higher risk of failure than those

not associated with acquisitions (i.e., products that acquiring firms developed in-house). To examine whether products that acquired firms develop are the main source of product failures for firms active in acquisitions, I compared the failure likelihood of products developed by acquired firms post-acquisition with the failure likelihood of products developed by acquiring firms (i.e., developed in-house).

In the product-level analysis, I observed incidents of product failure – measured by product recalls – experienced by each product in a given year. Thus, throughout the product-level analyses, the dependent variable is *product failure event*, a dummy variable, which is coded as 1 if the product is recalled, and 0 if otherwise. To identify whether developed products are associated closely with firms' acquisition, I created a dummy variable, *acquired firm's product*, which has a value of 1 if an acquired firm developed the product after being acquired, and 0 if the acquiring firm developed the product in-house. I predict that products developed by acquired firms are more likely to fail than products developed by acquiring firms in-house. In addition to control variables used in the firm-level analysis, I controlled for the nature of individual medical device products by indicating the riskiness of medical device products with a dummy variable, *risky product*, which is coded as 1 if the product is assigned to a Class III category.[17] Furthermore, I included dummy variables for each product based on their therapeutic areas, as designated by the FDA (product therapeutic area fixed effects) because the product-failure hazard may vary depending on the characteristics of the devices' medical functions (e.g., Zuckerman et al., 2011).[18]

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[17] The FDA classifies medical device products into three categories, depending on the risk level that the device poses to patients (Class III products being the riskiest and Class I products being the least risky). The FDA defines Class III devices as those that "usually sustain or support life, are implanted or present a potential unreasonable risk of illness or injury." Furthermore, Class III devices also are viewed as the most innovative and cutting-edge medical devices that can be subject to high risk of product recalls.

[18] The FDA uses 19 medical specialties to classify medical devices (e.g., anesthesiology, cardiovascular, dental, etc.). Zuckerman et al. (2011) show the variations in recall rates among medical devices categorized under different medical specialties.

Model 1 in Table 3 presents the results from product-level analysis using logit regression. The coefficient for *acquired product* is positive and significant, providing strong support for the prediction that products developed by acquired firms are more likely to fail than those that acquiring firms develop in-house ($\beta = 0.236$, $p < 0.05$). This positive relationship between acquired firms' products and product-failure likelihood suggests that products that acquired firms develop mostly are affected severely by acquisitions than those that acquiring firms develop in-house. In the next sets of analyses, I aim to examine possible underlying mechanisms of why acquisitions lead firms to experience more product failures.

Table 3.3 Effect of Acquisition on Product Failure (Product-Level Analysis)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Variables			DV: Product failure event			
Acquired product	0.236*					
	[0.099]					
Target age		-0.013*			-0.010+	
		[0.006]			[0.006]	
Public target			-1.995**		-1.938**	
			[0.682]		[0.680]	
Target's CEO remaining post-acquisition				-0.552*	-0.544+	
				[0.265]	[0.278]	
Partial acquisition						-0.638**
						[0.161]
Firm size	-0.121**	0.392*	0.432*	0.360+	0.394*	0.222+
	[0.042]	[0.194]	[0.200]	[0.198]	[0.196]	[0.117]
Firm R&D expenditure	0.079**	-0.363**	-0.320**	-0.323**	-0.319**	-0.095
	[0.028]	[0.117]	[0.114]	[0.116]	[0.114]	[0.075]
Firm advertisement expenditure	-0.072**	0.131	0.076	0.096	0.105	-0.043
	[0.017]	[0.093]	[0.088]	[0.089]	[0.091]	[0.050]
Firm cash	0.035+	0.160+	0.188*	0.127	0.167+	0.014
	[0.021]	[0.090]	[0.093]	[0.092]	[0.095]	[0.049]
Debt to equity	0.013	-1.651+	-1.720+	-1.692+	-1.932*	0.287
	[0.072]	[0.883]	[0.921]	[0.866]	[0.878]	[0.604]
ROA	0.152+	0.881	-0.308	0.914	0.666	-1.109
	[0.079]	[1.800]	[1.799]	[1.851]	[1.923]	[1.072]
Prior product failures	0.019**	0.011	0.003	0.014	0.005	0.010*
	[0.001]	[0.009]	[0.010]	[0.009]	[0.010]	[0.004]
Product count	-0.130**	-0.094	-0.013	-0.001	0.013	0.041
	[0.030]	[0.218]	[0.209]	[0.206]	[0.213]	[0.101]
Risky product	0.862**	-0.817	-0.900	-0.749	-0.952	1.829**
	[0.146]	[1.255]	[1.283]	[1.244]	[1.350]	[0.610]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Therapeutic area FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-1.166***	-2.736**	-3.168**	-2.440**	-3.007**	-1.820***
	[0.164]	[1.150]	[1.178]	[1.176]	[1.182]	[0.616]
Observations	9,289	570	570	570	570	1,302
Pseudo R2	0.095	0.220	0.229	0.219	0.237	0.104

Robust standard errors at the firm-level are in brackets.

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Information Asymmetry. As I discussed previously, one of the possible reasons why acquisitions lead to product failures may be because acquiring firms make suboptimal choices in

selecting their acquisition targets due to a lack of information on potential target firms. Building on this notion, I conducted subsample product-level analyses to examine the likelihood of a given product being a failure according to the degree of information asymmetry that the acquiring firms may encounter. Throughout the analyses, I examined only products that acquired firms developed (i.e., excluding products that acquiring firms developed). First, I analyzed whether product-failure likelihood is sensitive to acquired firms' age at the time of acquisition. The level of evaluative uncertainty between transaction partners is associated with the target's age (Capron & Shen, 2007). The quantity and quality of information that one can gather from young firms are highly limited (Shen & Reuer, 2005) because whereas old firms have accumulated information about their business, young and new firms have limited objective information about the firms to disclose to potential buyers (Sanders & Boivie, 2004). Therefore, inaccessibility of information on young potential targets may make it difficult for acquirers to evaluate the prospective value of targets' resources accurately. In this research context, acquirers may not evaluate potential targets' resources and technologies appropriately if the targets are younger and, thus, may face a greater chance of selecting firms with inferior products and underlying technologies.

Second, I examined further whether product-failure likelihood is influenced by acquiring firms selecting private targets, as opposed to public firms. The literature on acquisitions argues that objective data on public firms generally are accessible to buyers, whereas such information on private firms is not readily available to buyers because private firms have better control over their information (Reuer & Ragozzino, 2008). Therefore, acquirers may incur high search costs when buying private firms and face a greater possibility of adverse selections (Capron & Shen, 2007; Shen & Reuer, 2005). Similar to the argument above, acquiring firms may face a high risk of adversely selecting potential targets with inferior quality in resources and technologies if the

targets are private firms. Accordingly, I predicted that products developed by private targets post-acquisition exhibit a higher probability of failure compared with products that public targets develop.

Models 2 and 3 in Table 3 present the findings concerning my predictions. The coefficient for *target age* is negative and significant, providing support for the prediction that the younger the target's age, the higher the likelihood that the target's products developed post-acquisition will fail ($\beta = -0.013$, $p < 0.05$). The coefficient for *public target* is negative and significant, showing that public targets' products reveal less likelihood of product failures than those of private targets ($\beta = -1.995$, $p < 0.01$). Overall, I concluded that the relationship between the high likelihood of product failure and a target's young age and private status is a consequence of the high information asymmetry between acquiring firms and potential target firms.

