The Management, Organization, and Geography of Novel Innovation

by

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Business Administration
Duke University

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Dissertation submitted in partial fulfillment of the requirements for the degree of
Doctor of Philosophy in Business Administration
in the Graduate School of Duke University
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This dissertation develops new theory and evidence on the antecedents and consequences of innovation for firms, and includes three empirical studies focusing on various facets of the management, organization, and geography of novel innovation.

Chapter 1 examines the role of relationships in mitigating change to firm boundaries for new firms entering the medical device industry, focusing in part on how the timing of novel innovation influences whether firms integrate their sales function. Using a new dataset on more than 1,600 new medical device manufacturers that documents both their full product portfolios and sales governance modes over time, this paper finds evidence that relationships develop and influence sales governance choices only when they cross firm boundaries. Further, launching a novel innovation has a nuanced relationship with integration: early in a firm's life, it increases the likelihood of sales integration, but this relationship diminishes over time. This research offers new insights into the limits of relational governance, and contributes to our understanding of the nuanced impact of novel innovation on firm boundaries.

Chapter 2 examines the "dual role" of local inventive activity in firm innovation. On one hand, a vibrant, local research community provides inputs into internal research and development activities: the seeds of internal invention. On the other, external inventive activity provides inventions which can substitute for internally generated inventions: the fruit. Furthermore, inventive activities also provide fertile ground for imitation. This paper develops a simple model of how geographically

proximate inventive activity—or clusters—affect firms' innovation choices. Firm invention capability importantly conditions the value to a firm of local innovation-related inputs. The paper employs a recent survey of product innovation and the "division of innovative labor" among nearly 5,000 US manufacturing firms. Absent a direct measure, invention capability is treated as a latent, unobserved variable, and a latent class multinomial model is used to infer its value. Consistent with the model's predictions, more inventive firms make use of the richer soil whereas less inventive firms pick the fruit. Further, more capable firms make use of higher value external sources in clusters. This research expands our understanding of how location shapes both who innovates and how they innovate, and provides a novel method for identifying latent capability.

Chapter 3 examines how the novelty of a startup's invention conditions its likelihood of venture capital (VC) financing. In it, I argue novelty increases uncertainty about commercial viability, thus requiring startups to search more extensively to find willing VCs to fund them. Two factors lower the cost of search: prior startup experience and a thick VC market. Because these factors make extensive search cheaper, novel startups will disproportionately benefit from experience and cluster location. To test this, I build a hand-collected dataset of 4,700 patenting US medical device startups, and follow them from "birth" (first patent), to VC investment (if any), to eventual success or failure. While novelty has no impact on funding or success on average, firms with novel technologies who also have a lower cost of finding and attracting potential partners are much more successful than those with more incremental technologies. Further, thick markets are less useful for firms pursuing novel technologies if they lack prior startup experience, and experienced founders are not especially advantaged in thin markets. Advancing theories of innovation and entrepreneurship, this study highlights when, where, and for whom novelty pays.

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1

The limits of relationships: Sales strategy in the US medical device industry

1.1 Introduction

Over time, organizations involved in economic exchange develop relationships. Trust, shared norms, and routines emerge via repeated exchange. Collectively, these aspects of relationships help to coordinate activity, incentivize investment in relationship-specific resources, and encourage the development and transfer of valuable knowledge (Hoetker & Mellewigt, 2009; Kotabe et al., 2003; Poppo & Zenger, 2002). Such relationships affect future partnering choices (Elfenbein & Zenger, 2013; Gulati, 1995).

While prior research links relationships to external partner choice and related performance (Elfenbein & Zenger, 2013; Holloway & Parmigiani, 2016), and illuminates the complementarity between contractual and relational governance (Poppo & Zenger, 2002), it has not explored the conditions under which these relationships influence ongoing firm boundary choices.

Existing research largely focuses on how relationships drive firms to choose the same external partners over time, but has typically ignored the possibility of integration as an option when circumstances change. Further, the development and impact of exchange relationships inside firms (i.e. between different functional units) and how that differs from relationships that develop between firms has received little theoretical or empirical exploration in the context of firm boundary decisions. Understanding both facets—when valuable relationships develop along the value chain (and when they don't) and how relationships inhibit firm boundary change (or when and how they don't)—is necessary to situate relational governance within the larger literature on the boundaries of the firm.

With that in mind, in this paper, we explore how relational capital—the shared trust, norms, and routines that develop over time in exchange relationships—influences firm boundaries. We contrast external and internal inter-functional exchange, arguing that relational capital is more necessary, and therefore more likely to develop in a consequential way, in exchange across firm boundaries and not within them. We argue this is because the value of relationships lies in providing features—shared trust, norms, and emergent routines—that substitute for features of fiat control which are more likely to be available inside firms. Next, building on existing relational governance theory, we contend that relational capital will be most valuable when firms need to develop and share new, relationship-specific knowledge (Elfenbein & Zenger, 2013), i.e. when firms introduce a novel innovation to the market. However, such circumstances are also when we would expect firms to integrate complementary functions, e.g. sales (Williamson, 1971). To reconcile these two perspectives, we explore how the relationship between innovation and integration changes over time. Without relational capital, adding a new-to-the-world product should increase the likelihood of integration; with relational capital, innovating should decrease the likelihood of integration. Last, we also theorize that relational capital will be highly localized to the narrow market in which the exchanges take place, and therefore any changes to the focal market of the firm will lessen the impact of relational capital on firm boundaries over time. Collectively, we build theory about when relationships will matter for firm boundaries, focusing on illuminating the limits of relationships in shaping firm boundary choice.

To test our predictions, we build a novel dataset of U.S. medical device manufacturers that we follow from their entry into the industry, tracking both the products they sell and their mode of sales—internal or external. We focus on the sales boundary choice of US medical device firms, specifically when and whether they use internal or external sales, and the role that emergent relationships play in the ongoing choice of sales governance. Sales in general is an important strategic function: firms spend 10-40 percent of revenues on sales (Sinha & Zoltners, 2001), often more than they do on research and development, a subject of considerable inquiry in strategic management (e.g., Ahuja et al. (2008)). Prior work suggests the decision of how to manage sales is of key importance in settings where the ongoing transfer of knowledge to and from users is crucial for value creation and value capture (Grant, 1991, 1996; Danneels, 2002), which is a key feature of the medical device industry (Chatterji et al., 2008; Chatterji & Fabrizio, 2014).

We find evidence consistent with our theory. Specifically, while firms who initially chose external sales are less likely to internalize sales after the first two years, the likelihood of outsourcing doesn't significantly change over time for firms that initially have integrated sales. Focusing on the external-first firms, we also find evidence consistent with the value of external relationships being narrowly applicable. Firms that don't change their focal specialty are less likely to integrate over time, whereas firms that change their specialty are not. Last, we find that firms who introduce new-to-the-world products to the market in their first few years of operation are more likely to integrate sales compared to firms who don't add such products. However, this difference vanishes over time. While we don't estimate causal relationships in our analyses, because we find these asymmetries between external and internal and likelihood of change, our findings are not well explained either by governance capabilities (i.e. firms develop resources and abilities around the mode of governance they initially choose, and are therefore unlikely to change over time) or by a simple organizational inertia story.

By exploring relational capital's role in firm boundary choice, our paper makes several contributions. First, it highlights the limits on when relationships will develop. By looking at internal governance, typically ignored by relational governance work, we identify some boundary conditions on when repeated exchange makes a difference to a firm's future strategic choices (potentially to their detriment as in Holloway & Parmigiani (2016)). Relationships may drive firms away from choosing alternative external partners, but they don't appear to develop significantly inside of firms between functions, that is, in a way that changes the calculus of firm boundary choices over time. Second, by including integration as an option to deal with increased need for knowledge development and transfer, we re-integrate relational governance theory back into the broader literature on the theory of the firm.

Interestingly, we find that the role of inter-firm relationships in facilitating knowledge transfer may be weaker than we would have expected: we find no evidence that those who launch novel innovations are less likely to integrate than those who don't launch novel innovations. Related to this point, our findings also contribute to literature that explores how innovation might affect the boundaries of the firm (Teece, 1986; Kaul, 2012). We do so by illuminating the how the impact of novel innovation on the management of complementary downstream activities appears at least somewhat contingent on relationships. Specifically, innovation only increases integration likelihood in the very early years of a firm. Last, we provide a nuanced explanation for the lack of firm boundary changes generally observed in prior related research (Kapoor, 2013; Qian et al., 2012): that is, relationships change the difference between integrated and outsourced sales over time in specific ways. Even as innovation increases the need for the development of new knowledge and its transfer along the value chain, established relationships appear to have some role—although less than prior theory predicts—in mitigating the push towards integration.

1.2 Background: Relationships and Firm Boundaries

Strategy literature has long recognized the challenges inherent in coordinating productive activity across firm boundaries (Chandler, 1962; Grant, 1991; Williamson, 1971, 1975). When new, specific investments are required throughout the value chain, and when uncertainty about demand or technical aspects of a product looms large, classic strategy theorizing suggests firms should vertical integrate manufacturing, R&D, sales, marketing, and other complementary activities (Teece, 1986; Williamson, 1975).

While integration can help to mitigate exchange hazards and encourage knowledge development and transfer, recent theorizing suggests that inter-firm relationships that develop between partners in exchange can become similar to vertical integration (Elfenbein & Zenger, 2013; Gibbons & Henderson, 2012; Poppo & Zenger, 2002; Poppo et al., 2008). Over time, partners gain trust in one another, build up shared norms that dictate acceptable behavior and facilitate coordination, and develop and hone shared routines that enable efficient actions. These features, collectively labeled relational capital, facilitate the development and transfer of knowledge across firm boundaries (Poppo & Zenger, 2002). Based on these past-dependent features, and based on expectations of continued exchange into the future, separate-but-partnering firms make investments in developing knowledge and other assets specific to the relationship, somewhat akin to if they were within a single firm.

The relational governance literature typically positions relationships that emerge over repeated exchange and the consequent "relational governance", implicitly as a substitute for vertical integration and governing via fiat control. Existing literature typically tests for the impact of relationships by exploring the effects of past repeated partnering on future partner choice, implicitly assuming the choice is between external partners (including parts suppliers, legal service providers, and others) (Elfenbein & Zenger, 2013; Mayer et al., 2012).

In this paper, we explore the limit of relationships in shaping firm boundaries over time. We take seriously the idea that relationships, and their component features of trust, norms and routines, substitute for integration. We first argue that relationships develop in inter-firm exchange, where investment in specific assets, including the development and exchange of knowledge, is necessarily incentivized through relational mechanisms. In contrast, intra-firm exchanges and knowledge transfer can be governed by fiat. We further explore the contingencies of relational capital in driving inter-firm exchange choices, focusing on the role of increased need for ongoing knowledge exchange that results from novel innovation.

1.2.1 The Limits of Relational Governance

Relationships that emerge over repeated exchange influence the choice of future exchange partners. At a higher level, in the context of firm boundary decisions, relational capital should therefore drive firms away from changing their mode of governance. To explore this, we examine how: (1) the location of the exchange between units within the same firm or across firm boundaries, (2) changes in the need for knowledge development and transfer, condition the development of relational capital and its role in shaping ongoing governance choices.

As described above, relational capital is comprised of emergent shared trust, norms, and routines (Elfenbein & Zenger, 2013; Poppo & Zenger, 2002; Schepker et al., 2014). Shared trust in exchange relationships means that firm A (e.g. a medical device manufacturer) is willing to accept vulnerability based upon expectations that firm B (e.g. a medical device sales team) will act in a favorable, expected way

(Rousseau et al., 1998). In exchange relationships, shared trust means that both parties will assume and rely upon each other to make relationship-specific investments beyond those formally laid out in contracts, and both will act, and make investments themselves, according to that expectation (Zaheer et al., 1998). As argued by prior research, shared trust[1] is built over time through repeated exchange supported by norms (Adler, 2001). Importantly, for trust to emerge and influence expectations of partner behavior, and through that own behavior, there must be some risk of deviation and therefore an implicit or explicit demonstration of trustworthiness (Rousseau et al., 1998). Under complete contracts, or inside firms where there exists control by fiat, shared trust isn't as necessary to incentivize relationship-specific investments.

Similarly, for norms and emergent routines to build up and strengthen in value over time, there needs to be some gap to fill, i.e. an absence of formal rules and mandated routines in place governing the interaction and interdependencies. Inside of firms, formal routines help facilitate efficient transfer of knowledge relevant for the routinized activity (Easterby-Smith et al., 2008; Zheng & Yang, 2015). Prior work suggests that inter-firm routines develop over time (Dyer & Singh, 1998) as products are developed, bought, and sold, and know-how is transferred between the various actors involved, that is, as the routine is repeatedly performed (Feldman & Pentland, 2003; Zheng & Yang, 2015), and develops the potential for performance benefits (Zollo et al., 2002). By supporting the development of routines, repeated exchange also leads to the creation of shared norms of behavior—for example, shared language and patterns of communication, and mutual understanding of what constitutes appropriate behavior—that encourage effective exchange (Ring & Van De Ven, 1994).

[1] Whereas general trust is a context-level construct (e.g. how much do I trust a random organization or person?), shared trust is based on repeated interactions and is a set of informed beliefs about the behavior of a specific organization (Bottazzi et al., 2016). It is akin to "personalized trust" at the individual level. Some have argued for two bases for shared trust: calculative trust, based on the expectation of rewards and penalties (forward looking), versus relational trust, based on past behavior and characterized by a shared identity (backward looking) (Poppo et al., 2016).

Relational norms that support exchange include mutual expectations of flexibility, solidarity, joint responsibility, mutual accommodation, and other behaviors that facilitate ongoing exchange activities (Cannon et al., 2000; Macneil, 1980). Like trust and routines, however, the value of emergent, shared norms in exchanges will depend on them being necessary, something which is less likely to be true for exchanges that take place within firms.

In other words, relational capital emerges over time at least in part because of the absence of fiat control: there is little need for the valuable features of relationships to develop over time when joint ownership dictates jointly beneficial behaviors, outlines formal rules, and structures formalized routines. Following this logic, we hypothesize that there will be a decreased likelihood of integration over time when firms use external sales forces; however, the likelihood of outsourcing will not change over time for those using internal sales:

(H1a) The likelihood of integration will decrease over time for firms using external sales.

(H1b) The likelihood of outsourcing will not change over time for firms using internal sales.

In the above reasoning, we argue that relational capital emerges in inter-firm exchanges more so than in inter-functional exchanges that take place within firms, and that this has important consequences for the relative likelihood of firm boundary change over time. Yet, even for firms using external sales forces, the development of relational capital may be limited if firms change their downstream focus, which can interrupt the development of valuable relationships along the sales channel.