Integration Problem. Another possible explanation for the relationship between acquisition and product failure is the integration problem during the post-acquisition phase. A firm that engages in an acquisition as a corporate-level transaction may suffer from integration and coordination conflicts with the newly acquired organization (Agarwal, Anand, Bercovitz, & Croson, 2012). Acquirers in particular encounter an organizational dilemma of whether to integrate acquired firms and manage them in a coordinated manner, or to let them retain organizational autonomy to avoid disrupting their innovation efforts (Puranam et al., 2006; Ranft & Lord, 2002). Building on this notion, I analyzed whether product-failure likelihood is sensitive to whether target firms preserve organizational autonomy after acquisitions take place. To measure the extent to which a target firm is integrated, I identified whether a target firm's CEO remains in the firm after the acquisition. Acquiring firms replace acquired firm executives as a way to increase their control over the acquired firms and integrate them (Krug & Aguilera, 2005). Moreover, greater autonomy

may be given to top executives who remain at a newly acquired firm (Hambrick & Cannella, 1993). Because CEO replacement could impose significant pressure on acquired firms to change and could disrupt their operations, I conjecture that products developed by acquired firms whose CEOs remain post-acquisition exhibit less likelihood of product failures than those developed by acquired firms whose CEOs are replaced by the acquiring firms.

Next, I examined whether product failure likelihood depends on the degree to which acquired firms are integrated as measured by full or partial acquisitions. When target firms are acquired through full acquisitions, the acquired target firms may face a greater chance of organizational dissonance and may be under greater pressure to alter their operations or product development paths. On the other hand, when acquiring firms obtain targets through partial acquisitions of a single division or product line, the acquired firms may face less pressure to be integrated into the acquiring firms and, thus, less chance of experiencing integration problems with the acquiring firms. I conjecture that the products developed by acquired firms that are only acquired partially may exhibit less likelihood of product failures than those developed by acquired firms acquired fully.

Models 4 and 5 in Table 3 present the findings concerning my predictions. The coefficient for *target CEO remaining post-acquisition* is negative and significant, providing support for the prediction that products are more likely to fail when they are developed by acquired firms whose CEOs remain post-acquisition ($\beta = -0.552$, p < 0.05). The coefficient for *partial acquisition* is negative and significant, showing that products of target firms only partially owned by acquiring firms exhibit a lower likelihood of product failures than those of target firms fully owned by acquiring firms ($\beta = -0.638$, p < 0.01). Generally, these results support the claim that firms facing

high pressure to integrate post-acquisition may experience a disruption in their operations and innovations, which could turn into an unfavorable outcome.

3.4.3 Robustness Check: Mitigating Endogeneity Problem

Several studies have used propensity score matching to control the endogeneity of implementation of acquisition for seeking external knowledge as a robustness check for firm-level analyses. Some may argue that innate differences exist between firms that never have implemented acquisitions and others that have. During the sample period, 2003–2016, among 392 firms, 219 never implemented acquisitions, while 173 implemented at least one M&A transaction. I calculated propensity scores for firms, with the same variables used for firm-level analysis, and the process generated 154 firms that never have experienced acquisitions. Based on the propensity score, I matched 154 firms with other firms that experienced acquisitions located within a 0.05 caliper radius, thereby estimating average treatment effects of "make only." For this analysis, I used the *pscore*, *psmatch2*, and *attr* routine in Stata 16. As shown in Table 6, even when I controlled for endogeneity with propensity score matching, the result remains robust.

Table 3.4 Propensity Score Matching with Radius Caliper 0.05[19]

Propensity Matching Scheme	Firms not performing acquisition [A]	Firms performing acquisitions [B]	ATT	Bootstrapped Standard Error	[A]-[B]
Radius Matching Method	154	154	-0.773	0.400	-1.932*

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[19] The numbers of treated (make-only) and controls (at least one acquisition) refer to actual matches within the radius. "Treated" is a firm that never implements acquisitions during sample period; "control" is a firm that implements at least one acquisition. The results are robust to the use of different values for radius caliper (e.g., caliper [0.01] = t-diff [-1.68]; caliper [0.3]= t-diff [-1.71]). Bootstrapped replication is 1,000.

3.5 Conclusion and Discussion

This study examines the effect of acquisition on product failures. Although some scholars have focused on the negative impact of product failure on various organizational outcomes – including financial returns (Zhao, Li, & Flynn, 2013), product market share (Rhee & Haunschild, 2006), and market response (Davidson III & Worrell, 1992) – few scholars have examined the antecedents of product failures (see Wowak & Boone, 2015, for further discussions). This study proposes that acquiring firms' engagement in acquisitions is associated with product failures due to information asymmetry associated with target firms' pre-acquisition (Capron & Shen, 2007; Reuer & Ragozzino, 2008) and coordination costs during the post-acquisition process (Haspeslagh & Jemison, 1991; Puranam et al., 2006). Using a unique multi-level data set on acquisitions and product recalls at publicly traded U.S. firms in the medical device industry during the 2003–2016 period, I confirmed that a relationship exists between firms' engagement in acquisitions and their product failure rates.

To test the hypotheses and underlying mechanisms, I performed both firm-level and product-level analyses. Particularly in the firm-level analyses, I found that firms that expend greater resources on acquisitions experience more product failures. The suggested relationship is less prevalent when the firms are engaged in related acquisitions. In the product-level analyses, the results show that products that acquired firms develop are more likely to fail than those developed in-house by acquiring firms. Furthermore, among the products that acquired firms develop, products that young and private acquired firms develop are more susceptible to failure than those of established and public acquired firms. These results suggest that information asymmetry plays a critical role in explaining the relationship between acquisitions and product failures. Finally, I showed that products developed by acquired firms in which their CEOs remained post-acquisition and that were acquired partially by the acquiring firms exhibit a lower

likelihood of product failures. These findings suggest that acquiring firms face substantial costs in coordinating and integrating newly acquired firms post-acquisition. I believe that these results provide novel insight into understanding acquisition and innovation.

Previous studies have argued that acquisition is an effective means through which firms can obtain external resources and technologies to enhance their capabilities (e.g., Ahuja & Katila, 2001; Cassiman & Veugelers, 2006; Makri et al., 2010). However, this literature stream has paid less attention to the downside of firms' efforts to obtain external resources and technologies through acquisitions. In this study, I attempt to highlight the "dark side" of acquisitions by suggesting that they may lead to firms experiencing a high risk of product failure. The proposition in this study resonates with diseconomies of time compression (Dierickx & Cool, 1989), in that acquisition may be one of the fastest ways to acquire established products or further the development of radical innovative products, but such acquisitions simultaneously lead to a higher risk of product failure.

Like all other studies, this research has several limitations that could be addressed in future studies. Although I made an effort to address this issue through both firm- and product-level analyses, one of the important caveats in this study is that I was not able to fully carry out empirical analyses to claim a causal relationship between acquisition and product failures. I admit that a potential endogeneity problem is not fully addressed in this research. For instance, I cannot completely rule out the possibility that firms that implemented acquisitions are systematically different from those that did not experience acquisitions, which could support this study's claims. However, the purpose of this study is to help provide some initial evidence of the relationship. I hope that future studies can provide more robust empirical evidence by adopting more sophisticated identification strategies, such as field experiments and two-stage models using an

instrumental variable, to identify a causal relationship. Another important limitation to note is that the firm-level analyses using the lump-sum variables, acquisition intensity, and number of acquisitions may not fully capture each acquisition's motivation or efficacy. It would be better to have a more fine-grained variable for each acquisition transaction to tease out these issues clearly. Finally, another interesting topic might concern the effects from the top management team's perception of product recalls and their resolution processes. It may be possible for a founding CEO to take more responsibility for a firm's product failures and its processes, or may be more likely to make more risky acquisitions (i.e., acquisitions far from the firm's main technology domain) (e.g., Lee, Kim, & Bae, 2020; May, 1995). In future studies, it may be interesting to consider the effects from the specific CEO's status on the product recall process and resolution, then compare those results with the present findings.

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CHAPTER 4.   FAILURE CASCADE: PRODUCT FAILURES IN NEW PRODUCT DEVELOPMENT

4.1   Introduction

New product development is one of the key activities that firms engage in to achieve long-term growth and remain competitive in a dynamic environment (Damanpour, 1991; Katila & Ahuja, 2002; Schoonhoven, Eisenhardt, & Lyman, 1990). Extant research across the strategic management and innovation fields has argued that firms introduce new products often by making relatively incremental changes to existing products by exploiting the potential of established technology (Henderson & Clark, 1990; Tushman & Anderson, 1986). Alternatively, firms introduce radical changes to existing products by adopting a substantially different set of scientific and engineering principles (Danneels, 2002). Although the latter often elicits larger payoffs and greater competitive advantage for firms, they are bound to lock themselves in or out of certain technological trajectories, thereby making it difficult for them to pursue radical changes to their existing knowledge set (Henderson & Clark, 1990). In other words, firms' product development history constrains their options for future product development sequences (Danneels, 2002; Helfat & Raubitschek, 2000). Therefore, firms have a tendency to develop new products by drawing on an existing, closely related knowledge base (Helfat, 1994; Martin & Mitchell, 1998).

Prior studies have suggested that a firm building new products upon existing ones enjoys certain benefits. For instance, products that draw on a firm's existing capabilities may create more usable spillover information than products that require a new knowledge base (Cohen & Levinthal, 1990; Martin & Mitchell, 1998). Moreover, building on past products may be less expensive and increase the chances of synergy among related products (Henderson, 1994). Despite the benefits of utilizing a firm's existing knowledge base in new product development, extant literature sheds

less light on the potential downside of firms relying on their existing knowledge base, especially when the quality of existing products and the knowledge base surrounding them are questionable. If existing products suffer from product failures (e.g., functional defects and unexpected side effects), the failures may persist in products introduced subsequently, ultimately causing the affected firms to incur additional financial and reputational costs (Davidson III & Worrell, 1992; Rhee & Haunschild, 2006).

To that end, the primary goal of this research is to analyze whether there are any downsides associated with developing innovation through incremental approaches. The core argument is that a firm may experience failure with newly introduced products when the products that they are built upon are inherently defective. When a problem in an existing product is identified before introducing a new product, a firm may be less likely to build new products based on that technology because the preexisting product's negative value is identified sufficiently (Greve & Seidel, 2015). However, when a quality problem with a preexisting product is unidentified before a firm develops a new product, it inadvertently may adopt the underlying set of technologies and knowledge inherent in the preexisting product without taking precautions, leading to similar problems (Levinthal & March, 1993). Therefore, I argue that an incremental approach in new product development may create the risk of a persistent chain of failures in the new product development system.

To delve into the mechanism underlying the main argument, this research further examines the contingent effect of the persistent chain of failures in product innovation. In particular, I argue that the predicted relationship is amplified when firms are constrained strongly by existing routines to develop new products. I propose that when firms are better off than their competitors in existing product markets, they increasingly may resort to developing new products based on existing

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products. Because continuous incremental learning processes could lead to firms overlooking failures (Levinthal & March, 1993), newly introduced products may experience a high probability of product failure like that manifested in the source product. Furthermore, I suggest that one of the ways in which firms can overcome this chain of failure is by looking beyond their organizational boundaries to search for new knowledge.

I make two important contributions through this study. First, this research suggests an alternative perspective to a stream of prior literature that has long discussed the benefits of incremental innovation (Cohen & Levinthal, 1990; Henderson & Clark, 1990; Martin & Mitchell, 1998). Extant studies in this area stress that innovation evolves over time, along with knowledge and capabilities, and enables firms to achieve a competitive advantage by incrementally adding value to existing innovations (Helfat & Raubitschek, 2000). Exploiting existing knowledge and competence in a given domain enables firms to be more efficient and refined and, thus, develop greater knowledge and competence in that activity (Cyert & March, 1963; Levinthal & March, 1993). However, in this study, I find that an incremental approach to introducing innovations may not always confer a competitive advantage on firms, and could even harm them, particularly when preexisting innovations used as the foundation for the newer innovations inherently are defective.

Second, this study is one of few studies to examine why some high-tech firms may experience quality issues associated with their product innovations. Many extant studies have focused on identifying the sources of successful product innovations among technology-based firms by examining their product-innovation productivity, measured by the number of new products introduced into the market (e.g., Chatterji & Fabrizio, 2014; Katila & Ahuja, 2002; Pahnke, Katila, & Eisenhardt, 2015; Rothaermel & Deed, 2004) or by examining the speed of product innovation, measured by how long it takes to introduce new products (e.g., Hellmann &

Puri, 2000). However, we have a limited understanding of what induces quality issues associated with products after they are introduced into the market (exceptions include Rhee & Haunschild, 2006; Wowak, Mannor, & Wowak, 2015). Identifying potential factors that lead to product failures associated with safety issues is important, as product-related issues can present important societal implications. By examining firms' product recalls, I aim to contribute to this literature stream by proposing quality concerns as a critical dimension when examining firms' product innovation outcomes.

4.2   Theory and Hypotheses Development

4.2.1   Path Dependence in New Product Development and Product Failures

New product development is a critical factor for firm performance and survival (Damanpour, 1991). By introducing new products, firms can develop new technologies, establish new markets, and fulfill new market demands (Burgelman, 1991; Brown & Eisenhardt, 1995). Most importantly, new products are a stable source of financial returns from their R&D activities (Katila & Ahuja, 2002; Schoonhoven et al., 1990). Without a continuous rollout of new products, firms in high-tech industries may not be able to reach their financial goals (Tyler & Caner, 2016).

A common premise in extant literature on new product development is that a firm's ability to develop and create knowledge is an important factor regarding its rate of new product development (Cohen & Levinthal, 1990; Katila & Ahuja, 2002). So, how do firms enhance their ability to introduce new products continuously? Helfat and Raubitchek (2000) theorize that technological and organizational knowledge embedded within firms can establish the foundation for introducing new generations of existing products, replacement products, and completely new products that target different markets. Technological knowledge can be used to develop products

within and across different product markets and achieve economies of scope and scale (Teece, 1980). Furthermore, organizational knowledge enables improved coordination and consequent cost reductions in value chains (Helfat & Raubitchek, 2000).

In addition to embedded knowledge, new product development involves incremental learning in which firms improve their knowledge without departing fundamentally from current knowledge systems (Helfat & Raubitchek, 2000). Through incremental learning, firms obtain new knowledge close to the domain of their existing knowledge and create path dependence in learning processes (Nelson & Winter, 1982; Helfat, 1994). One of the benefits of exploiting existing knowledge in a given domain is that it enables future exploitation in the same knowledge domain even more efficiently. As firms improve their competence at a specific activity, they continuously participate in the activity, consequently increasing competence and the opportunity cost of exploring new knowledge (Levinthal & March, 1993). For instance, when firms develop new generations of existing products, they learn to improve engineering and user-oriented features particular to preexisting products (Rosenberg, 1982). Furthermore, firms improve products by increasing their familiarity with the product through similar features (Gomory & Schmitt, 1988). Thus, incremental learning and the knowledge underlying the product affect the future of product development path over time, that is, a firm's portfolio of products acts as a platform for future product development, evolving over time jointly with incremental accumulations in knowledge and capabilities, and providing avenues for a competitive advantage in a given product domain (Helfat & Raubitchek, 2000).

However, embedded knowledge and incremental learning in a particular product domain could constrain a firm's choice of future product development. Due to the path dependent nature of product development, when firms develop and introduce new products through such an

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incremental approach, they may face the risk of their new products being exposed to the failure

associated with the products and underlying technologies upon which the new products are built.

In the case of product development, a failure refers to unanticipated design defects associated with

product quality (Ball, Macher, & Stern, 2019).

However, when the quality problem with the new product's source product (i.e., the

product that the new product is building upon) is identified before the new product is developed,

the firm may be less likely to adopt the knowledge or routine used in the source product because

the underlying technology's negative value is identified sufficiently (Greve & Seidel, 2015).

Similarly, when firms encounter failure, they may take actions to correct the problems (Baum &

Dahlin, 2007; Greve, 2003). Consequently, when identified, such technical and quality problems

may allow firms to learn and improve their new product development process and, thus, prevent

such failures from repeating (Thirumalai & Sinha, 2011).