In our context of medical device sales, relationships develop through repeated exchange between the product manufacturing firm and sales forces (typically focused on narrow specialties), and between sales forces and customers, who are specialized within single markets (i.e. physicians with narrow medical specialties). The manufacturer-sales and sales-customer relationships develop in parallel: as relational capital develops and facilitates the flow of knowledge between manufacturers and sales representatives, shared trust, emergent routines, and norms also develop between the sales representatives and physicians in the key specialty areas of the manufacturer. Specifically, physicians value maintaining their ties to particular sales representatives.[2] Over time, sales representative-physician relationships become "deep personal relationships" that are fundamentally built upon "the trust level that the physician, the physician's office and the hospital have with the individual rep" (Snowbeck, 2008).[3] Sales representatives facilitate knowledge transfer to physicians about how products are intended to be used, and, conversely, transfer that valuable knowledge back to manufacturers. Conversely, surgeons rely on a technically knowledgeable, trusted sales representative to attend relevant procedures, as their "special product expertise enhances patient safety" by ensuring devices are used correctly,[4] and their product-specific knowledge enables efficiency in performing surgery.[5]

Any changes to the focal specialty of the firm will therefore disrupt the development of valuable relational capital not only between device firms and their sales forces, but also the development of manufacturer-specific relational capital between

[2] Further to this point, the ongoing connection between manufacturers and physicians has been anecdotally described as highly dependent on the sales representative-physician relationship. For example, Norman Dann, a former venture capitalist and Medtronic executive who started his career in sales described an experience in which one of the manufacturers he sold products for ended its relationship with his sales company (from the Minnesota Star Tribune): "[Dann's] reps had to go to docs and explain that they would no longer be handling a main product line. According to Dann, their response? 'We don't care, you're still going to be taking care of us, right?' "

[3] From medical device industry analyst Thomas Gunderson, in reference to a legal case in which medical device firm Ev3 was suing Cardiovascular Systems Inc. for poaching their specialized sales reps.

[4] According to Medtronic spokesperson Charles Grothaus (Hilzenrath, 2009).

[5] Stryker CEO Kevin Lobo suggests the detailed knowledge of devices that specialized sales forces hold is "an engine of growth" for the company (Saxena, 2015), and that without sales representatives' product- and context-specific specialized knowledge, "operating rooms just don't flow effectively and efficiently" (Johnson, 2015).

the sales force and the end customer. Changing focal specialty will therefore mitigate the otherwise negative relationship between time and likelihood of integration. In other words, we predict:

(H2) The likelihood of integration will decrease over time for firms using external sales only if they remain focused in the same downstream market.

Now that we've argued that relational capital only builds up in focused, external exchange relationships, we turn to explore how relational capital conditions the impact of novel innovation on integration. Notably, prior literature suggests that the need for investment in relationship-specific knowledge—resulting from novel innovation—can be a driver of integration (Macher, 2006), but also increases the value of existing relational capital, and therefore may also drive firms away from integrating (Elfenbein & Zenger, 2013).

In more detail, *novel innovation* requires the development and sharing of new, specific knowledge to use and to sell, and therefore requires both the manufacturer and sales force to make specific investments and rely on the commitment of each other to transfer knowledge. A classic transaction cost argument would suggest that as the need for relationship-specific investments increases, the risk of opportunism by external actors also increases (Anderson, 1985; Argyres & Zenger, 2012; Williamson, 1971; Macher, 2006). Building from TCE theory, we would therefore expect that adding a new-to-the-world product would increase the likelihood of integration. However, the relational governance literature suggests that when exchange hazards and the need for knowledge development and exchange increase, relational capital will have a higher value in exchange, since shared trust that has developed over time, combined with the shadow of future, valuable exchange will act to inhibit opportunistic behavior (Elfenbein & Zenger, 2013). In other words, adding a new-to-the-world product should decrease the likelihood of integration.

To reconcile these perspectives, we hypothesize that adding a new-to-the-world product without relational capital will increase a firm's likelihood of integration; by contrast, if a firm adds a new-to-the-world product once they've developed relational capital with their external sales force, it will decrease their likelihood of integration.

(H3) For firms without relational capital, adding a new-to-the-world product will increase their likelihood of integration; by contrast, for firms with relational capital, adding a new-to-the-world product will decrease their likelihood of integration.

Further, building from our arguments in *Hypothesis 2* we posit that the value of relational capital in exchange will depend on whether the new knowledge that needs to be developed and transferred falls within the established sales channel. New-to-the-world products added to the same channel (i.e. within the focal specialty of the firm) can leverage any developed relational capital, whereas those in new channels largely will not, as they will involve selling to different physicians and through potentially different sales forces. Thus, we predict:

(H4) Adding a new-to-the-world product outside *the firm's focal specialty will increase the likelihood of integration regardless of time since entry.*

1.3 Empirical Setting

We test our hypotheses by looking at a panel of firm divisions in the U.S. medical device industry. The U.S. medical device industry includes the producers of U.S. Food and Drug Administration (FDA) regulated medical devices and diagnostic tests,[6] as

[6] The FDA definition of a medical device is as follows: "an instrument, apparatus, implement, machine, contrivance, implant, in vitro reagent, or other similar or related article, including a component part, or accessory which is: (1) recognized in the official National Formulary, or the United States Pharmacopoeia, or any supplement to them, (2) intended for use in the diagnosis of disease or other conditions, or in the cure, mitigation, treatment, or prevention of disease, in man or other animals, or (3) intended to affect the structure or any function of the body of man or other

well as other related medical product suppliers. Medical devices generally fall into discrete medical specialty areas, reflecting distinct customer markets (i.e., physician specialties), including, for example, cardiovascular—devices such as artificial hearts and pacemakers—and orthopedics—for example, replacement joints—among other specialty groups. The alignment of products within specialties allow us to differentiate the focal markets of firms. For example, we can identify if a manufacturer adds products to its existing focal medical specialty (e.g., a new pacemaker added to an existing portfolio of cardiovascular devices) or to a new specialty, or if they change focal specialties over time. In addition, medical device sales representatives typically focus within a specialty, for example, by selling cardiovascular devices to interventional cardiologists. The alignment of both devices and sales representatives within discrete specialties allows us to identify if new products build on existing sales relationships.

Several other features of the medical device industry during our study period make this setting ideal for exploring the role of relationships in firm governance changes, focusing on the sales boundary. First, prior research has shown the sales function is particularly important for capturing value from new medical devices (Martin, 1984; Mitchell, 1989; Teece, 1986). In his foundational paper on complementary assets, Teece (1986) suggested that ownership of sales and distribution networks helped incumbent General Electric (GE), a technological follower, to capture the market for CT scanners from the pioneering innovator Electric and Musical Industries (EMI), who lacked sales assets. Similarly, in the case of cardiac pacemakers, an "easy to imitate" technology, firms with in-house, specialized sales capabilities performed better than those without them (Teece, 1986).

Another strength of our setting is that during our sample period (1983 to 1996)

animals, and which does not achieve its primary intended purposes through chemical action within or on the body of man or other animals and which is not dependent upon being metabolized for the achievement of any of its primary intended purposes." (FDA - CDRH, 2013) physicians had significant freedom to make purchasing decisions (Anderson, 2012; Makower et al., 2010b; Schafer, 2013) and, correspondingly, device firms cultivated close relationships with key physicians (Chatterji et al., 2008; Chatterji & Fabrizio, 2014). Building on that point, authors' conversations with medical device sales managers confirmed the importance of sales-force continuity for maintaining important manufacturer-customer relationships. Last, the market for external distributors of medical devices was relatively competitive during our analysis period (Cohen, 1999), suggesting the availability or cost of sales representatives did not constrain the choice between internal and external sales, leaving room for manufacturers to choose their sales strategy.

1.4 Data and Empirical Approach

To build our sample, we used the Medical Device Register (MDR) directory for the years 1983-1996. The MDR is a comprehensive directory of U.S. medical device manufacturers at the firm division level (Cecchino, 2010; Medical Device Register, 2012; Prasek, 1999). It includes a listing of the products sold by each manufacturer (at the division level) in each year, the medical specialties for each product (e.g., Cardiovascular), and, at the firm division level (e.g., 3M Imaging Systems), the mode of sales, as well as the number of employees, and other descriptive information. We use the yearly MDR directories to create a firm division-year panel of medical devices sold and sales mode used (i.e., internal or external sales). Thus, our unit of analysis is at the annual, firm division level, focusing on sales and the marketed product portfolio. We include all manufacturers entering in 1984 or later, for which we know the full history of products and sales relationships.

Alongside the MDR, we employed FDA medical device data. We used the standardized, generic product name listed in the MDR (e.g., "Prosthesis, Shoulder") to link to FDA data at the product level. For all devices linkable to FDA data, we assigned both a product classification category and a device class. We categorized products as "new-to-the-world" if they entered the market during the first year of a product approval for their respective FDA product classification category. We further segmented new-to-the-world products by FDA class: class III devices tend to be implantable, semi-permanent or permanent devices that take the place of bodily functions (e.g., artificial hearts, pacemakers), and are usually required to follow pre-market approval processes prior to entering the market (U.S. GAO, 2009); class II devices are somewhat less risky but still require reasonable assurance of safety and effectiveness (e.g. most prosthetic devices); and class I devices are low-risk devices for external use (e.g., tongue depressors). In robustness checks, we exclude class I devices from our measure of new-to-the-world products. Overall, we consider new-to-the-world products to signify devices that at the time of their introduction require new, product-specific, tacit information about their use to be transferred via the manufacturer-sales force and sales force-customer interfaces. We segment new-to-the-world products into inside versus outside the existing focal specialty of the firm, where we define the focal specialty of each firm division (in each year) as the specialty in which they have largest number of products.

The MDR data also list the corporate parent of each firm division (if any) in each year. Using this information, we created corporate-level firm-year measures, including the share of co-divisions with internal sales forces, and documented any changes to ownership of firm divisions over time.

To generate our final analytical sample, we dropped those firm divisions that did not have information on our key measures.[7] Because many of our explanatory and

[7] The raw MDR data contain 5,768 firm divisions. We necessarily included only those firms that entered in 1984 or after. We also dropped firm divisions from our sample that had no products, or sales/distribution information throughout the period of analysis, or if they were located outside of the United States. Because our analyses are focused on product development and sales, we further dropped firm divisions that only distribute products for other firms (neither developing nor manufacturing them), and similarly firm divisions that manufacture products for others but do not

control variables are lagged year-over-year changes, and our dependent variable is forward looking, we also omit firm divisions for which we have limited time series.

Our theory predicts that relational capital will only develop in external sales relationships (and not internal sales) and suggests that aspects of relationships mean that external governance can substitute for internal governance over time. Thus, to test our hypotheses, we first split our analytical data into two subsamples: (1) external-first manufacturers, who initially use external sales forces, where we explore the likelihood of integration, and (2) internal-first manufacturers, where we look at the choice to outsource sales. Manufacturers enter a subsample in the year they first market a product. They leave the subsample in the year of sales force change, or for those that did not change, either the year of exit, or in 1996 (the end of our observation window). In total, in our analyses, we had (1) in the external-first sample, 545 firm divisions for an average of five years (2,798 firm division years), including 102 integration events, and (2) in the internal-first sample, 1,070 firm divisions similarly for five firm division years on average (5,032 firm division years), and 59 outsourcing events.

In setting up our analyses, we wanted to reduce the potential for reverse causality, as prior literature has suggested that complementary activities, including sales, can shape innovation and firm outcomes (Dosi, 1982; Helfat & Raubitschek, 2000). We therefore estimate the relationship between future year integration or outsourcing (in *t+1*) and time since entry or product introductions (in *t*). In other words, we are not modeling the relationship between concurrent firm characteristics and sales force type, but instead the relationship between product and firm changes and the likelihood of subsequent firm-boundary change.

actually develop new products. Finally, we dropped firm divisions without key control variables, e.g., employees, and those that were in our sample for 3 years or less (necessary because of the lagging and forward looking structure in our main analyses, and additionally so that we aren't analyzing one year of data for a firm division).

1.4.1 Measures

Dependent Variable

Our dependent variable in our external-first analysis is an event variable that takes the value of 0 for all years the firm division uses external sales, and a value of 1 for the year of integration. In the internal-first analysis, we code the dependent variable in a similar fashion.[8] Because we are running event-history analyses (described below), we drop the firm divisions from the relevant analytical sample for the years after they change, as they are no longer at risk of the relevant change.[9] Firm divisions that never change are 0 for all years they remain in the sample until firm exit or 1996. Variables and data sources are described below.

Key Explanatory Variables

Following prior literature, we use length of time as a proxy measure for relational capital or a potential relationship (Elfenbein & Zenger, 2013; Kotabe et al., 2003). We use years since entry (in 2-year bands) to estimate the main effects of emergent relationships on integration (or outsourcing). As argued in *Hypothesis 1*, we expect years since entry to be negatively related to integration for external-first and insignificant in predicting outsourcing for internal-first firms.

We then test *Hypothesis 2*, or how the relationship between years since entry and integration for external first firms is hindered by any change in the specialty focus of the firm, or a specialty change. Specialty change is defined as a firm moving from one focal specialty (e.g. Cardiovascular) to another from one year to the next, which

[8] To construct this measure, we grouped MDR distribution types into internal sales (manufacturer direct, direct, sold direct, manufacturer through manufacturer reps) and external sales (distributor, manufacturer through distributor, dealer, manufacturer through dealer).

[9] Changes in one direction (e.g., outsourcing) do not in theory preclude a future change in the other direction. Concretely, once an internal-first firm division outsources sales, it becomes at risk of integration (i.e. switching back). These cases are extremely rare within our study period. For simplicity in our analysis, we exclude them; however, our results are robust to their inclusion.

involves a shift in the specialty in which they have the largest number of marketed products.

To test *Hypotheses 3* and *Hypothesis 4*, we also explore how relationships moderate how novel innovation (launching a new-to-the-world product) influences the likelihood of integration. We use new-to-the-world product introductions to represent changes in the need for the development and sharing of new, relationship-specific knowledge. To further explore the moderating effect of relationships, we look at this separately within the main specialty (where, we argue, established sales relationships will matter) and outside the main specialty of the manufacturer.

Control Variables

To isolate the relationship between our key predictors and the likelihood of sales-boundary changes, we control for other firm division, corporate, and specialty-level factors and antecedent firm changes that might be related to the sales-boundary-change decision. To account for firm division growth, which may contribute to the feasibility of integration, we control for lagged changes in the number of firm division employees: we expect the relationship between lagged growth and likelihood of integration to be positive. We also control for changes to size and scope of the product portfolio of the firm division, which may have effects relevant for change. We control for changes to the number of products sold by the firm (changes in size), and changes in the number of specialties covered by the portfolio (changes in scope) both of which shape the marginal costs of having internal versus external sales (Chandler & Hikino, 1994). We expect increases in product portfolio size to have a positive relationship with integration, and expect the reverse to be true for increases in scope (controlling for size). We also control for several corporate-level changes and characteristics, including the share of other medical device subsidiaries of the same corporation with internal sales, share internal, which we expect to have a positive relationship with integration at the firm division level. We also account for any changes to ownership of the firm division.