However, when a new product is built upon a source product that is potentially defective

(i.e., defects are unidentified before the new product is developed), it is possible that such product

failure could persist in the newly built product. Thus, source-product failure can disrupt a firm's

existing product development system because firms may rely on preexisting technologies and

knowledge without taking precautions. Levinthal and March (1993) argue that an incremental

learning process sometimes can limit organizations' ability to improve their capabilities. One form

of inherent problems in incremental learning is that learning produces a biased representation of

past reality, thereby leading to organizations overlooking failures. In other words, as learning

produces an increasing number of successes, it breeds organizational confidence in control over

outcomes and a tendency to under-sample failures. As a result, organizations easily may overlook

potential failures and fail to learn from them as their learning deepens and continues to generate

successes. In the context of new product development, exploiting existing knowledge and improving preexisting products incrementally increase the chances of successfully introducing new products to the market, but under-sample product failures (Levinthal & March, 1993). Therefore, a product built upon a preexisting product with inherent, yet unidentified, quality problems may have a high probability of experiencing similar problems.

Taken together, I argue that the likelihood that a new product may suffer from product failure increases when the product that the new product is built upon has an inherent, unidentified quality problem:

Hypothesis 1. There is a positive association between the (unidentified) failure of a source product and the failure of a focal product.

As an extension of the above argument, I propose that a product's likelihood of experiencing quality problems associated with the source product's problem increases when the defective source product is developed by a focal firm, compared with when the product is developed by other firms:

Hypothesis 2. The positive association between the (unidentified) failure of a source product and the failure of a focal product becomes greater when the defective source product also is developed by the focal firm.

4.2.2 Firm's Relative New Product Development Performance and Product Failures

The above argument that product failure persists in a sequence of products is based on the assumption that the path-dependent nature of a firm's product development process leads to firms overlooking failures. In the next hypothesis, I infer a firm-specific property that increases a firm's dependence on its existing knowledge and incremental learning, thereby augmenting the persistence of product failures in new product development.

A product's likelihood of experiencing quality problems associated with the source product's problem would depend on the focal firm's competitive nature and relative performance level in a given product market. Prior research suggests that high competition in product markets forces firms to focus on defending their market position by improving their existing products through minor changes based on the same knowledge (Anderson & Tushman, 1990). Because competing products typically target customers with similar preferences and provide improvements over functional features, they quickly could take away the firms' market share (Martin & Mitchell, 1998). To prevent firms from losing their market share, they need to promptly develop and market their new products promptly, building on their current technology and product features. Furthermore, firms' swift responses to competitors' strategies in the product market could diminish the time that the firms have to pursue distant and exploratory search (Toh & Polidoro, 2013). This time urgency in competitive markets further induces firms to direct their product development efforts away from exploratory approaches, as exploratory search requires longer time horizons to find solutions to a given problem (March, 1991; Sorenson & Sørensen, 2001). Instead, the firms under great competitive pressure in the product market may increase their dependency on incremental approaches to develop and refine new products. Under such competitive conditions, a firm's tendency to overlook a source product's problem may increase, thereby increasing the likelihood that its new product will experience failure.

Associated with competitive pressure, a firm's willingness to resort to incremental approaches in developing new products may depend on the firm's performance relative to competitors in the product market. In high-tech industries, new product development represents the potential commercial value of a firm's R&D activities, so it is critical for firms to improve and introduce new products continuously to reap financial returns (Tyler & Caner, 2016). However,

under high competition, future return opportunities from new product development could be eroded by the competitors that may lead firms to be conscious of their competitors' product development outcomes. From this perspective, firms' relative new product development performance as they face off with their competitors may determine their tendency toward developing new products. Behavioral theorists have argued that depending on whether firms' performance is above or below their reference points, often vis-à-vis their competitors' performance levels, firms pursue different search paths (Cyert & March, 1963; Greve, 1998). Particularly in high-tech industries, in which continuous introduction of new products is crucial in attaining financial goals, when firms are outcompeted by their competitors in terms of new product development, the firms may perceive that their existing search routines and knowledge are no longer sufficient to remain competitive in a given product market and, therefore, may search for solutions from distant sources (Greve, 2003; Tyler & Caner, 2016).

On the other hand, when certain firms are outcompeting others, they are reluctant to pursue exploratory search, fearing a drop in performance from radical changes (Hill & Rothaermel, 2003) and cannibalization of their existing strengths, should search succeed (Henderson, 1993). Such firms are likely to satisfice (Winter, 2000) because they assume that their existing knowledge and incremental learning are sufficient and find little incentive to explore (Eggers & Kaul, 2018; Tripsas & Gavetti, 2000). Instead, these outperforming firms may increase their dependence on exploiting their familiar knowledge and making incremental changes to existing products. As a firm's tendency toward exploiting its local knowledge domain increases, it may increase the chances of the firm overlooking the failure inherent in the product development path, making products more susceptible to a greater chance of failure:

Hypothesis 3. The positive association between the source product's (unidentified)

failure and the focal product's failure becomes greater when the focal firm's new

product introduction performance in a given product market is greater than that of

the focal firm's competitors.

4.2.3 Firm's Search Scope and Product Failures

In the above three hypotheses, I argued that failures may persist in new product developments as firms make incremental improvements based on preexisting products. Firms often resort to a knowledge base within the organization to innovate. However, prior literature argues that relying on internally created knowledge and capabilities may lead to competency traps (Levitt & March, 1988; Levinthal & March, 1993). For instance, Sørensen and Stuart (2000) suggest that although firms pursuing organizationally localized search achieve more innovation, such innovation is less relevant. Therefore, I further argue that one of the ways through which a firm can overcome such a failure cascade is by expanding its scope of knowledge repository and recombining knowledge from multiple sources.

One of the ways in which firms can overcome a problem such as competency traps is by expanding their scope of organizational boundaries to search for and integrate new knowledge. Firms that emphasize looking beyond their knowledge achieve more novel and breakthrough innovations. Indeed, researchers have suggested that organizational boundary spanning when searching for and integrating new knowledge yields significant impacts on subsequent technological developments (Henderson & Cockburn, 1994; Nagarajan & Mitchell, 1998; Rosenkopf & Nerkar, 2001). In the product development context, firms that develop new products by integrating products and underlying technologies developed by other organizations may take advantage to overcome the problem of the path-dependent nature of their product development

processes. When firms develop new products by applying knowledge from external sources, the firms may integrate the external knowledge in a complementary manner to address inherent problems in their product development trajectories. Integration of external knowledge may provide a way to discover novel approaches to develop new products and, thus, lower the possibility of reproducing problems in developing new products in a given product domain. As opposed to the myopic nature of incremental learning, which increases the chance of overlooking potential failures, building new products based on knowledge from external sources may lower the risk of overlooking potential failures of external knowledge because firms may evaluate the product and underlying knowledge objectively before adopting them to their new products. Therefore, firms developing new products by incorporating knowledge external to their organizational boundaries may lower the risk of making the problem inherent in a given product domain. Thus, I propose:

> *Hypothesis 4. The positive association between the source product's (unidentified)*
>
> *failure and the focal product's failure becomes weaker when the focal product is*
>
> *built upon a source product developed external to the focal firm.*