To control for variations in the supply of external sales forces, we include location (region) and specialty controls.[10] We also control for post-1990 years to account for aggregate-level changes in the supply of external sales forces over time.[11] We control for changes in the number of competitor firms focused in the same specialty over time (# competitors) as a measure of changes in demand for external sales and other changes to the competitive environment of the firm (we use the full MDR data to count and classify all medical device competitors, not just those in our analytical sample).

Last, we control for measures of the firm characteristics at the time of entry, including: the count of products, count of specialties in which the firm has products, count of new-to-the-world products, and count of filed patent applications. We used the Harvard US Patent dataverse (Lai et al., 2011) to link the firm divisions to patent assignee names. We specifically counted medical device patents (identified based on patent classifications). Because of knowledge development and transfer needs, we expect that firms that enter with patents (i.e. the antecedent of novel innovation) or new-to-the-world products (novel innovations themselves) that initially select external sales may be more likely to integrate in the near future.

[10] We control for diagnostic-focused firm division and separately laboratory diagnostic and radiology specialties, because each involve the development of either tests used in clinical labs or large capital purchases, and are therefore sold differently compared to single-use tools and implantable devices.

[11] Results are robust to more disaggregated specialties and more year controls, although lack of events in certain specialties and years means some observations are dropped in the internal-first analyses. Because the disaggregated fixed effects aren't significant, we use the more aggregated version.

1.4.2 Analysis of Events

Because we use discrete, annual data to explore our hypotheses relating relationships and product changes to sales-related firm-boundary change, we employ discrete event history analysis (EHA) techniques. EHA methods predict the conditional probability of an event occurring given that it has yet to happen within a population at risk of the event (Allison, 1984; Singer & Willett, 2003). In our case, discrete EHA is preferable to continuous-time methods because we do not know the precise timing of integration (or outsourcing) within each year, and because we have numerous simultaneous events or ties (i.e., more than one change event in each year) (Franco et al., 2009; Allison, 2010). For the population under study, the conditional probability of the event using discrete EHA is:

$$P_{it} = Pr[T_i = t | T_i \geqslant t, x_{it}] \tag{1.1}$$

where T is the discrete time of event occurrence and x is a vector of explanatory and control variables predicting event occurrence. EHA allows us to identify factors associated with change events. Discrete EHA can be estimated using maximum likelihood methods (Allison, 1984; Singer & Willett, 2003); for our main analyses, we used a complementary log-log model[12] and lagged our explanatory and control variables:

$$Pr[Sales\ boundary\ change_i = 1 | x_{it-1}] = 1 - exp(-exp(x_{it-1}\beta)) \tag{1.2}$$

In our external-first analysis, we treat a firm division using external sales as the unit of risk, and estimate the conditional probability of integration; for the internal-first analysis, we similarly estimate the conditional probability of outsourcing.

[12] The complementary log-log model is suggested when modeling events (or non-events) that are rare because the function is asymmetrical. We also ran all models using a logit model, and our results were the same qualitatively and in terms of statistical significance. Further, given the events are relatively rare, to supplement the logistic regressions, we also estimated Firth logit models, and again our results were the same qualitatively and in terms of statistical significance.

1.4.3 Self-selection into Sales Mode at Entry

An important potential source of bias in our estimates comes from the fact that firm divisions are not randomly assigned into their initial sales-governance mode. Firm divisions will vary in their likelihood of choosing internal or external sales when they first enter, depending on initial transaction-cost considerations, firm capabilities, and the market for knowledgeable sales forces and sales representatives at the time. In other words, observable factors at entry, such as firm division size and scope, whether they have a new-to-the-world product, their focal specialty, location, the size of their parent firm, and when they enter may shape this choice. Further, those that are highly likely to choose external (or internal) sales at entry, based on the observable characteristics, are also arguably less likely to change sales over time. When combined with the need to survive to be at risk of change in later years in our sample, this may bias our estimates relating time and decreasing likelihood of integration. To control for this, we estimate their propensity to have internal sales at entry, both balance and re-weight our data using inverse propensity scores (Bennett, 2013; Hirano & Imbens, 2001), and run additional supplementary analyses including the propensity score. We describe and document this process in detail in the related sections below. All analyses are run in Stata 13.

1.5 Results

Over the full period of our analyses, we find boundary changes in either direction are rare events. Outsourcing is far less common than integration among the separate populations at risk of each event (annually 1.1% vs. 3.5%). Most of the sample firm divisions enter using internal sales (66%), and do not change their sales boundaries over our window of observing them.

Our main regression results are provided in Tables 1.1, 1.2, and 1.3 (with corresponding marginal effects in Tables 1.4, 1.5, and 1.6). In Table 1.1, we explore Hypotheses 1a and 1b by modeling the relationship between time since entry and the likelihood of sales governance change for both firms that start with external sales and those that start with internal sales. We hypothesized that the likelihood of integration will decline over time as relational capital builds up for firms who enter the medical device industry using external sales. In contrast, the likelihood of outsourcing should not decline over time for firms who enter using internal sales. We see that, compared to the reference category of 1 to 2 years since entry, firms that enter using external sales are less likely to integrate over time, although it isn't a linear relationship: the average marginal decrease in likelihood of integration as compared to in the first two years is 2.8% in years 3 and 4 ($p < 0.01$) and 2.7% in years 5 and 6 ($p < 0.05$), and is 1.7% in years 7 or more ($p > 0.1$). Comparatively, firms that enter using internal sales forces aren't less likely to outsource over time, and are more likely to outsource 7 or more years from entry as compared to in the first 1 or 2 years (the reference period), with average marginal increase of 1% ($p < 0.1$).

Now focusing on firm divisions using external sales only, we test Hypothesis 2 by interacting time since entry and change in focal specialty in predicting likelihood of integration in Table 1.2. We expect that time since entry will have a negative relationship with integration likelihood only for those who don't change focal specialty, as changing focus will hinder the development of relational capital. The regression results suggest support for our hypothesis, since the baseline coefficients on time remain negative (for firms without a specialty change). Since we estimate a nonlinear regression, true interaction effects are better described via average marginal effects of time since entry for those with and without a specialty change. We find that firms that don't change their focal specialty have an average marginal decrease in likelihood of integration of 3.4% ($p < 0.01$) in years 3 to 4 and 3.0% ($p < 0.05$) years 5 to 6 as compared to the first two years. In contrast, for firms that do change their focal specialty, there is no evidence of a decrease in likelihood of integration in years 3-4 or 5-6 as compared to the first two years.

We test Hypothesis 3 by exploring the association between novel innovation (changes to the count of new-to-the-world products in the product portfolio) and the likelihood of integration, and evaluate how this relationship varies across time since entry. We predict that adding new-to-the-world products early (when there is little relational capital) will increase the likelihood of integration while adding new products later (when relational capital has had time to develop) will decrease likelihood of integration. Table 1.3 highlights our results for all new-to-the-world products, as well as results that separate out new-to-the-world products into those within versus those outside the focal specialty of the firm division. Consistent with our hypothesis, and with a standard TCE logic, adding a new-to-the-world product is associated with an increase in likelihood of integration on average (by 2.8%, $p < 0.1$). However, this is true only if said product is added in the early years of the firm division. Specifically, in year 1 or 2, adding such a product increases the likelihood of integration by 9.7% ($p < 0.01$) whereas adding such a product later has no significant relationship with integration likelihood in later years; (0.6% ($p > 0.1$) in years 3-4, -0.2% ($p > 0.1$) in years 5-6, and 1.4% ($p > 0.1$) in years 7 or more.

When we separate new-to-the-world products into inside versus outside specialty, we see that inside specialty new-to-the-world products drive our results (Table 1.3); however we also see that outside specialty new-to-the-world products are not associated with an increased likelihood of integration regardless of time, in contrast to the latter half of our predictions from Hypothesis 4.

1.5.1 Competing Risks Model to Control for Exiting Firms

To check the robustness of our main findings, we include supplementary analyses that model the likelihood of firm exit alongside the likelihood of sales integration as a competing potential event for firms. Since many firms in our sample exit at some point during our study period, we want to ensure our findings are not driven by comparing firms that change sales to failing (or acquired) firms, but instead to those that survive until the following period but don't integrate sales.

Tables 1.7, 1.8, and 1.9 provide the results from a discrete event hazard regressions modeled as a multinomial logit with three outcomes: survive but don't integrate sales (our reference category), survive and integrate sales (the event of interest), and exit (the competing event). These results are consistent with our main findings.

1.5.2 Controlling for Initial Self-Selection

As mentioned above, the firms in our samples select whether to enter the industry using an internal or external sales force. Therefore, the above analyses estimate the likelihood of integration among those that first chose to use external sales (and vice versa for internal first). A potential concern with such analyses is that those that first choose external sales likely do so based on performance expectations, and as such, are unlikely to change sales mode over time for reasons other than the accumulation of relational capital. A popular method to control for selection in strategy research is the Heckman method; however, it was built for use in linear regression models in the second stage, and our main analysis uses a non-linear model (cloglog). Hence we use the inverse propensity weight method and propensity score adjustment in supplementary analyses to control for selection based on baseline observable characteristics. The IPW method down-weights those firms that have a high propensity to be external first (or internal first) in their respective samples, where propensity is estimated based on characteristics at entry. For propensity score adjustment, the propensity to be internal first is included as a regressor in our analyses.

We want to control for self-selection because firms that are well matched to their initial choice based on characteristics at entry are, arguably less likely to change their sales strategy over time for reasons other than relational capital, and are potentially more likely to remain in the sample (and not exit). The IPW and propensity score adjusted results are consistent with our findings without controlling for initial selection (see Tables 1.12, 1.13, 1.14, and 1.15); however, some estimates become less precise.

1.5.3 Alternative Explanations and Robustness Checks

Given that we infer relationships and relational capital from time since entry, a major potential concern is that we are capturing in our measure of "relational capital" other features that develop over time and might plausibly affect the choice to integrate (or outsource), notably including governance capabilities (Aggarwal & Hsu, 2009). Our results are, however, not consistent with a simple governance capabilities logic. First, we find no evidence that firms using internal sales are less likely to outsource over time, suggesting time provides a poor proxy for integrative capabilities. Second, we find that even for firms using external sales, firms who change specialties (but continue to use external sales) aren't less likely to integrate over time.

We assume that the degree to which firms have a choice to switch is independent of the scale of their enterprise. An alternative view would be that very small firms cannot feasibly have internal sales forces (since they likely involve fixed costs), and thus some of our external-first analytical sample is not at risk of integration. Several descriptive facts suggest this isn't an issue in our study. First, if we look at the initial choices of sales-governance-mode firm divisions entering the medical device industry and compare the size of firms with internal versus external sales at entry, we find firms with more products are less likely to choose internal sales at entry (average size of product portfolio for firms with internal-first is 6 versus 8 for external: Table 1.11). Second, the size in terms of employees has no significant relationship with either initial sales choice or likelihood of later integration.

Later in our sample period, firm divisions that use both internal and external sales—or hybrid sales forces—emerge in our data. Consequently, some firm divisions appear to go from using either purely internal or purely external sales to using both types of sales forces simultaneously. In our analyses, we treat these occurrences (6 of the integration events (6% of the total) and 12 of the outsourcing events (20%)) as if they were full switches. We also ran analyses dropping the firm divisions that adopt hybrid sales forces, and our results do not change (results available from authors). Unfortunately, given their rare occurrence, we are unable to separately explore the drivers of hybridization or plural sourcing of sales, and leave that inquiry to future research.

1.6 Discussion and Conclusion

In this paper, we explore how relational governance influences firm boundaries, focusing on the sales boundary of a sample of US medical device manufacturers. In this setting, the sales boundary is of key importance to innovation and firm performance, as the ongoing transfer of knowledge to and from users is crucial for value creation and value capture (Grant, 1991, 1996; Danneels, 2002; Chatterji et al., 2008; Chatterji & Fabrizio, 2014).

The focus of this paper is on mapping out the limits of relational capital in shaping firm boundary decisions. We argue, and find support for the idea, that relational capital only develops consequentially across firm boundaries and not within them. Specifically, while firms who initially chose external sales are less likely to internalize sales after the first two years, the likelihood of outsourcing doesn't change over time for firms that initially have integrated sales. We also find that firms that change their focal specialty do not appear to develop relational capital whereas firms that don't change their specialty do appear to. Relationships between firms—built on trust, norms, and routines—should be most valuable when firms need to develop and share new, relationship-specific knowledge, the very same circumstances when we expect firms to integrate. We find evidence that relational capital mitigates the push towards integration for firms introducing novel innovations, but not strongly enough to make firms less likely to integrate vis-a-vis non-innovating firms. Novel innovators are more likely to integrate sales if they launch a new innovation in their first few years of operation, and this vanishes (but does not reverse) over time.

This paper highlights the boundaries of relationships. While relationships may drive firms away from choosing alternative external partners, they don't appear to develop meaningfully inside of firms. Interestingly, we find no evidence that those firms with relational capital who launch novel innovations are less likely to integrate than those who don't launch novel innovations. Yet, they are less likely to integrate than firms that innovate earlier in their life. Related to this point, we find that the effects of novel innovation on the management of downstream activities is largely dependent on when the firm innovates. This provides some reconciliation of the literature that suggests innovation sparks changes in firm boundaries (e.g. Teece (1986); Kaul (2012)) and the lack of firm boundary changes generally observed (Kapoor, 2013; Qian et al., 2012).