4.3   Methodology

4.3.1   Sample and Data Sources

To implement my proposed agenda, I plan to investigate product innovations and failures in the context of the medical device industry. I selected the medical device industry for my research setting for several reasons. First, the continuous introduction of new products is a key activity for medical device firms, enabling them to stay competitive in their industry. Second, product failures frequently occur and are observable in this industry. The FDA's Center for Devices and Radiological Health (CDRH) regulates medical devices both as a pre-market gatekeeper and as a

post-market regulator. CDRH overseas the new product submission process by reviewing whether the products are safe and effective for patients before they reach the commercial market. After the devices are released into the market, CDRH monitors the approved devices' safety and efficacy. One of the ways in which CDRH ensures patient safety is by demanding that medical device manufacturers and hospitals report any medical devices' malfunctions to CDRH. When these product defects are found to be systematic, the medical device firms voluntarily recall their products overseen by CDRH (Ball et al., 2019). Therefore, medical device manufacturers recall their products when manufacturing defects, functional defects, and unexpected side effects that present a potential threat to patients' well-being are identified in their products. Therefore, I examined product recalls as an indicator of product failures, as they are an apparent sign that a firm was unsuccessful in providing reliable, quality products and in meeting customers' needs and safety requirements. Third, the medical device industry setting enables me to identify existing products upon which the new product is built. CDRH's 510(k) regulatory pathway is designed to accommodate incremental improvements in marketed products. CDRH states that "the [510(k)] regulatory process allows manufacturers to modify existing devices and submit supporting data for regulatory review on a shortened time frame" (CDRH Innovation Initiative, 2011). CDRH requires applicants to demonstrate that new products' intended use and technological characteristics are substantially similar to the device currently on the market, known as a predicate device. Thus, the new devices approved through this process are modifications to preexisting predicate devices. Therefore, in the medical device industry, trails of technological knowledge between products can be identified clearly by exploiting the similarities between a focal product and its predicate device.

I began by constructing the sample, in which I first collected a list of U.S. public companies between 2006 and 2015 from Compustat. I limited the sample to include only U.S. public companies that had at least five FDA-approved medical devices on the market during the sample period so that I could include only firms that exhibited substantial commitment to the medical device business.[20] I used the FDA's Premarket Notification databases to collect information about ventures' FDA-approved medical device products. These databases include the names of approved products, the applicants of these products, and the dates when these products were approved, enabling me to identify marketable products that each firm developed.

Next, I gathered information on drug and medical device product recall incidents from the public product recall databases that the FDA made available. I downloaded product recall data from the OpenFDA website, an FDA Office of Health Informatics initiative that provides FDA regulatory datasets. From each recall announcement, I identified the name of the product being recalled, the recalling firm, the first recall date, and the class of the recall, which enabled me to examine whether each sample product was recalled.

Finally, I manually collected sample focal products' list of predicate devices from the FDA's Premarket Notification product approval reports, also known as 510(k) summary reports. A summary report includes specific information about the FDA-approved product, including a list of one or more predicate devices. I went through summary reports for each focal product and identified each product's corresponding predicate device. In cases in which a focal product is associated with more than one predicate device, I included all the listed predicate devices as the focal product's predicate devices.

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[20] I used three FDA-approved medical devices as an alternative cutoff, and the results were consistent with the main findings.

With the baseline sample, I tracked the product recalls of all products for a period of up to three years from the year in which the products were granted FDA approval. Excluding products with missing summary reports and unidentifiable predicate devices, I came up with a final sample of 5,442 FDA-approved 510(k) products owned by 143 U.S. public medical device firms. Out of 5,442 products, 324 were recalled.

4.3.2   Measures

Dependent variable. Following extant studies using product recalls as a measure for *product failure* (Liu & Shankar, 2015; Thirumalai & Sinha, 2011), I selected this measure as an indicator of product failures. *Product failure event* is a dummy variable set to 1 if product i was recalled within three years after the product was approved, and 0 if otherwise.

Independent variables. *Source product failure* represents product failures that occurred to the focal product's predicate devices within three years after the focal product is applied for FDA approval. Considering that I only account for predicate device recalls announced "after" the focal product is submitted for FDA approval, it is reasonable to believe that the focal product applicant did not know about the recalls of the potential predicate device before the applicant finished developing the focal product. *Source product failure* is a dummy variable that has a value of 1 if the focal product's predicate device was recalled after the focal product had been applied for an approval, and 0 if otherwise.

I created two nested binary variables, *source product failure (same firm)* and *source product failure (different firm)*, based on the organizational origins of the defective predicate device. I created this variable by first identifying whether focal product i's predicate device was recalled. I then determined whether the defective source product was developed by the focal product's firm. Thus, *source product failure (same firm)* has a value of 1 if the focal product's

predicate device was recalled and developed by the focal firm, and 0 if otherwise. *Source product failure (different firm)* has a value of 1 if the focal product's predicate device was recalled and developed by a firm other than the focal firm, and 0 if otherwise. As the reference group is the focal products whose source products did not experience any recalls, these products are set to 0 for these two nested binary variables.

The moderating variable of interest is the focal product developing firm's new product development performance relative to its competitors in a given product market. I constructed this measure in two steps. I first calculated the average of competitors' new product development performance by dividing the total number of products competing with those of the focal firm in a given product market by the total number of competitors in a given product market. I then compared the number of products that the focal firm has gotten approved in a given product market with the competitor's average new product development performance. If the firm's new product development performance is greater than the competitor's average, then the dummy variable, *performance above competitor average*, has a value of 1, and 0 if otherwise.

External search scope represents the extent to which a new focal product is built on preexisting products that are external to the focal firm. To operationalize this variable, I first identified focal product *i*'s predicate devices and the applicants for those devices. I then counted the number of predicate devices that belong to different applicants from focal product *i*'s applicant. Thus, this variable captures the extent to which a focal product is built upon predicate devices and their underlying technologies external to the focal firm.

Control variables. To rule out alternative explanations, I included various control variables. First, I included a set of product-specific covariates. I controlled for focal products' *pre-application source product failure*, which is a dummy variable set to 1 if the predicate device was

recalled before the focal product was applied for approval, and 0 if otherwise. This variable represents whether there were any known product defects in the source product that the focal product is built upon. *Source product complexity* was measured by the number of different predicate device product classes associated with the focal product: The more the number of different product classes associated with the focal product, the higher the complexity. *Source product count* was measured by the number of different predicate devices associated with the focal product. *Focal-source product time gap* was measured by the difference between the years in which the focal product and predicate device were approved. Focal products with shorter time gaps may exhibit a higher likelihood of failure because the source product's defects may not have been disclosed in the market due to being in the market for a short time. In cases in which multiple predicate devices are present, I use the average year of these predicate devices. *FDA review time* is measured by the number of days it took for a focal product to receive FDA approval since its day of application. The longer it took for an approval, the more the FDA scrutinized the product during the approval process, which could affect product recall likelihood. To control for firm-specific factors, I included *firm's product count* within to represent focal firms' product development capabilities. I also controlled for *firm's product failure count*. I further controlled for *firm size* (log of number of employees), *profitability* (ROE), and *R&D intensity* (R&D expenses/total assets). I included *product market competition,* representing the degree of competition in the focal product's market. Following prior studies suggesting that the number of firms in an industry influences the intensity of competition (Hannan & Freeman, 1984; Katila & Shane, 2005), I measured *product market competition* as the number of firms (both public and private) that have at least one product in product *i*'s product market in the year in which the focal product *i* was applied. For all variables, I applied a three-year window.

4.3.3 Empirical Strategy

I primarily used a linear probability model to estimate each product's likelihood of product recall. In the empirical model, I also included year-fixed effects to address unobserved temporal differences in failure likelihood. Finally, I controlled for product-market fixed effects using product codes defined by the FDA to capture variations in different demands for medical devices and failure rates. Robust standard errors are clustered at the firm level throughout the models. I selected a linear probability model instead of a logit model because logit models with many fixed effects (i.e., product-market fixed effects) potentially could suffer severe incidental parameters problem (Wooldridge, 2002). Although linear probability models carry the risk of generating predicted values outside the actual data range, out-of-sample predictions in my analysis were very rare, providing evidence that the models were performing adequately (Carnahan, Agarwal, & Campbell, 2012). To ensure robustness, I performed the analyses using alternative models, including conditional logit models and a Cox proportional hazard model, and they yielded results that were similar to my main results.