Table 1.1: Time Since Entry and Likelihood of Integration (for External-First) or Outsourcing (Internal-First)

	External-first		Internal-first	
	(1a)	(2a)	(1b)	(2b)
Years since entry (3-4)		-0.781**		0.506
		(0.313)		(0.389)
Years since entry (5-6)		-0.747**		0.295
		(0.336)		(0.440)
Years since entry (7+)		-0.391		0.854**
		(0.289)		(0.417)
# products (Δ)	0.052**	0.055**	0.016	0.018
	(0.026)	(0.026)	(0.023)	(0.023)
# specialties (Δ)	-0.558***	-0.528***	-0.072	-0.046
	(0.209)	(0.204)	(0.259)	(0.264)
# division employees (Δ)	-0.043	-0.039	-0.000	-0.000
	(0.027)	(0.026)	(0.000)	(0.000)
Firm size (# divisions) (Δ)	-0.014	-0.010	0.022	0.018
	(0.078)	(0.074)	(0.038)	(0.041)
Share internal (corporate)	0.429	0.414	-0.931	-0.938
	(0.297)	(0.292)	(0.576)	(0.580)
Ownership change	-0.042	-0.023	0.077	0.102
	(0.503)	(0.497)	(0.714)	(0.717)
# competitors (Δ)	-0.008**	-0.008**	0.009***	0.008**
	(0.003)	(0.003)	(0.003)	(0.003)
# products at entry	-0.030**	-0.030**	0.010	0.011
	(0.014)	(0.013)	(0.022)	(0.021)
# specialties at entry	0.065	0.061	-0.042	-0.040
	(0.083)	(0.082)	(0.108)	(0.104)
# patents at entry	0.080**	0.076**	0.018***	0.018***
	(0.034)	(0.031)	(0.002)	(0.002)
# NTTW products at entry	0.094*	0.098*	-0.019	-0.044
	(0.057)	(0.055)	(0.070)	(0.075)
Year, region, specialty controls	Y	Y	Y	Y
N (firm division years)	2798	2798	5032	5032
n (firm divisions)	545	545	1070	1070
Events	102	102	59	59
LL	-420.0	-415.2	-303.2	-300.6
Chi^2 ($p < 0.001$)	51.50	72.49	473.4	465.5

The likelihood of sales force change (either integration or outsourcing) over time. RHS variables lagged one period. Standard errors (clustered at the firm level) in parentheses. *p<0.10, **p<0.05, ***p<0.01

Table 1.2: Specialty Change, Time Since Entry, and Likelihood of Integration

	(1)	(2)
Years since entry (3-4)	-0.787**	-0.944***
	(0.315)	(0.348)
Years since entry (5-6)	-0.756**	-0.764**
	(0.336)	(0.344)
Years since entry (7+)	-0.387	-0.452
	(0.289)	(0.310)
Specialty Change (Δ)	-0.267	-0.608
	(0.305)	(0.491)
Specialty (Δ) * YSE (3-4)		1.033
		(0.803)
Specialty (Δ) * YSE (5-6)		-0.070
		(1.161)
Specialty (Δ) * YSE (7+)		0.523
		(0.693)
# products (Δ)	0.056**	0.057**
	(0.026)	(0.026)
# specialties (Δ)	-0.550**	-0.570**
	(0.213)	(0.223)
# division employees (Δ)	-0.040	-0.034
	(0.027)	(0.028)
Firm size (# divisions) (Δ)	-0.010	-0.012
	(0.074)	(0.073)
Share internal (corporate level)	0.417	0.428
	(0.294)	(0.293)
Ownership change	-0.022	-0.010
	(0.496)	(0.496)
# competitors (Δ)	-0.008**	-0.008**
	(0.003)	(0.003)
Entry controls	Y	Y
Year, region, specialty controls	Y	Y
N (firm division years)	2798	2798
n (firm divisions)	545	545
Events	102	102
LL	-414.8	-413.9
Chi^2 ($p < 0.001$)	72.55	73.52

The likelihood of sales force integration over time and specialty change. RHS variables lagged one period. Standard errors (clustered at the firm level) in parentheses. *p<0.10, **p<0.05, ***p<0.01

Table 1.3: New-to-the World Products Conditioned by Time Since Entry and Likelihood of Integration

	(1)	(2)	(3)	(4)
Years since entry (3-4)	-0.776**	-0.723**	-0.779**	-0.735**
	(0.312)	(0.317)	(0.314)	(0.315)
Years since entry (5-6)	-0.763**	-0.711**	-0.755**	-0.717**
	(0.338)	(0.338)	(0.337)	(0.335)
Years since entry (7+)	-0.392	-0.371	-0.390	-0.372
	(0.289)	(0.290)	(0.288)	(0.288)
NTTW product (Δ)	1.206***	1.921***		
	(0.461)	(0.598)		
NTTW * YSE (3-4)		-1.681**		
		(0.658)		
NTTW * YSE (5-6)		-2.032***		
		(0.659)		
NTTW * YSE (7+)		-1.493**		
		(0.733)		
NTTW product in (Δ)			1.255**	1.779**
			(0.620)	(0.772)
NTTW in * YSE (3-4)				-1.433
				(0.873)
NTTW in * YSE (5-6)				-1.671**
				(0.824)
NTTW in * YSE (7+)				-1.660*
				(0.953)
NTTW product out (Δ)			0.623	1.131
			(0.656)	(1.114)
NTTW out * YSE (3-4)				-1.129
				(1.156)
NTTW out * YSE (5-6)				-1.246
				(1.201)
NTTW out * YSE (7+)				-0.493
				(1.221)
Firm controls	Y	Y	Y	Y
Entry controls	Y	Y	Y	Y
Year, region, specialty controls	Y	Y	Y	Y
N (firm division years)	2798	2798	2798	2798
LL	-413.0	-411.7	-413.3	-412.3
Chi^2 ($p < 0.001$)	74.68	79.84	74.95	82.61

The likelihood of sales force integration over time and innovation (nttw). RHS variables lagged one period. Standard errors (clustered at the firm level) in parentheses. *p<0.10, **p<0.05, ***p<0.01

Table 1.4: Average Marginal Effects of Years Since Entry (ref: Years Since Entry=1-2)

	External	Internal
Years since entry (3-4)	-0.028***	0.005
	(0.010)	(0.004)
Years since entry (5-6)	-0.027**	0.003
	(0.012)	(0.004)
Years since entry (7+)	-0.017	0.010*
	(0.012)	(0.005)

Table 1.5: Moderating Effect of a Change in Specialty on the Years Since Entry, for External-First (Average Marginal Effects) (ref: Years Since Entry=1-2)

	No Specialty Change	Specialty Change
Years since entry (3-4)	-0.034***	0.003
	(0.011)	(0.024)
Years since entry (5-6)	-0.030**	0.018
	(0.013)	(0.021)
Years since entry (7+)	-0.020	0.002
	(0.014)	(0.021)

Table 1.6: Moderating Effect of Years Since Entry on New-to-the-World Product Launches, for External-First (Average Marginal Effects)

	All NTTW	NTTW inside	NTTW outside
Years since entry (1-2)	0.097***	0.090**	0.057
	(0.032)	(0.039)	(0.056)
Years since entry (3-4)	0.006	0.008	0.000
	(0.005)	(0.007)	(0.005)
Years since entry (5-6)	-0.002	0.003	-0.003
	(0.006)	(0.007)	(0.011)
Years since entry (7+)	0.014	0.003	0.022
	(0.013)	(0.018)	(0.017)

Table 1.7: Sales Integration or Exit, as Compared to Continuing on with External Sales (competing risk model (MNL))

	Time	
	Integrate	Exit
Years since entry (3-4)	-0.778**	0.238
	(0.318)	(0.181)
Years since entry (5-6)	-0.728**	0.335*
	(0.346)	(0.190)
Years since entry (7+)	-0.384	0.203
	(0.299)	(0.200)
# products (Δ)	0.055*	-0.044
	(0.031)	(0.028)
# specialties (Δ)	-0.541**	0.001
	(0.214)	(0.135)
# division employees (Δ)	-0.053	-0.071
	(0.035)	(0.066)
Firm size (# divisions) (Δ)	-0.028	-0.102***
	(0.079)	(0.037)
Share internal (corporate)	0.426	-0.024
	(0.304)	(0.235)
Ownership change	0.051	0.650**
	(0.512)	(0.269)
# competitors (Δ)	-0.009***	-0.003
	(0.003)	(0.002)
# products at entry	-0.030**	-0.002
	(0.014)	(0.009)
# specialties at entry	0.072	0.071
	(0.085)	(0.049)
# patents at entry	0.073**	-0.053
	(0.033)	(0.041)
# NTTW products at entry	0.097*	-0.017
	(0.058)	(0.038)
Year, region, specialty controls	Y	Y
N (firm division years)	2798	
LL	-1289	
Chi^2 ($p < 0.001$)	163.7	

The likelihood of sales force integration as compared to either not exiting and not integrating sales (reference category) or exiting (competing risk category) over time. RHS variables lagged one period.Standard errors (clustered at the firm level) in parentheses. *p<0.10, **p<0.05, ***p<0.01

Table 1.8: Specialty Change and Sales Integration or Exit, as Compared to Continuing on with External Sales (competing risk model (MNL))

	Specialty Change			
	Specialty Change		Specialty Change*time	
	Integrate	Exit	Integrate	Exit
Years since entry (3-4)	-0.785**	0.235	-0.938***	0.286
	(0.320)	(0.181)	(0.354)	(0.199)
Years since entry (5-6)	-0.738**	0.330*	-0.738**	0.387*
	(0.346)	(0.189)	(0.355)	(0.204)
Years since entry (7+)	-0.379	0.203	-0.445	0.218
	(0.299)	(0.200)	(0.322)	(0.220)
Specialty Change (Δ)	-0.283	-0.119	-0.613	0.066
	(0.314)	(0.170)	(0.506)	(0.310)
Specialty (Δ) * YSE (3-4)			1.010	-0.363
			(0.821)	(0.519)
Specialty (Δ) * YSE (5-6)			-0.131	-0.453
			(1.183)	(0.550)
Specialty (Δ) * YSE (7+)			0.522	-0.098
			(0.710)	(0.447)
# products (Δ)	0.055*	-0.045	0.057*	-0.045
	(0.032)	(0.028)	(0.032)	(0.028)
# specialties (Δ)	-0.561**	0.003	-0.581**	0.006
	(0.222)	(0.136)	(0.231)	(0.134)
# division employees (Δ)	-0.053	-0.072	-0.047	-0.071
	(0.034)	(0.066)	(0.035)	(0.066)
Firm size (# divisions) (Δ)	-0.028	-0.102***	-0.030	-0.103***
	(0.079)	(0.037)	(0.079)	(0.037)
Share internal (corporate)	0.427	-0.025	0.437	-0.024
	(0.306)	(0.236)	(0.305)	(0.237)
Ownership change	0.052	0.650**	0.063	0.645**
	(0.512)	(0.269)	(0.513)	(0.269)
# competitors (Δ)	-0.009***	-0.003	-0.009***	-0.003
	(0.003)	(0.002)	(0.003)	(0.002)
Entry controls	Y	Y	Y	Y
Year, region, specialty controls	Y	Y	Y	Y
N (firm division years)	2798		2798	
LL	-1289		-1287	
Chi^2 ($p < 0.001$)	163.5		167.0	

The likelihood of sales force integration as compared to either not exiting and not integrating sales (reference category) or exiting (competing risk category) over time and specialty change. Standard errors (clustered at the firm level) in parentheses. *p<0.10, **p<0.05, ***p<0.01

Table 1.9: NTTW and Sales integration or Exit, as Compared to Continuing on with External Sales (competing risk model (MNL))

	All FDA new-to-the-world			
	NTTW product (1)		NTTW *time (2)	
	Integrate	Exit	Integrate	Exit
Years since entry (3-4)	-0.771**	0.238	-0.721**	0.243
	(0.318)	(0.180)	(0.323)	(0.181)
Years since entry (5-6)	-0.741**	0.336*	-0.691**	0.337*
	(0.348)	(0.190)	(0.348)	(0.191)
Years since entry (7+)	-0.381	0.203	-0.363	0.198
	(0.299)	(0.200)	(0.300)	(0.200)
NTTW product (Δ)	1.222***	-0.040	2.009***	0.735*
	(0.474)	(0.447)	(0.624)	(0.437)
NTTW * YSE (3-4)			-1.788***	-0.989
			(0.676)	(0.855)
NTTW * YSE (5-6)			-2.247***	-1.439
			(0.695)	(1.061)
NTTW * YSE (7+)			-1.669**	-1.515
			(0.762)	(0.949)
# products (Δ)	0.053*	-0.045	0.050*	-0.046
	(0.030)	(0.028)	(0.030)	(0.029)
# specialties (Δ)	-0.553**	0.001	-0.553***	-0.001
	(0.215)	(0.134)	(0.213)	(0.135)
# division employees (Δ)	-0.053	-0.071	-0.053	-0.071
	(0.035)	(0.066)	(0.036)	(0.066)
# products at entry	-0.033**	-0.002	-0.035**	-0.002
	(0.014)	(0.009)	(0.014)	(0.009)
# specialties at entry	0.072	0.071	0.075	0.069
	(0.086)	(0.049)	(0.085)	(0.049)
# patents at entry	0.073**	-0.053	0.076**	-0.053
	(0.033)	(0.041)	(0.033)	(0.041)
# NTTW products at entry	0.098*	-0.017	0.103*	-0.015
	(0.058)	(0.038)	(0.058)	(0.037)
Firm-level, Comp., Year, region, specialty controls	Y	Y	Y	Y
N (firm division years)	2870		2870	
LL	-1471		-1469	

The likelihood of sales force integration as compared to either not exiting and not integrating sales (reference category) or exiting (competing risk category) over time and innovation (nttw). Standard errors (clustered at the firm level) in parentheses. *p<0.10, **p<0.05, ***p<0.01

1.7 Supplementary Tables

Table 1.10: Propensity Score: Likelihood of Internal-First at Entry (probit)

	Coefficient	Avg marginal effects
# patents	0.023*	0.007*
	(0.013)	(0.004)
# products	-0.013**	-0.004***
	(0.005)	(0.002)
# specialties	-0.065**	-0.021**
	(0.030)	(0.009)
NTTW products	0.098***	0.031***
	(0.023)	(0.007)
Firm size (# divisions)	-0.006	-0.002
	(0.006)	(0.002)
Cardiovascular	0.344	0.110*
	(0.210)	(0.067)
Gastro / Urology	0.611**	0.195**
	(0.271)	(0.086)
Lab Diagnostics	-0.028	-0.009
	(0.171)	(0.054)
Obstetrics	-0.657**	-0.210**
	(0.282)	(0.089)
Orthopedics	-0.197	-0.063
	(0.282)	(0.090)
Physical Med	-0.481**	-0.153**
	(0.223)	(0.071)
Radiology	0.409*	0.130*
	(0.212)	(0.067)
Surgery	0.487**	0.155**
	(0.237)	(0.075)
Region & Entry Year FE	Y (4, 12)	Y (4, 12)
Constant	0.042	
	(0.190)	
n (firm divisions)	1615	
LL	-909.0	
Chi^2 ($p < 0.001$)	247.1	

This results highlight the predictors of sales mode choice at entry. The Reference specialty category is Anesthesiology/Pulmonary Medicine. Specialties that are also included, but are not significantly different from the reference category and are therefore excluded due to room constraints are: Dental, Ear, Nose & Throat, General, Neurology, and Ophthalmology

Table 1.11: Comparing Characteristics at Entry Between the Internal-First and External-First Samples