4.4 Results

4.4.1 Main Results

Table 1 reports the descriptive statistics and correlations for the variables used in the analysis. Table 2 reports the results from the linear probability model, predicting focal products' *product failure*. Model 1 shows the result from the linear probability model, including only the baseline control variables. Model 2 indicates that the coefficient for *source product failure* is positive and significant ($\beta = 0.154$, $p < 0.001$), suggesting that focal product failure is associated with source product failure. This result provides strong support for Hypothesis 1.

Table 4.1 Descriptive Statistics and Correlations

		Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13
1	Product failure	0.06	0.24													
2	Source product failure	0.09	0.29	0.31												
3	Product market competition	40.16	50.13	0.01	-0.01											
4	Relative performance	0.49	0.50	0.06	0.08	0.31										
5	Pre-application source product failure	0.08	0.26	0.15	0.22	0.05	0.07									
6	Source product complexity	0.72	1.30	-0.01	0.05	-0.02	-0.09	0.04								
7	Source product count	2.40	2.09	0.00	0.08	0.15	0.07	0.07	0.61							
8	Focal-predicate time gap	5.54	5.05	-0.05	-0.07	-0.13	-0.19	0.00	0.03	0.00						
9	FDA review time	106.62	86.97	0.02	0.02	-0.07	-0.12	0.02	0.06	0.07	0.08					
10	Product count	78.53	72.36	0.01	0.04	0.04	0.13	0.00	0.11	0.09	0.01	-0.05				
11	Failure count	5.34	12.98	0.14	0.16	0.13	0.15	0.21	-0.03	-0.03	-0.06	0.02	0.24			
12	Company size	9.33	2.02	0.08	0.08	-0.06	0.07	0.06	-0.02	-0.05	0.12	-0.01	0.68	0.39		
13	Profitability	0.10	0.35	0.00	-0.01	-0.02	0.02	0.00	0.00	-0.01	0.06	-0.01	0.18	0.04	0.26	
14	R&D intensity	0.06	0.05	-0.05	-0.07	-0.04	-0.01	-0.06	0.01	0.00	-0.09	-0.04	-0.07	-0.23	-0.43	-0.19

Coefficients greater than 0.02 are significant at the 0.05 level.

Table 4.2 Product Failure Likelihood Using LPM

	Model 1	Model 2 H1	Model 3 H2	Model 4 H3	Model 5 H4	Model 6 Full
Source product failure		0.154***		0.081**	0.180***	0.112***
		[0.034]		[0.028]	[0.036]	[0.030]
Source product failure (same firm)			0.179***			
			[0.035]			
Source product failure (different firm)			0.040			
			[0.032]			
Source product failure				0.121*		0.102+
x Relative performance				[0.056]		[0.055]
Source product failure					-0.034*	-0.026*
x External search scope					[0.013]	[0.012]
Relative performance		-0.004	-0.005	-0.014+	-0.004	-0.012+
		[0.009]	[0.009]	[0.007]	[0.009]	[0.007]
External search scope		-0.002	0.000	-0.001	0.001	0.001
		[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Pre-application source product failure	0.049+	0.034	0.034	0.035+	0.035	0.035+
	[0.025]	[0.021]	[0.021]	[0.021]	[0.021]	[0.021]
Source product complexity	-0.002	-0.003	-0.003	-0.002	-0.001	-0.001
	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]
Source product count	0.001	0.001	-0.000	-0.000	0.000	-0.000
	[0.002]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Focal-predicate product time gap	-0.001	-0.000	-0.000	-0.001	-0.000	-0.001
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
FDA review time	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Firm's product counts	-0.000	-0.000+	-0.000+	-0.000+	-0.000+	-0.000+
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Firm's product failure count	-0.001	-0.001+	-0.001+	-0.001+	-0.001+	-0.001+
	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Firm size	0.007*	0.007*	0.006*	0.006*	0.006*	0.006*
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Profitability	-0.010	-0.009	-0.010	-0.009	-0.010	-0.010
	[0.009]	[0.008]	[0.008]	[0.008]	[0.008]	[0.008]
R&D intensity	0.101	0.104	0.106	0.102	0.104	0.102
	[0.079]	[0.073]	[0.074]	[0.072]	[0.073]	[0.073]
Product market competition	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	[0.001]	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]
Year fixed effects	Included	Included	Included	Included	Included	Included
Product market fixed effects	Included	Included	Included	Included	Included	Included
Constant	-0.021	-0.025	-0.023	-0.017	-0.024	-0.017
	[0.033]	[0.029]	[0.029]	[0.027]	[0.029]	[0.027]
Observations	5,442	5,442	5,442	5,442	5,442	5,442
R-squared	0.251	0.275	0.279	0.279	0.278	0.281

Robust standard errors clustered at the firm-level are in brackets.

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Model 3 shows evidence to support Hypothesis 2. As predicted, the coefficient for source product failure (same firm) is positive and significant ($\beta = 0.179$, $p < 0.001$), and the coefficient for long investment horizon is positive, but insignificant ($\beta = 0.179$, $p > 0.01$). A chi-square test confirmed that the difference between these two coefficients is statistically significant ($\chi^2 = 10.00$, $p < 0.001$). This result indicates that the association between source product failure and focal product failure is more prevalent when the source product with inherent defects and focal product are both developed by the same firm, suggesting that product failure is more likely to persist within an organization. This provides strong support for Hypothesis 2.

Model 4 includes an interaction term between *source product failure* and *performance above competitor average*. As predicted, the coefficient of this interaction term is positive and significant ($\beta = 0.121$, $p < 0.05$), suggesting strong support for Hypothesis 3. This result indicates that, when the focal firm's new product introduction performance in the given product market is better than its competitors, the effect of source product failure on focal product failures is amplified.

Model 5 includes an interaction term between *source product failure* and *external search scope*. As predicted, this interaction term's coefficient is negative and significant ($\beta = -0.034$, $p < 0.05$), suggesting strong support for Hypothesis 4. This result indicates that, when the focal product is built on source products developed outside the focal firm's organizational boundary, the effect from *source product failure* on focal product failure weakens. The main independent variables' statistical significance remains consistent in the full model (Model 5).

4.4.2   Robustness Checks

FDA's scrutiny. To validate the main results and rule out alternative explanations, I performed several additional analyses. First, one might argue that the association between focal product failure and predicate device failure may be driven by strong FDA scrutiny. Focal products

building on failed predicate devices (or products with a high chance of failure) could experience strong FDA scrutiny during the approval process. If a focal product is under heavy FDA scrutiny during the approval process, I assume that FDA surveillance may continue to remain strong even after the product has entered the market, thereby increasing the likelihood of product recall. To test whether the increase in the FDA's surveillance explains the results, I tested whether predicate device failure is associated with the time it takes for a focal product to receive FDA approval (*FDA review time*). *FDA review time* is measured by the number of days it takes for a focal product to receive FDA approval after its application day. The longer it takes for approval could mean the more the FDA is scrutinizing the product during the approval process. I regressed *FDA review time* against s*ource product failure* and other covariates used in my main analysis using an OLS regression. As Table 3 indicates, no significant relationship exists between source product failure and FDA review time, ruling out the possibility that the FDA's scrutiny argument explains the main results.

Table 4.3 FDA Review Time Estimate Using OLS Model

Dependent variable	Model 1 Review time	Model 2 Ln(Review time)
Source product failure	-2.755	-0.021
	[4.039]	[0.035]
Relative performance	-8.625**	-0.064*
	[2.856]	[0.029]
External search scope	7.680**	0.088***
	[2.343]	[0.018]
Pre-application source product failure	-1.258	-0.000
	[5.241]	[0.042]
Source product complexity	2.224	0.030+
	[2.169]	[0.017]
Source product count	0.852	0.001
	[2.195]	[0.014]
Focal-predicate product time gap	0.857**	0.010**
	[0.323]	[0.003]
Firm's product counts	-0.010	-0.000
	[0.036]	[0.000]
Firm's product failure count	0.100	0.004***
	[0.114]	[0.001]
Firm size	0.789	-0.000
	[1.707]	[0.018]
Profitability	2.805	0.039
	[3.037]	[0.032]
R&D intensity	70.290	0.673
	[49.754]	[0.439]
Product market competition	-0.340*	-0.001
	[0.162]	[0.002]
Year fixed effects	Included	Included
Product market fixed effects	Included	Included
Constant	56.680***	3.834***
	[14.671]	[0.160]
Observations	5,442	5,442
R-squared	0.338	0.332

Robust standard errors clustered at the firm-level are in brackets.
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Information advantage. Another possible explanation as to why source product failure leads to subsequent product failure is not because some firms are path-dependent, but because some firms are less informed about the potential failure of source products. Some firms may have

the capabilities to obtain information about predicate devices' risk for potential failure in the future. These firms then intentionally could avoid developing new products based on potentially defective predicate devices. On the other hand, firms, without having such an informational advantage in identifying predicate devices' potential failure risk, may be more susceptible to experiencing product failures. To address this alternative explanation, I created an alternative measure of source product failure in which I excluded any predicate device recalls that occurred within six months after the focal product application (i.e., I set the value to 1 if the focal product's predicate device is recalled at least six months after the focal product is applied for FDA approval, and 0 if otherwise). The rationale behind using this lagged independent variable is that the effect of some firms with an informational advantage over predicate devices' potential failure risk in the future may be limited because of the six-month grace period. Model 1 in Table 4 shows that even after applying a six-month grace period for the source product failures, the coefficient for *source product failure* is still positive and significant, supporting my claim that the path-dependent nature of product development leads to a persistence of failure in new product development.

Table 4.4 Product Failure Likelihood Using LPM (6 Months Grace Period)

	Model 1 H1	Model 2 H2	Model 3 H3	Model 4 H4	Model 5 Full
Source product failure	0.158***		0.083**	0.184***	0.114***
	[0.045]		[0.028]	[0.049]	[0.030]
Source product failure (same firm)		0.194***			
		[0.041]			
Source product failure (different firm)		0.046			
		[0.036]			
Source product failure x Relative performance			0.124+		0.107+
			[0.063]		[0.059]
Source product failure x External search scope				-0.035*	-0.027*
				[0.016]	[0.014]
Relative performance	-0.004	-0.004	-0.013+	-0.003	-0.011
	[0.009]	[0.009]	[0.008]	[0.009]	[0.008]
External search scope	-0.002	0.000	-0.001	0.001	0.001
	[0.003]	[0.003]	[0.003]	[0.002]	[0.002]
Pre-application source product failure	0.033+	0.032+	0.033+	0.033+	0.033+
	[0.019]	[0.019]	[0.019]	[0.019]	[0.019]
Source product complexity	-0.002	-0.002	-0.001	-0.001	-0.001
	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]
Source product count	0.000	-0.001	-0.000	-0.000	-0.001
	[0.002]	[0.002]	[0.003]	[0.002]	[0.002]
Focal-predicate product time gap	-0.001	-0.001	-0.001	-0.001	-0.001
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
FDA review time	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Firm's product counts	-0.000*	-0.000+	-0.000*	-0.000*	-0.000*
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Firm's product failure count	-0.001+	-0.001	-0.001+	-0.001+	-0.001+
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Firm size	0.008**	0.007*	0.007**	0.007**	0.007**
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Profitability	-0.011	-0.011	-0.011	-0.012	-0.011
	[0.008]	[0.009]	[0.008]	[0.008]	[0.008]
R&D intensity	0.115	0.111	0.110	0.114	0.111
	[0.074]	[0.075]	[0.073]	[0.075]	[0.073]
Product market competition	-0.000	-0.000	-0.000	-0.000	-0.000
	[0.001]	[0.001]	[0.000]	[0.001]	[0.000]
Year fixed effects	Included	Included	Included	Included	Included
Product market fixed effects	Included	Included	Included	Included	Included
Constant	-0.030	-0.027	-0.022	-0.029	-0.023
	[0.030]	[0.030]	[0.027]	[0.030]	[0.027]
Observations	5,442	5,442	5,442	5,442	5,442
R-squared	0.274	0.279	0.278	0.277	0.280

Robust standard errors clustered at the firm-level are in brackets.

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Unobserved characteristics. Another possible empirical challenge of my main model is that a firm's behavior in building upon failed source products is likely endogenous with respect to subsequent product failure. Although I included control variables that represent firms' observable characteristics (e.g., product count, failure count, company size, etc.), it is difficult to control unobservable factors that may drive a correlation between the two. For instance, firms managed by CEOs with no background in product development may be more inclined to experience product failures.

As an attempt to overcome this empirical challenge, I exploited a quasi-natural experiment in the form of a U.S. Supreme Court decision in *Riegel v. Medtronic Inc.* (hereafter the *Riegel* case). On February 20, 2008, the high court ruled that the approval process demonstrates federal requirements and that state tort law claims that impose additional or different requirements on medical device manufacturers are preempted under the preemption clauses of the Medical Device Amendment (MDA). It has been evaluated that the decision has created a federal judicial shield for medical device manufacturers against lawsuits in state court actions for liability for damages (Pastner, 2009). I took advantage of this feature to provide exogenous variations in firms' tendencies to rely on preexisting products and, subsequently, overlook potential failures in the product development process. I assumed that because medical device manufacturers gained a certain degree of federal protection against product liability, they may be less cautious in developing new products and, thus, the chances of building on potentially defective source products may increase after the Supreme Court ruling. To estimate the treatment effect on subsequent product failures, I used a difference-in-differences approach. Specifically, if a focal product's source product fails after the focal product is applied for FDA product approval (i.e., *source product failure* = 1), I computed the difference in the likelihood of focal product failure

before and after the court ruling. I then compared this difference with the corresponding difference with a control product, which is a product that did not build on a potentially defective product (i.e., *source product failure* = 0).

Figures 1 and 2 present product failure likelihood trends pre- and post-*Riegel*. Each data point shows the average product failure ratio for groups of products whose source products have inherent product defects (i.e., treated) or do not have any known product defects (i.e., control) after focal product approval. The parallel trend between two curves in the figures prior to the *Riegel* shows that evolution of product failure likelihood is virtually similar among treated and control products in the two years preceding treatment.
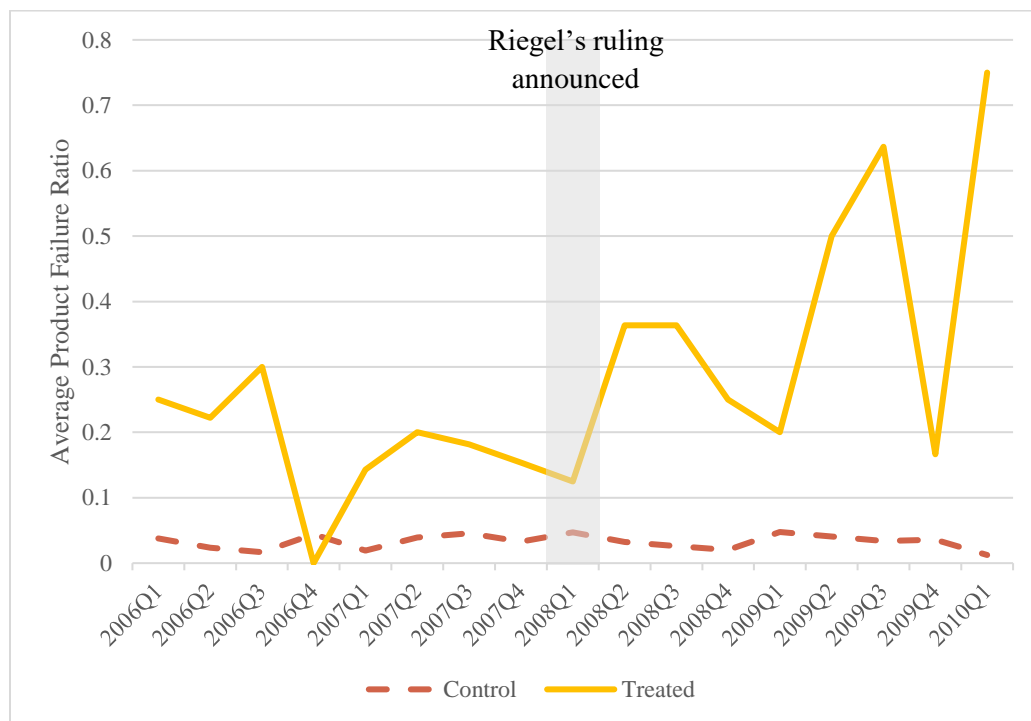