	Pre-match, pre-trim sample (n=1615)				Post-match, post-trim sample (n=1598)			
	Int-First	Ext-First	%bias	p(ttest)	Int-First	Ext-First	%bias	p(ttest)
# patents	1.03	0.52	9.50	0.11	0.72	0.77	-1.90	0.70
# products	5.89	8.11	-18.00	0.00	5.86	6.36	-4.20	0.26
# specialties	2.08	2.45	-20.70	0.00	2.08	2.14	-3.80	0.34
# NTTW products	0.51	0.79	-12.20	0.02	0.51	0.51	0.00	0.99
Firm size (# divisions)	3.39	3.49	-1.70	0.74	3.39	3.17	3.80	0.35
Anesthesiology / Pul Med	0.04	0.05	-3.50	0.50	0.04	0.05	-0.90	0.83
Cardiovascular	0.08	0.04	15.80	0.00	0.08	0.11	-14.50	0.01
Dental	0.04	0.03	4.70	0.38	0.04	0.07	-12.30	0.02
Ear, Nose, and Throat	0.01	0.02	-5.10	0.32	0.01	0.01	5.30	0.11
Gastro / Urology	0.04	0.02	12.40	0.03	0.04	0.03	6.60	0.17
General	0.35	0.38	-6.30	0.23	0.35	0.32	5.90	0.17
Lab Diagnostics	0.18	0.23	-13.80	0.01	0.18	0.19	-3.60	0.39
Neurology	0.01	0.01	-5.40	0.29	0.01	0.01	-1.90	0.63
Obstetrics	0.01	0.03	-13.30	0.01	0.01	0.01	-0.70	0.85
Ophthalmology	0.05	0.04	6.60	0.22	0.05	0.03	9.40	0.03
Orthopedics	0.02	0.02	-5.00	0.33	0.02	0.02	-3.40	0.42
Physical Med	0.04	0.05	-8.60	0.09	0.04	0.03	0.90	0.82
Radiology	0.08	0.04	18.00	0.00	0.08	0.08	0.30	0.95
Surgery	0.06	0.03	13.90	0.01	0.05	0.04	7.10	0.13
Propensity Score (int-first)	0.71	0.56			0.66	0.66		
Stdzed Bias (mean)	11.0				4.8			

Pre-trimming: 545 External first, 1070 Internal first. Post trimming: 534 External first, 1064 Internal first. Standardized Bias: the % diff. of the sample means across treatment as a percentage of the square root of the average of the sample variances in the groups. Bias score <5 is rule of thumb (Caliendo and Kopeinig, 2008). Matching also includes Region and Entry Year dummies.

Table 1.12: Time Since Entry and Likelihood of Integration (for External-First) or Outsourcing (Internal-First): Inverse propensity score weighted and propensity score adjusted

	External-first		Internal-first	
	IPW (1a)	PScore (2a)	IPW (1b)	PScore (2b)
Years since entry (3-4)	-1.002***	-0.749**	0.391	0.478
	(0.376)	(0.314)	(0.381)	(0.390)
Years since entry (5-6)	-0.553	-0.617*	0.268	0.202
	(0.415)	(0.358)	(0.430)	(0.447)
Years since entry (7+)	-0.525	-0.158	0.758*	0.714
	(0.366)	(0.330)	(0.404)	(0.460)
# products (Δ)	0.057*	0.052**	0.038	0.021
	(0.034)	(0.026)	(0.028)	(0.025)
# specialties (Δ)	-0.364	-0.526**	-0.072	-0.057
	(0.361)	(0.208)	(0.282)	(0.270)
# division employees (Δ)	-0.003	-0.036	-0.000	-0.000
	(0.030)	(0.023)	(0.000)	(0.000)
Firm size (# divisions) (Δ)	0.108	-0.008	0.016	0.019
	(0.132)	(0.072)	(0.055)	(0.043)
Share internal (corporate)	0.372	0.390	-0.735	-0.939
	(0.360)	(0.293)	(0.578)	(0.576)
Ownership change	-1.062	-0.024	0.034	0.115
	(0.991)	(0.501)	(0.720)	(0.716)
# competitors (Δ)	-0.009**	-0.008**	0.009**	0.008**
	(0.004)	(0.003)	(0.004)	(0.003)
# products at entry	-0.030	-0.029**	0.008	0.009
	(0.019)	(0.013)	(0.020)	(0.021)
# specialties at entry	-0.003	0.088	-0.105	-0.065
	(0.094)	(0.085)	(0.104)	(0.112)
# patents at entry	0.061**	0.074**	-0.012	0.020***
	(0.028)	(0.031)	(0.080)	(0.003)
# NTTW products at entry	0.138**	0.086	0.030	-0.032
	(0.066)	(0.053)	(0.060)	(0.086)
P score		0.928		-0.993
		(0.642)		(1.132)
Year, region, specialty controls	Y	Y	Y	Y
N (firm division years)	2739	2798	5013	5032
LL	-1302	-414.3	-476.9	-300.2
Chi^2 ($p < 0.001$)	71.82	71.97	58.67	498.2

The likelihood of sales force change: integration (for external-first) or outsourcing (for internal-first) over time. Standard errors (clustered at the firm level) in parentheses. *p<0.10, **p<0.05, ***p<0.01

Table 1.13: Specialty Change, Time Since Entry and Likelihood of Integration (for External-First) or Outsourcing (Internal-First): Inverse propensity score weighted and propensity score adjusted

	IPW		P Score	
Years since entry (3-4)	-1.009***	-1.141***	-0.755**	-0.910***
	(0.378)	(0.423)	(0.315)	(0.347)
Years since entry (5-6)	-0.572	-0.549	-0.621*	-0.625*
	(0.410)	(0.420)	(0.358)	(0.368)
Years since entry (7+)	-0.513	-0.584	-0.143	-0.208
	(0.363)	(0.391)	(0.331)	(0.349)
Specialty Change (Δ)	-0.684*	-0.970*	-0.288	-0.620
	(0.360)	(0.575)	(0.308)	(0.490)
Specialty (Δ) * YSE (3-4)		1.064		1.021
		(0.889)		(0.801)
Specialty (Δ) * YSE (5-6)		-0.790		-0.114
		(1.223)		(1.161)
Specialty (Δ) * YSE (7+)		0.645		0.517
		(0.796)		(0.690)
# products (Δ)	0.061*	0.060*	0.053**	0.054**
	(0.036)	(0.036)	(0.026)	(0.026)
# specialties (Δ)	-0.388	-0.378	-0.551**	-0.569**
	(0.405)	(0.420)	(0.219)	(0.229)
# division employees (Δ)	-0.013	-0.003	-0.038	-0.032
	(0.035)	(0.038)	(0.024)	(0.025)
Firm size (# divisions) (Δ)	0.108	0.104	-0.007	-0.009
	(0.129)	(0.129)	(0.072)	(0.071)
Share internal (corporate)	0.413	0.425	0.395	0.404
	(0.358)	(0.357)	(0.294)	(0.293)
Ownership change	-1.005	-1.010	-0.023	-0.014
	(0.955)	(0.968)	(0.500)	(0.500)
# competitors (Δ)	-0.009**	-0.009**	-0.008**	-0.008**
	(0.004)	(0.004)	(0.003)	(0.003)
P score			0.968	0.969
			(0.651)	(0.650)
Entry controls	Y	Y	Y	Y
Year, region, specialty controls	Y	Y	Y	Y
N (firm division years)	2739	2739	2798	2798
LL	-1294	-1290	-413.8	-412.9
Chi^2 ($p < 0.001$)	78.88	81.07	71.78	72.83

The likelihood of sales force integration over time and specialty change. Standard errors (clustered at the firm level) in parentheses. *p<0.10, **p<0.05, ***p<0.01

Table 1.14: NTTW Products Conditioned by Time Since Entry and Likelihood of Integration: Inverse propensity score weighted

	All FDA	**new-to-the-world**
Years since entry (3-4)	-0.997***	-0.961**
	(0.376)	(0.383)
Years since entry (5-6)	-0.564	-0.524
	(0.415)	(0.417)
Years since entry (7+)	-0.527	-0.508
	(0.366)	(0.368)
NTTW product (Δ)	1.332**	1.973***
	(0.552)	(0.662)
NTTW * YSE (3-4)		-1.686**
		(0.775)
NTTW * YSE (5-6)		-1.901***
		(0.708)
NTTW * YSE (7+)		-1.634**
		(0.763)
# products (Δ)	0.045	0.034
	(0.037)	(0.040)
# specialties (Δ)	-0.358	-0.344
	(0.370)	(0.368)
# division employees (Δ)	-0.003	-0.003
	(0.031)	(0.031)
# products at entry	-0.033	-0.035*
	(0.020)	(0.020)
# specialties at entry	-0.003	0.005
	(0.096)	(0.096)
# patents at entry	0.062**	0.063**
	(0.028)	(0.028)
# NTTW products at entry	0.142**	0.146**
	(0.067)	(0.068)
Firm-level, Comp., Year,	Y	Y
region, specialty controls	Y	Y
N (firm division years)	2739	2739
LL	-1295	-1291
Chi^2 ($p < 0.001$)	75.29	83.92

The likelihood of sales force integration over time and innovation (nttw). Standard errors (clustered at the firm level) in parentheses. *p<0.10, **p<0.05, ***p<0.01

Table 1.15: NTTW Products Conditioned by Time Since Entry and Likelihood of Integration: Propensity score

*P score	**All FDA**	**new-to-the-world**
Years since entry (3-4)	-0.747**	-0.693**
	(0.313)	(0.318)
Years since entry (5-6)	-0.630*	-0.580
	(0.361)	(0.360)
Years since entry (7+)	-0.158	-0.136
	(0.330)	(0.333)
NTTW product (Δ)	1.216***	1.927***
	(0.462)	(0.595)
NTTW * YSE (3-4)		-1.720***
		(0.659)
NTTW * YSE (5-6)		-1.993***
		(0.647)
NTTW * YSE (7+)		-1.533**
		(0.719)
# products (Δ)	0.049*	0.046*
	(0.026)	(0.026)
# specialties (Δ)	-0.540***	-0.540***
	(0.208)	(0.206)
# division employees (Δ)	-0.037	-0.037
	(0.023)	(0.024)
# products at entry	-0.032**	-0.034**
	(0.014)	(0.014)
# specialties at entry	0.088	0.092
	(0.086)	(0.085)
# patents at entry	0.074**	0.077**
	(0.031)	(0.031)
# NTTW products at entry	0.088*	0.093*
	(0.053)	(0.053)
P score	0.936	0.935
	(0.646)	(0.651)
Firm, Comp, Year, region, specialty	Y	Y
N (firm division years)	2,798	2,798
LL	-412.1	-410.8
Chi^2 ($p < 0.001$)	74.21	79.87

The likelihood of sales force integration over time and innovation (nttw) Standard errors (clustered at the firm level) in parentheses. *p<0.10, **p<0.05, ***p<0.01

2

Sowing seeds or picking fruit: Firm capabilities and external inputs to innovation

2.1 Introduction

Successful innovation is a costly and risky activity that relies on the cumulation and combination of knowledge from inside and outside the innovating firm. Because knowledge is inherently sticky, geographic proximity to the ideas and inventions of others clearly should (and, prior research suggests, does) make successful innovation more likely.

Existing research (e.g., Delgado et al. (2014a)) typically presumes that being in a location with relatively high amounts of related inventive activity—a cluster—increases innovation through knowledge spillovers, and thus by making it easier to invent. Yet, innovating firms need not generate the inventions behind their innovations (Jewkes et al., 1958; Cassiman & Veugelers, 2006; Arora & Gambardella, 2010). In fact, a recent estimate suggests that nearly half of all innovating U.S. firms did not generate the foundational invention for their most important innovation, instead acquiring an external invention (Arora et al., 2016). This suggests another channel by which cluster location may influence innovation: proximity to supply of external inventions. In other words, clusters can catalyze internal invention through knowledge inputs, but may also increase innovation by enabling acquisition of the inventions of others. Moreover, these dual effects may differ across firms. Technically sophisticated firms—firms with high technical capability—may benefit from nearby knowledge to produce internal inventions that are the basis for significant new products. Less sophisticated technology followers may, instead, leverage external knowledge to introduce "me-too" products that imitate existing products, or potentially acquire an external invention to launch a new product of their own.

Our goal in this paper is to unpack the dual role of clusters in firm innovation. To do so, we present a simple model of the process of innovation, in which firms choose to invest in R&D, realize or acquire inventions, and commercialize the invention they think will be most valuable. To build our arguments, we distinguish between internally generated inventions and those acquired externally. A second key distinction is between significant new products and me-too or imitative products. R&D investment increases the likelihood of internal invention. Clusters offer dual benefits: knowledge inputs that increase the productivity of internal R&D, but also a greater supply of external inventions that a potential innovator can acquire. The essence of our argument is that only those firms with invention capabilities will find it worthwhile to invest in R&D and thus be equipped to make use of knowledge inputs in clusters. For them, the role of clusters in innovation outcomes will be dual. In contrast, for those without invention capabilities, clusters offer the chance to more easily access external inventions, or more easily imitate others. We infer the dual roles of clusters by comparing their impact across different types of firms, controlling for firm characteristics and industry.

For all of our empirical analyses, we use a survey of U.S. manufacturing business units during 2007 to 2009 (Arora et al., 2016) that focuses on innovation and the division of innovative labor. The survey samples from all manufacturing firms, not just those with prior R&D spending or patents, allowing us to explore innovation related choices for a wide spectrum of firms, to explore how cluster location and capability relates to both the propensity to innovate and sourcing of invention, and to generate findings that are generalizable to the U.S. manufacturing sector as a whole. This is in contrast to much of the literature that explores use of external sources, which focuses on samples of innovators or R&D performing firms (as surveyed by (Vivas & Barge-Gil, 2015)) or on firms in industries where innovation is the basis of competition, e.g. pharmaceuticals or semiconductors (Ceccagnoli et al., 2010; Fabrizio, 2009). We link the survey data to other datasets, including patenting data, and various measures of the local environment based on business unit location.

We situate our arguments within two overlapping but often separate literatures: the geography of innovation (Jaffe, 1986; Feldman, 1993; Audretsch & Feldman, 1996), and the open innovation or markets for technology literature (Cassiman & Veugelers, 2006; Arora et al., 2001a; Veugelers & Cassiman, 1999). Geography of innovation typically focuses on knowledge spillovers, knowledge inputs, and other agglomeration benefits of cluster location for inventing, presuming innovating firms invent for themselves. We allow for a division of innovative labor. Comparatively, literature on open innovation focuses on the capability-related cost determinants of external sourcing while largely ignoring the role of location. Our paper contributes to the theory on the role of clusters in innovation which has relevance for both for geography of innovation and open innovation literatures. We highlight the role of clusters as supplying both R&D inputs and invention outputs, and use variation in the capability of firms, which maps to different relative value of each cluster innovation component, to identify this dual role of clusters.

We do not estimate the causal impact of clusters on innovation. Instead, our interest is in how this impact is conditioned by firm invention capability. However, unlike the literature, we do not measure capability using empirical proxies (such as patents, R&D, innovation, or sales) that are the consequence of capability. Instead, we make a methodological advance by treating firm-capability as an unobserved latent variable. Specifically, we use a semi-parametric finite-mixture model approach, (e.g., McLachlan & Peel (2004)) in which the observed distribution of outcomes (e.g., innovation) is composed of a mixture of two or more underlying (but unobserved) distributions that reflect firms of different capabilities. By treating firm-capability as a latent variable, we avoid the circularity implicit in using R&D or patenting as measures of invention capability to study the effect of capability on innovation performance.[1]

We find that being located in an inventive cluster has a positive relationship with innovation and imitation, consistent with findings from geography of innovation literature (Audretsch & Feldman, 2004). However, we find the positive relationship between cluster location and innovation is largely driven by less capable firms, who use clusters to access the inventions of others. In contrast, more capable firms are largely unaffected in terms of their likelihood of innovation by being located in a cluster. Instead, clusters seem to provide them easier access to high cost external inventive inputs, including inventions from startups, and those acquired via market channels.

Our findings have several implications for our ongoing understanding of the role of clusters in innovation. First, we find that differences in firm invention ability determine the role of clusters in innovation across firms, with clusters seemingly having a substantial role for low-capability firms and matching them to lower value or "me-too" inventions. Hence, the geography of innovation is best understood by accounting for markets for invention, and not simply as providing easier access to knowledge in-

[1] Finite mixture models have been used extensively by marketing scholars, e.g. Kamakura & Russell (1989); Colombo & Morrison (1989). Their use in strategy research has been more limited, e.g., DeSarbo et al. (2001); Mani & Nandkumar (2016).

puts for highly capable firms to generate new-to-the-world inventions and thereby innovate. Second, while current open innovation research largely suggests own invention ability increases the use of external innovation inputs (West & Bogers, 2014), we instead find a negative relationship between capability and external sourcing, driven by lower capability firms in clusters. This suggests the relationship between own ability and the sourcing of external inventions itself depends on capability.

Broadly, our results point to the need to focus not just on R&D performers or otherwise defined "potential innovators" in building and testing theories of the drivers of innovation, especially when markets for technology enable those who can't themselves invent to successfully innovate by buying the inventions of others.

2.2 Background

This paper focuses on the dual role of clusters in innovation. Clusters are geographic areas where groups of interdependent economic actors, including firms, other organizations like university labs, and individuals, closely co-locate (Porter, 1998). Silicon Valley was, as the name suggests, a prototypical example of an inventive cluster for semiconductors (typically made of silicon) and related industries beginning in the mid-20th century (Saxenian, 1996).

To unpack the dual role of clusters in innovation, we distinguish between invention, which results in the creation of a new design or prototype for a new product, and innovation, which is the commercial introduction of a new product based on an invention (cf. Arora et al. (2016)). Clusters provide inputs to both activities. They benefit inventive firms (i.e., firms with high invention capability) by lowering the costs of inputs to inventive activity: new knowledge, skilled employees, specialist service providers, and the like, are relatively abundant and in close proximity (Carlino & Kerr, 2015). Clusters also provide access to others' inventions, which less inventive firms can also imitate or acquire. Overall, clusters enhance innovation by lowering the cost of accessing both external knowledge, helping firms to invent, and external inventions, helping firms to innovate.

2.2.1 Clusters as Seeds: Knowledge Inputs to Internal Invention

The literature has argued that being geographically close to the producers of new knowledge, for example, near university biomedical research activity, increases the likelihood and quality of firm invention. New knowledge is an important input into invention. However, such knowledge is tacit and sticky, and its transmission is on-going and iterative and is not a simple, codifiable, one-off transaction (Von Hippel, 1994) easily done from far distances. Hence, proximity of the knowledge source will increase the likelihood and quality of knowledge transmission (Audretsch & Feldman, 2004), and increase the chances of a successful invention. However, new, local knowledge is not equally accessible to all. For example, firms that have high invention capability are more able to absorb knowledge spillovers from the leading edge (Alcacer & Chung, 2007).[2] In addition to "spillovers", clusters of inventive activity are also sources of more tangible knowledge inputs, including skilled employees from other firms or nearby universities. Skilled employees act as conduits bringing new knowledge into the internal inventions of firms, and are presumably more likely to match with firms with existing internal invention ability.

2.2.2 Clusters as Fruit: External Sources of Invention

A separate stream of recent literature has focused on the role that external inventions, e.g. prototypes or product ideas, play in firm innovation (Cassiman & Veugelers (2006); Arora et al. (2001a) and others). Instead of coming up with inventions

[2] High invention capability firms are also likely to suffer from knowledge leakages and thus may choose not to locate in a cluster (e.g., Alcacer et al. (2015)). Notice that the knowledge "spillovers" need not be free to firms aiming to absorb them. Logically, clusters will enhance invention if inventive firms can access the required knowledge more readily (i.e. more cheaply) if they are located inside clusters versus outside them.

internally, innovating firms may in-license or buy technologies from external actors, including startups, customers, suppliers, independent inventors, or university labs. Innovating firms may also acquire whole firms for their technologies (e.g. Google, Pfizer, Medtronic, among others). The open innovation literature typically presumes innovators source via a make-buy-collaborate choice, and decide based on variations in costs, in particular the balance between production costs (lower when firms specialize, i.e. innovators focus on commercialization and external source inventions) and transaction costs, which include the costs of search, evaluation, and productive application of external ideas (Veugelers & Cassiman, 1999).

For the most part this literature ignores the role of clusters and geographic proximity to inventive activity in shaping the sourcing decision (West & Bogers, 2014). However, tangentially related papers on acquisitions and alliances suggest that closeness will increase the likelihood of acquisition (Chakrabarti & Mitchell, 2013, 2016; Alcacer et al., 2017) by lowering the cost of searching for, assessing the value of, and integrating external resources. In addition, being in a cluster also means the firm can collect knowledge about other firms and their ideas through a localized network of similar co-located firms (Mccann et al., 2016), which minimizes the chance for adverse selection, and therefore increases the likelihood that a firm will take what would otherwise be a risky gamble (e.g. buy rather than ally). Cluster location will mean thicker markets for technology, which should increase both innovation and the potential for external sourcing of invention.

External invention can affect the introduction of new products in another form as well: firms may choose to imitate an existing product instead of inventing a new one. That is, a firm can introduce a product into the market that is new to the firm but not new to the market. These "me-too" innovations may also benefit from location in a cluster. Insofar as clusters are rich, not just in invention but also innovation, a firm can either directly imitate an existing innovation, or, perhaps acquire a "me-too" invention from an external source as a basis for a new product. Put differently, the knowledge spillovers in clusters not only help firms invent, but also imitate.

2.2.3 The Role of Invention Capability

To unpack the dual effect of clusters on innovation and the division of innovative labor, and integrate the geography of innovation with open innovation, we highlight the role of invention capability and absorptive capacity of firms.

Invention capabilities are the ability to deploy resources to invent. Invention capabilities reduce the cost of inventing (Amit & Schoemaker, 1993; Arora & Nandkumar, 2012; Helfat & Lieberman, 2002), and, because they involve accessing and combining new knowledge, are also foundational to absorptive capacity, or the ability to access and assess external knowledge (Cohen & Levinthal, 1989, 1990). We differentiate firms by their invention capabilities, and suggest that such capabilities distinguish those able to absorb knowledge spillovers and therefore get dual benefits from clusters, from those who can only benefit from cluster location via easier access to external inventions to innovate or imitate.

2.3 Model

To explore the relationship between clusters and firm innovation outcomes we construct a simple model of innovation and the sourcing of invention. The basic structure involves firms choosing whether to invest in R&D to support internal invention efforts. Firms then (probabilistically) generate an internal invention (either novel or imitative), find an invention to source externally (again, either novel or imitative), both, or neither. Firms choose which invention, if any, to commercialize.[3] Clus-

[3] Our data uses a survey that asks about the firms "most significant innovation", and therefore we model firms choosing which input to develop into a new product selecting the most valuable one. Alternatively, we could allow that they choose all that materialize and have a net positive value. This would involve some modest changes to our predictions.

ter location plays a dual role in our model, first by lowering the cost of R&D (via knowledge spillovers) and thereby indirectly increasing the probability of having an internal invention, and second by increasing the probability of finding a viable external invention. In the model, invention capability lowers the cost of internal R&D.

There are potentially four options from which a firm chooses: a novel, internally-generated invention (with value x); a novel, externally-generated invention (with value θx); an imitative, internally-generated invention (y); or an imitative, externally-generated invention (θy). We assume in this simple set up that the value of not commercializing an invention is 0. We further assume that $0 \leqslant \theta < 1$, or that internal inventions are higher gross value since externally sourced inventions have acquisition costs, and that $\theta x > y$, or that the net benefits of being first to market using an external invention are greater than commercializing an internally generated "me-too" invention.[4]

The likelihood of having each type of invention at the commercialization stage depends on the supply of proximate external inventive activity (s) and on firm invention capability (δ), which are exogenous. The likelihood of having an internal invention, λ, depends on firm investment in R&D, where the marginal cost of R&D depends on both capability δ and cluster location s. We assume R&D has a fixed cost component F such that those of low capability (δ_L) will not invest in R&D whereas those of high capability (δ_H) will invest $F + r^*$. The likelihood of finding an external invention, γ is higher if the firm is located in a cluster, s. Last, the likelihood that either the internal or external invention available to the firm is novel is p.[5] So, for

[4] This means there is a strict ordering of the values of inventive inputs: $x > \theta x > y > \theta y$. Put differently, the highest gross returns are for a novel internally invented product, followed by a novel product based on an external invention, followed by an internally generated imitative product, and last of all, an imitative product based on an external invention. The underlying assumption is that the benefit of being novel outweighs the cost of acquiring an external invention (θ).

[5] Allowing the likelihood of novelty to vary across internal and external complicates the model, but, with some additional assumptions on relative parameter values, is consistent with our predictions.

example, the likelihood that the firm will have the option to commercialize a novel, externally generated invention will be $\gamma(s)p$, with an expected value of θx.

In detail, firms choose to undertake R&D (r) directed at internal invention, based on their expected profit of innovation. The expected profit, or value function, can be written as follows:

$$E(\Pi) = \lambda px + (1-p)\gamma p\theta x + \lambda(1-p)(1-\gamma p)y + \gamma(1-\lambda)(1-p)\theta y - c(r;\delta,s) - F \tag{2.1}$$

where:

$$\begin{aligned}
\lambda &= \text{probability the firm gets internal invention}\\
\gamma &= \text{probability the firm gets external invention}\\
p &= \text{probability an invention is } \textit{novel}\\
\delta &= \text{invention capability}\\
s &= \text{cluster location}\\
r &= \text{R\&D investment}\\
c &= \text{variable R\&D cost}\\
F &= \text{fixed cost of R\&D}
\end{aligned}$$

and:

$$\begin{aligned}
\lambda &= \lambda(r(\delta,s))\\
\gamma &= \gamma(s)
\end{aligned}$$

The expected profit or value function is comprised of four potential outcomes. First, the expected value of a novel (*i.e.* new to the market), internally invented product is λpx. Since x is the highest value outcome, if a firm internally generates a novel innovation, it will choose to commercialize that over other alternatives. Second, if a firm does not internally generate a novel invention but does acquire a novel invention from the outside, an event with probability $(1-p)\gamma p$, it earns θx. The third component represents the outcome where the firm fails to generate a novel internal invention and also fails to acquire one from the outside, but generates an internal "me-too" invention. The probability of this event is $\lambda(1-p)(1-\gamma p)$, and the firm's payoff is y. Finally, the least attractive means of introducing a new product on the market is a me-too invention, acquired from the outside. The probability of this event is $\gamma(1-\lambda)(1-p)$, and the corresponding payoff is θy.

We use this simple framework to generate predictions about the probability of innovation, imitation, and sourcing of invention by innovators. We explore the dual role of cluster location (s) and invention capability (δ) in predicting innovation outcomes, as well as how clusters and invention capability shape patterns of external sourcing of invention among innovating firms.

2.3.1 The Dual Effects of Clusters and the Role of Invention capability

Our first objective is to explore how cluster location s and invention capability δ interact to affect the probability of innovation, imitation, or not commercializing a new product. We use this model to interpret the latent classes. For ease of exposition, and with an eye towards the empirical model, suppose that invention capability can take two values, δ_H, and δ_L, where $\delta_H > \delta_L$. Recall that the existence of a fixed cost of R&D, F, implies that only firms with high enough level of invention capability will invest in R&D. Based on the above framework, the probability of innovation , imitation, and none, are:

$$P[innovation|\delta_H] = \lambda p + (1-\lambda p)\gamma p \tag{2.2}$$

$$P[imitation|\delta_H] = \lambda(1-p)(1-\gamma p) + \gamma(1-\lambda)(1-p) \tag{2.3}$$

$$P[none|\delta_H] = (1-\lambda)(1-\gamma) \tag{2.4}$$

For low invention capability firms, the relevant probabilities are:

$$P[innovation|\delta_L] = \gamma p \tag{2.5}$$

$$P[imitation|\delta_L] = \gamma(1-p) \tag{2.6}$$

$$P[none|\delta_L] = (1-\gamma) \tag{2.7}$$

As expected, invention capability increases the probability of innovation because it lowers the cost of R&D, which in turn increases the likelihood of internal invention λ.

However, the effect of invention capability on the probability of imitation is more nuanced: it will be positive only if γ, or the probability of having an external invention, is less than $\frac{1}{1+p}$. Since $0 \leqslant p \leqslant 1$, a sufficient condition for this is $\gamma < \frac{1}{2}$.[6]

Size, capability, and innovation

As noted, we use this model to help guide the latent class model and the interpretation of the latent classes. A key variable that conditions the expected benefits from innovation is business unit size. We predict that whereas size should increase both innovation and imitation for high capability firms, the effect should be absent for low capability firms. Intuitively, if the payoff from introducing a new product is greater for larger firms (Cohen & Klepper, 1996), then an increase in size will imply

[6] The difference in imitation between high and low capability firms is $\lambda(1-p)(1-\gamma p-\gamma)$, which is positive as long as $\frac{1-\gamma}{\gamma} > p$

a greater investment in R&D. However, this will only apply to high capability firms. For low capability firms, increases in size may increase the payoff but since they do not invest in R&D, there is no change in their likelihood of innovation. Formally, $P[innovation|\delta_H] = \lambda p + (1 - \lambda p)\gamma p = \gamma p + \lambda p(1 - \gamma p)$. If λ is increasing in R&D investment, which is increasing size, then $P[innovation|\delta_H]$ must increase in size. However, $P[innovation|\delta_L] = \gamma p$ is independent of size. A similar argument applies for imitation.