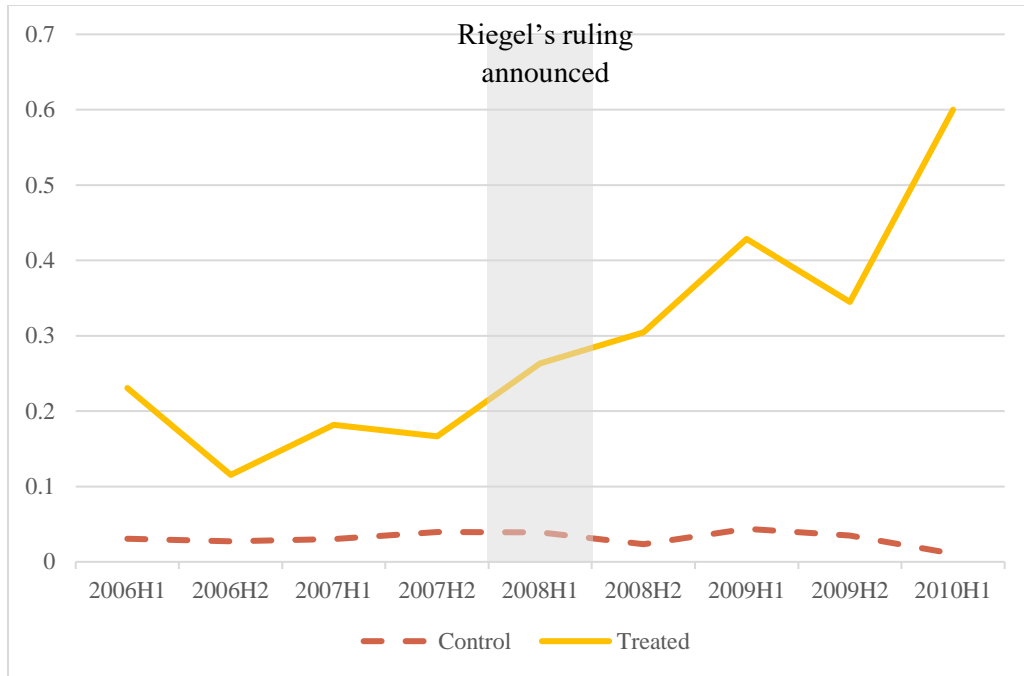Figure 4.1 Product Failure Trends by Quarters in Treatment and Control Group

Figure 4.2 Product Failure Trends by Half-Years in Treatment and Control Group

Table 5 presents the results from the difference-in-differences regression analysis, exploiting the *Riegel* ruling. In all regression models, the dependent variable is the product failure event two years afterward, compared with two years before treatment. In Model 1, the coefficient for the interaction term *Post-Riegel x source product failure* is positive and significant ($\beta = 0.161$, $p < 0.10$), implying that products building on defective preexisting products are experiencing a higher probability of product failure afterward when medical device manufactures' product liability presumably decreased due to the ruling. Figure 1 shows that after treatment, the two curves diverge: Treated products face a significantly higher chance of failure compared with control products. I further interacted the interaction term with other independent variables that I used in the main analysis, and the results are generally consistent.

Table 4.5 Difference-in-Differences Estimating Product Failure Likelihood

	Model 1 H1	Model 2 H2	Model 3 H3	Model 4 H4
Source product failure x Post-Riegel	0.161+ [0.085]			
Source product failure (same firm) x Post-Riegel		0.181+ [0.105]		
Source product failure (different firm) x Post-Riegel		0.050 [0.099]		
Source product failure x Post-Riegel x Relative performance			0.304* [0.144]	
Source product failure x Post-Riegel x External search scope				0.002 [0.035]
Controls	Included	Included	Included	Included
Year fixed effects	Included	Included	Included	Included
Product market fixed effects	Included	Included	Included	Included
Constant	-0.033 [0.042]	-0.032 [0.042]	-0.031 [0.043]	-0.032 [0.044]
Observations	2,413	2,413	2,413	2,413
R-squared	0.335	0.342	0.342	0.338

Robust standard errors clustered at the firm-level are in brackets.

*** $p<0.001$, ** $p<0.01$, * $p<0.05$, + $p<0.1$

4.5 Conclusion and Discussion

New product development is a critical factor for firms' growth and survival in a dynamic environment (Damanpour, 1991; Katila & Ahuja, 2002; Schoonhoven et al., 1990). Previous studies have documented that many firms develop new products by making relatively incremental changes to existing products and exploiting established technology's potential (Helfat & Raubitschek, 2000; Henderson & Clark, 1990; Tushman & Anderson, 1986). Despite some of the advantages of taking an incremental approach to new product development – mentioned in previous research – in this study, I highlight the downside of firms relying on their preexisting products and underlying technologies. I posit that developing new products by building on preexisting products and their underlying technologies could act as a pathway through which product failure persists.

Specifically, I argue and show that when the source product upon which a new product is being developed is inherently defective, the newly developed product may have a high likelihood of experiencing product failure. One of the possible reasons is that firms may make incremental changes from their preexisting products without taking precautions, thereby overlooking failures prevalent in preexisting products. I provide several conditions under which firms increasingly may neglect preexisting failures and make failures prevalent in their product development systems. I show that the positive association between source product failure and focal product failure becomes greater when the failed source product is an internally developed product. This finding supports the claim that product failures may persist in the firm's internal product development system. I further claim that firms' tendency toward resorting to incremental changes in their existing products may increase when they perform better than their peers as outcompeting firms are reluctant to make radical changes from their existing routines and search path. Lastly, this research suggests that firms may expand their search scope to over this issue of persistent of failures in their product development systems.

In this paper, I exploited a unique data set on medical device recalls and predicate devices to test proposed hypotheses empirically. I used information on the focal product-predicate relationship manually collected from the FDA product summary reports to identify incremental changes in medical device products. Employing product-level analyses to estimate the likelihood of product failure, I find empirical results that support my proposed hypotheses.

I contribute to extant literature in several dimensions. First, this research complements prior literature on incremental innovation, which has argued for the positive aspects of incremental innovation (Cohen & Levinthal, 1990; Martin & Mitchell, 1998). Incremental developments in innovation provide firms with opportunities to gain competitive advantage by incrementally

adding value to existing innovations (Helfat & Raubitschek, 2000). However, in this research, I emphasize that incremental changes to innovations sometimes can destroy companies' value, particularly when preexisting innovations, being the foundation of newer innovations, are inherently defective. Therefore, this study provides new insight on the costs of incremental innovation.

Second, this study is one of the few studies to investigate the causes of failures in product development that high-tech firms experience. Many extant innovation and product development studies have focused on the antecedents of firms' successful innovations (e.g., Chatterji & Fabrizio, 2014; Katila & Ahuja, 2002; Schoonhoven et al., 1990). Our understanding on precursors that induce firms to have a higher likelihood of experiencing product failures is very limited. Because product-related problems are often associated with firm's financial and reputational consequences, finding potential factors for product failures may provide important implications. By empirically examining firm's product recall events, I argue that product failure is a critical dimension in understanding and assessing firm's product innovation outcomes.

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