Proposition 1: Innovation & imitation increase with size for high capability but not low capability firms.

Clusters, capability, and innovation

The effect of cluster location on innovation and imitation is unambiguously positive for firms of lower invention capability, since cluster location s increases the likelihood of having an external invention γ. The effect of cluster location on innovation by higher capability firms is also positive, since s lowers the cost of R&D as well as increases the likelihood of having an external invention, whereas the main effect of cluster location on imitation by high capability firms is ambiguous; however, a sufficient condition for this to be positive would be that both $\gamma < \frac{1}{2}$ and $\lambda < \frac{1}{2}$.[7]

Importantly, we expect that the effect of cluster location on innovation (and imitation) will be stronger for firms with lower invention capability. Intuitively, this is because more capable firms are able to innovate (or imitate) without access to external inventions. Formally, taking the extreme case where external knowledge spillovers and external sources of invention are present only in clusters, so that $\gamma = 0$ outside clusters, we see that, first, the effect of capability on innovation inside cluster

[7] The full condition is that $\frac{\partial \lambda}{\partial s}(1 - p)(1 - \gamma p - \gamma) + \frac{\partial \gamma}{\partial s}(1 - p)(1 - \lambda p - \lambda)$. It follows that the condition that both $\gamma < \frac{1}{2}$ and $\lambda < \frac{1}{2}$ is sufficient but not necessary.

is $\lambda p(1-\gamma)$, and outside cluster is λp. Second, the effect of capability on imitation inside clusters is $\lambda(1-p)(1-\gamma p-\gamma)$ and outside clusters is $\lambda(1-p)$. Hence, the impact of cluster location on innovation and imitation is greater for lower capability firms than for higher capability firms. This is formally equivalent to *Proposition 2*.

Proposition 2: Innovation & imitation increase with capability faster outside clusters than in clusters.

Clusters, capability, and the share of external sources in innovation

The key objective of this paper is to understand how clusters condition the external sourcing of inventions by innovating firms, and how firm capability conditions this relationship. The probability of using an external source conditional on innovating is:

$$P[external|innovation, \delta_H] = \frac{(1-\lambda p)\gamma p}{\lambda p + (1-\lambda p)\gamma p} \tag{2.8}$$

$$P[external|innovation, \delta_L] = 1 \tag{2.9}$$

By assumption, firms lacking invention capability can innovate only by acquiring external inventions. More generally, our model suggests that, for low capability firms, cluster location s will unambiguously increase external sourcing. For high capability firms, cluster location may or may not increase external sourcing, depending on the balance of the knowledge spillover effect (which decreases external sourcing) and the external invention effect (which increases external sourcing). Formally, the difference between high and low capability firms in share of external inventions for innovations is given by:

$$P[external|innovation, \delta_H] - P[external|innovation, \delta_L] = \frac{(1-\lambda p)\gamma p}{\lambda p + (1-\lambda p)\gamma p} - 1$$
$$= \frac{-\lambda p}{\lambda p + (1-\lambda p)\gamma p} < 0 \tag{2.10}$$

As long as $\frac{\lambda}{\gamma}$ decreases in s, the share of external inventions will rise faster in clusters for low capability firms than for high capability firms. Put differently, $P[external|innovation, \delta_H] - P[external|innovation, \delta_L]$ will fall with s. In the extreme case where $\gamma = 0$ outside clusters, $P[external|innovation, \delta_H] = P[external|innovation, \delta_L] = 0$.[8] In this case, the difference-in-difference of the effect of clusters and capability on the share of external sources of invention is simply $\frac{-\lambda p}{\lambda p+(1-\lambda p)\gamma p} < 0$, yielding the result summarized in Proposition 3 below.

Proposition 3: Low capability firms rely more heavily on external sourcing of inventions than high capability firms. If $\frac{\lambda}{\gamma}$ decreases in s, then the difference in the use of external invention between low and high capability firms is higher in clusters than outside clusters.

2.4 Data

We base our empirical analysis on a "division of innovative labor" survey of firms in U.S. manufacturing sector. The survey was performed in 2010 and refers to new product development activities at the level of the business unit within a firm during 2007 through 2009. The sampling frame for this survey was the Dun and Bradstreet Selectory database, the most complete publicly available frame for the United States

[8] Note that $\frac{\lambda}{\gamma}$ decreasing in s is sufficient but not necessary for the result, as this extreme case shows.

at the time.

The survey sampled all American manufacturing firms, not just R&D performers, unlike prior innovation-related surveys (e.g. Cohen et al. (2000); Levin et al. (1987)). Such a sample is key for us to build a measure of invention capability that is not conditional on endogenous innovation inputs (e.g. R&D) or outcomes (e.g. patents), and also one that allows us to see the relationship between cluster location and innovation for all types of firms.

Sampling was stratified along multiple dimensions, including by industry (at the 4 digit NAICS level), and by size (categories: Fortune 500, over 1000 employees but not F500, 500 to 1000 employees, 100 to 499 employees, and 10 to 99 employees, and less than 10 employees). For Fortune 500 firms, the sampling unit was the firm's activity within an NAICS; for other firms it was based on primary NAICS. The initial sample was 28,709. Initial screening (for out-of-business or out-of-population) left a final sample of 22,034. The final respondent count was 6,685 or an adjusted response rate of 30.3%. A more detailed description of the sampling process and complete description of the phone survey procedures, along with tables of response rates across industries, detailed tests of response bias, and other related information are outlined in (Arora et al., 2016).

The survey asked respondents about whether the firm had introduced a new product in the previous three years, and if so, whether the product was new to the market or merely new to the firm.[9] A firm that had introduced a product that was new to the market is termed an innovator. A firm that introduced a product that was merely new to the firm itself is considered to be an imitator. Innovating firms were further asked whether they had acquired the key invention underlying their product innovation from an external source, such as a customer, supplier, technology

[9] More precisely, of all the new products introduced, firms were asked to answer with respect to the most significant product, that which accounted for the largest share of revenues.

specialist, or university. In addition, we matched each respondent to a location, and use the characteristics of the location as a measure of whether or not it is a cluster of inventive activity.

In the present study, we use business units operating across all manufacturing industries (NAICS 31-33) with 10 or more employees, or 5,175 respondents. Because of item non-response on key variables (e.g., business unit size), our final sample for our latent class analysis is 4,692, out of which there are 1,124 innovators.

In all analyses we use survey sample weights, constructed using Census data on the population of firms stratified by industry, size strata, and age to correct for non-response bias. We link the survey data to outside data sets at the level of respondent (using Duns number or other firm identifiers), industry (NAICS 3 or 4 digit level), and location (county or metropolitan statistical area). Descriptions of relevant variables are below.

2.5 Analysis

Our analysis involves two main steps, following from our theoretical predictions about innovation choices and sourcing by innovators. First, we predict the likelihood of innovation, imitation, or no new product by business units. We use latent class discrete choice methods to simultaneously develop a measure of latent invention capability and to explore how invention capability, alongside cluster location, business unit size, and other firm and industry characteristics shape the innovate-imitate-none choice. Second, we use our measure of latent invention capability from our first analysis to test how capability moderates the role of cluster location on the use of external inventions and the types of external sources used by innovating firms.

2.5.1 Latent class model

Our model predicts that cluster location will have different effects on innovation choices depending on the invention capability of the firm. Instead of using past behavior (e.g. patenting, R&D spending) to infer invention capability, we use latent discrete choice models to generate a measure of capability based on outcomes and innovation characteristics across firms. Latent class discrete choice models are a special case of finite mixture models. Finite mixture models assume that the data generated are from mixture of two (or more) distributions, e.g. a mix of two normal distributions, each with different means. Each data point or observation has an unknown probability of belonging to one of the distributions (and, in the case of two distributions, one minus that probability of belonging to the other). These distributions are the latent classes, and the unknown probabilities, along with the parameters of the distribution, are jointly estimated. Finite mixture models are widely used in epidemiology, machine learning, and other areas.

Latent class models, a special case of finite mixture models, are widely used to categorize consumers by their revealed preferences (Bordley, 1989; Boxall & Adamowicz, 2002; Bucklin & Gupta, 1992; Colombo & Morrison, 1989; Kamakura & Russell, 1989; Kamakura et al., 1996). These models allow for the attributes of various choices (e.g. price) and characteristics of the choosers (e.g. income) to differentially shape choices across endogenously determined classes. For example, Kamakura et al. (1996) predict consumers choice of peanut butters, segmenting those insensitive to price (i.e. brand loyalists) from those who make choices based on price.

In our setting, we use latent class models to segment firms, allowing firm characteristics and industry features to differentially shape innovation choices and outcomes. We model innovation outcomes as a function of firm and industry factors that are either observed (e.g., size, location in a cluster) or unobserved (e.g. invention capabilities) by the analyst. There are three potential innovation outcomes: (1) innovation, (2) imitation, or (3) no new product, here indexed by j. The probability of each outcome is: $P_i(j) = Prob(y_i = j)$ or, in the multinomial logit formulation:

$$P_i(j) = \frac{e^{x_i \beta_j}}{\sum_{j=1}^{3} e^{x_i \beta_j}} \tag{2.11}$$

where x_i are the observed characteristics of firm i, and β_j are the coefficients associated with the j^{th} outcome.

If we allow these probabilities to vary across latent classes (hereafter q), the class conditional probabilities are $P_{i|q}(j) = Prob(y_i = j|class = q)$ or, in the multinomial logit formulation:

$$P_{i|q}(j) = \frac{e^{x_i \beta_{qj}}}{\sum_{j=1}^{3} e^{x_i \beta_{qj}}} \tag{2.12}$$

We do not directly observe membership in latent classes, and therefore it must be estimated. Estimation of class membership (i.e., probability of being in a class q) and the corresponding class-specific coefficients (the β_{qj}s) is an iterative process, starting with estimation of prior probability of being in a class (see Table 2.9 for our prior probability estimates, which are based on industry).

To estimate a latent class model, an analyst must first choose the number of classes q, trading off interpretability (and thus fewer classes) and the potential additional fit from a higher number of classes.[10] As described in the results section, we choose two classes.

Latent class models simultaneously estimate both class probabilities and class

[10] To inform this choice, following prior literature we used the Akaike and Bayesian Information Criteria (AIC and BIC) as well as R^2 values (Greene & Hensher, 2003; Grimpe & Sofka, 2009; Roeder et al., 1999).

conditional probabilities of the various innovation outcomes. Let H_{iq} denote the prior probability of being in class q for firm i, and z be a set of observable characteristics

$$H_{iq} = \frac{e^{z_i' \phi_q}}{\sum_{q=1}^{Q} e^{z_i' \phi_q}} \quad \text{where} \quad \boldsymbol{\phi_q} = 0 \tag{2.13}$$

The choice probability for respondent i is the sum of the class-level probabilities weighted by class probabilities, or: $P_i = \sum_{q=1}^{Q} H_{iq} P_{i|q}$.

After obtaining estimates of ϕ_q from the two class model, the Latent class routine then computes choice probabilities and posterior estimates of the firm-specific class probabilities conditional on choice probabilities via Bayes theorem:

$$\hat{H}_{q|i} = \frac{\hat{P}_{i|q} \hat{H}_{iq}}{\sum_{q=1}^{Q} \hat{P}_{i|q} \hat{H}_{iq}} \tag{2.14}$$

These steps are repeated until the process converges. In the end, this analysis produces firm-specific estimates of latent class probabilities ($\hat{H}_{q|i}$), as well as class-specific estimates of the propensity to innovate, imitate, or do nothing ($\hat{P}_{i|q}$) and class-specific coefficients for our predictor variables ($\hat{\beta}_{jq}$).

The above steps were performed in NLOGIT 5 using LCLOGIT routines. For comparison, we also estimated the standard Multinomial logit (MNL) model (i.e., one latent class).

2.5.2 Analysis: Innovation, Imitation, and Invention Capability

Dependent variable

We categorize business units as *innovators* if they earned revenue from a "new-to-the-market" product launched from 2007 to 2009. If the business unit earned revenue from a "new-to-the-firm" product launched over the same period that was not new-to-the-market, we categorized them as *imitators* or “me-too”. Those that did neither are categorized as *none*.

Key variables

To identify *cluster location*, we measure the invention activity at the region-industry level. Ideally, we’d like a measure that captures the supply of invention inputs—both knowledge spillovers and inventions—potentially available to our focal firms. For our main measure, we use the (log) count of R&D specialist firms in the MSA (metropolitan statistical area) of the respondent business unit weighted by use of such services in the industry of the respondent.[11] In the literature, as in our theory, clusters are associated with knowledge inputs as well as the supply of external invention. Our primary measure focuses on the supply of technical inputs. We note, however, that R&D specialists also act as diffusers of knowledge and sources of invention (Arora et al., 2001b). We also use two alternative measures of cluster location based on: (1) counts of patents within the cluster-region of the respondent, as defined by the Clustermapping project (Delgado et al., 2014a) and (2) relevant university R&D spending within a 100-mile radius of the respondent. The results from patents are nearly identical to our main measure. Relevant patents is a more direct measure of inventions, and therefore we would expect it to be measuring external supply of inventions more than knowledge inputs. However, it is plausible that this also proxies for supply of technical inputs (e.g., the inventors). The university R&D spending measure certainly captures one source of knowledge inputs for inventing firms (i.e.

[11] Specialist R&D suppliers consist of suppliers of Architectural, Engineering, and Related Services (5413), suppliers of Specialized Design Services (5414), Computer Systems Design and Related Services (5415), Management, Scientific, and Technical Consulting Services (5416), and Scientific Research and Development Services (5417). For our measure, we take a log of the count the number of large establishments (>100 employees) in NAICS 5413-5417 in the relevant MSA. For the industry weights, we use Bureau of Economic Analysis input-output tables to get the share of inputs coming from R&D specialists for each industry.

knowledge spilling out of universities), yet there are many sources of knowledge inputs, including related firms and other firms (Cohen et al., 2000; Arora et al., 2016). It is also plausible that a measure based on proximate universities will also capture the supply of trained personnel, an internal input into invention. Further, inventions resulting from university research also form part of the supply of external inventions (although a small share (Arora et al., 2016)). In robustness analyses described below, we use relevant, proximate university R&D spending as an alternative measure of cluster to highlight more narrowly the knowledge input aspect of clusters.

At the level of the respondent, we measure *size* as the logged number of employees of the business unit. Prior research suggests that scale of the business unit will increase the likelihood of R&D (Cohen & Klepper, 1996) and, through that, the likelihood of innovation (Henderson & Cockburn, 1996). In our theory, we predict that size will matter for high capability firms but not low capability firms.

Control variables

We include an indicator for whether or not the business unit is *multi-industry* (=1 if the business unit has more than one associated 6-digit NAICS) since the scope of related firm activities has been found to be positively associated with innovation success (Cockburn & Henderson, 2001; Henderson & Cockburn, 1996).

We control for whether the business unit is part of a larger firm or is a *standalone* company. Being a part of a firm may influence business-unit level innovation positively (i.e. via internal capital markets), or negatively via scale-related resource constraints (e.g., limited managerial attention). We also control for *firm age* which we expect to decrease the likelihood of innovation while increasing the likelihood of imitation.

At the industry level, we include a dummy for whether or not the respondent is in a *high tech industry*, which is measured based on the share of firms in the industry of the business unit who perform R&D (high tech =1 for above median industries). On average, we expect firms in high tech industries to be more likely to innovate. We also control for whether or not the business unit is a *homogeneous market*, that is, whether the market for the firm's innovation is relatively homogeneous (Sutton, 1998). Homogeneity is based on the share of total industry-level sales (4 digit NAICS) made up by the largest 7 digit NAICS category within the industry. We use total shipment values at the 4 and 7-digit NAICS level from the 2002 US Economic Census (homogeneous =1 for above median industries). Homogeneity should have competing effects on the choice between innovation and imitation. On one hand, homogeneity may increase the size of the expected market for an innovation; on the other, homogeneity may heighten the risk of (and opportunity for) imitation, since there are likely more competitors.

2.5.3 Results: Innovation, Imitation, and Invention Capability

We expect that one of the latent classes will identify those with high (latent) invention capability, as those with higher innovation and imitation rates. That is, one class—which we label higher capability—should be much more likely to have commercialized new products than the other class of firms (Proposition 1.i). Further, firms that are members of the high capability latent class should have larger, positive coefficients for size in the innovation equation compared to lower capability firms (Proposition 1.ii). Finally, innovation and imitation by lower invention capability firms should be enhanced by cluster location more significantly than for firms with high invention capability (Proposition 2). These predictions are useful ways of checking that the separation into the latent classes is indeed based on invention ability.

Table 2.1 outlines the results from simple multinomial logit (or single class) and latent class multinomial logit models (Table 2.9 outlines the prior probabilities of being in latent class 1 across various industries). Table 2.2 includes the corresponding marginal effect estimates and average probability of each outcome for all three models. As a part of the latent class analysis, we needed to select the number of latent classes. We choose two based on fit statistics outlined and described in Table 2.3.

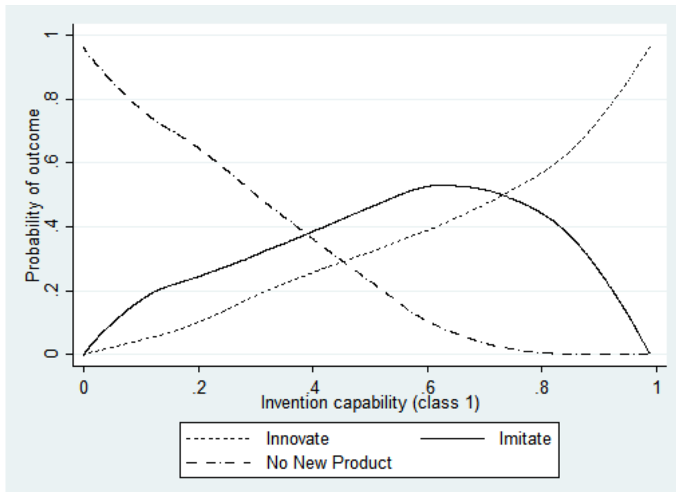
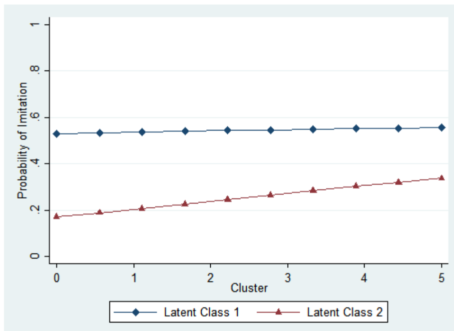


FIGURE 2.1: Likelihood of Innovation, Imitation and No New Product, by Invention Capability

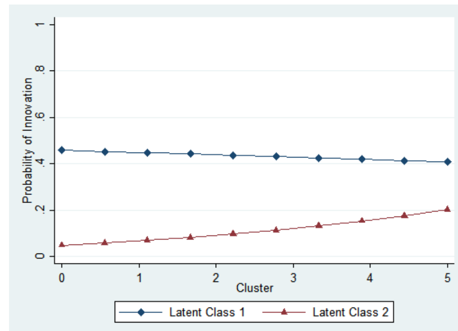
Overall, the average rate of innovation is 17%, of imitation is 25%, and 58% of business units did not commercialize a new product over the three year period of analysis (2007 to 2009). As described above, each respondent is assigned an estimated probability of belonging to each of the two latent classes: the average probability of latent class 1 is 35%, and of latent class 2 is 65%. For class 1, the predicted probability of innovation is 35%, of imitation 40%, and of no new product 24%. For latent class 2, the corresponding probabilities are 8% innovation, 16% imitation, and 76% none. Clearly, both innovation and imitation are, on average, much more likely for those that have a higher probability of being in latent class 1.[12] Henceforth, we

[12] These outcome probabilities were generated using the full sample, using the probability associated

refer to latent class 1 as “high capability”, and use the likelihood that a respondent belongs to latent class 1 as a continuous measure of the invention capability of the firm. In Figure 2.1, we further see how the predicted probability of each outcome changes as their invention capability (probability of being in latent class 1) increases.



(a) Imitation



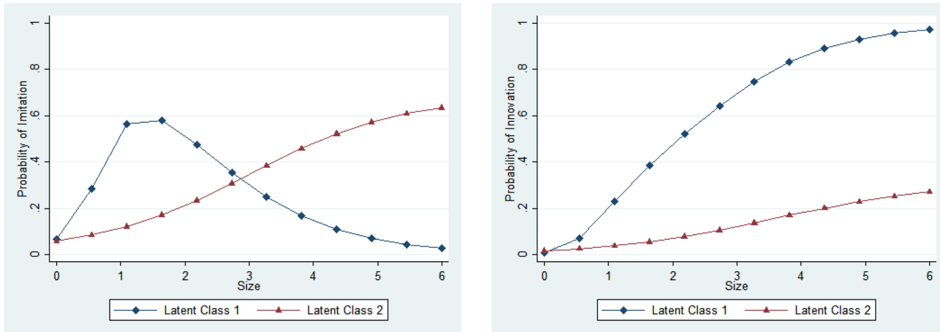
(b) Innovation

FIGURE 2.2: Likelihood of Innovation and Imitation, by Cluster and Invention Capability

Consistent with our predictions associated with invention capability, not only are the rates of innovation and imitation (in sum, new product introduction) higher for high capability firms (i.e. class 1), we also see that there is no relationship between cluster location and innovation for high capability firms, but there is a positive relationship for low capability firms (i.e. class 2). In Figure 2.2 we see imitation and innovation increase alongside the (log) count of R&D specialists in the local area for low capability but not high capability firms.

As one can also see in Table 2.1, (Columns 4-9), business unit size increases the likelihood of innovation and imitation for all firms. However, whereas size increases the likelihood of innovation relative to imitation for high capability firms (Column 6), there is no such relationship for low capability firms (Columns 9). Further,

with being in each class as weights. If we instead use the class probabilities and assign each respondent to either class 1 (prob> 0.5) or class 2, we get: class 1 innovation is 45%, of imitation 53%, and of no new product 2%. For latent class 2, the breakdown is 4% innovation, 12% imitation, and 84% none.



(a) Imitation (b) Innovation

FIGURE 2.3: Likelihood of Innovation and Imitation, by Size and Invention Capability

consistent with expectations, the coefficients of size in innovation and imitation are larger for high capability (Columns 4-5) than low capability firms (Columns 7-8). For low capability firms, both innovation and imitation increase with size. Innovation, however, increases consistently with size for high capability firms whereas imitation first increases with size and then decreases. For high capability firms, likelihood of imitation is the highest for mid-sized business units (Figure 2.3).[13]

To better understand the size results (Fig. 2.3), it is helpful to keep in mind that firms have three options: innovate, imitate, or not commercialize a new product. As firm size increases, the attractiveness of doing nothing falls. For high capability firms, the relative attractiveness of innovation rises faster than imitation. Therefore the likelihood of a high capability firm imitating is maximized at an intermediate size level: whereas initially, imitation is substituting for doing nothing (no new product), as size increases, innovation substitutes for imitation. However, for low capability firms, since internal R&D is not significant and both innovation and imitation are

[13] Other results are consistent with latent class 1 representing "high capability" firms: (1) for latent class 1, being in a high tech industry is also positively associated with innovation, having a large effect (+20%), compared to latent class 2, where being in a high tech industry increases the probability of imitation by 5%; (2) for latent class 1, being in a more homogeneous market increases the likelihood of innovation by 11%, and of doing nothing by 20%, compared to latent class 2, where being in a more homogeneous market increases the likelihood of imitation by 13%.

largely driven by external offerings, increases in size result in a monotonic increase in innovation and imitation. For the same reasons, innovation and imitation by low capability firms (latent class 2) is more responsive to cluster location than for high capability firms, as can be seen by comparing Columns 4-6 with Columns 7-9 in Table 2.1, and in Figure 2.2. This highlights a key point of our paper: high and low capability firms seek different things from their environment in order to innovate. Low capability firms seek external inventions, whereas for high capability firms external inventions are a substitute for internal inventive efforts. However, the internal inventive efforts of high capability firms benefit from their external environment via knowledge inputs (i.e. ideas or skilled employees). To put it starkly, low capability firms are largely incapable of introducing new products without external help, whereas high capability firms are capable of doing so.

Further Validating our Invention Capability Measure

We performed some additional analyses to investigate the robustness of our capability measure. One possible concern is that we are simply identifying "better" firms and hence capturing a generic, latent quality measure and not specifically a measure of *invention* capability. To explore this, we examine the relationship between our measure and performance (growth in market share).[14] We find, unsurprisingly, our latent invention capability measure is associated with increased likelihood of growth (see Table 2.10). However, this is only the case for innovating firms (and not firms that imitate or do not introduce a new product) consistent with our measure being related specifically to innovation performance.

We also explored the relationship between our measure and two other proxies for

[14] In the survey, firms were asked if they experienced market share growth from 2008 to 2009. We also used National Establishment Time-Series (or NETS) data linked to our survey at the establishment level to build a similar growth measure using establishment-level sales.

invention capability that we didn't use in building it: prior patenting (in the years 2004-2006) and R&D performance. Both have been used in prior literature as a measure of invention capability (Tripsas & Gavetti, 2000; Gambardella & Giarratana, 2013; Arora & Nandkumar, 2012; Kotha et al., 2011; Sears & Hoetker, 2014). We find that both are positively correlated with our measure, even when controlling for industry. We also ran all analyses using prior patenting (filing for at least one patent in the years 2004-2006) in place of our latent capability measure and our findings were qualitatively similar. That is, we found that cluster location increases the likelihood of innovation and/or imitation for firms without prior patents, but not for firms with prior patents. Collectively, these tests, alongside our main analyses, give us confidence in our latent capability measure.

2.6 Invention Capability and External Sourcing by Innovators

Given our findings on invention capability, we now turn to understanding how the use of external inventions differs among those of varying capability, and how that is related to cluster location. Recall from prediction 3, that we expect that the conditional probability of using external inventions among innovators will be lower for high capability firms, and that this relationship will be stronger inside clusters.

Outside the scope of our simple model, but consistent with its logic, we also unpack and empirically explore varying use of different types of external inventions by high invention capability vis-a-vis their less capable counterparts. To do so, we categorize external inventions into into high value (i.e. unique, startups, those acquired through market channels) and low value. We expect the negative relationship between capabilities and use of external invention to be driven by low value external inventions (those that are cheaper to acquire and/or easier to access, evaluate, and commercialize).

Dependent Variable

External sourcing =1 if the respondent said one or more of the following was the main source of the main idea, prototype or design underlying the innovation: a supplier; a customer; another firm in the industry; a consultant, commercial lab, or engineering service provider; an independent inventor; or universities or government labs. The alternative source was that the innovation was based on an internal invention.

Key Variables

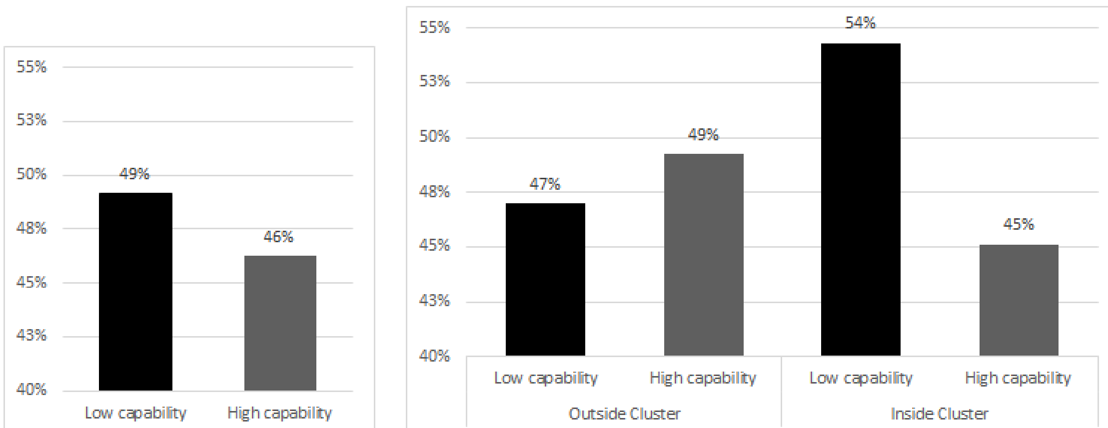
Our focal explanatory variables are *cluster location* as defined above, and also split into above and below median value by location, and *invention capability*, which is estimated via the latent class regression. We estimate all regressions for the full sample of innovating firms, and split our sample into outside and inside cluster.

Control Variables

In all regressions, we include industry fixed effects (3 or 4 digit NAICS). We also control for business unit and firm level variables that may relate to the use of external sources. Most importantly, we account for whether or not the respondent is in a *vertically integrated* firm, that is, if another division or business within the firm of the focal business unit is a main customer and/or supplier. Having internal customers or suppliers may facilitate the use of external sources, or may preclude its necessity. We also control for whether the focal respondent is a *multi-industry* business unit since internal diversity of inputs may lower demand for external invention sources.

2.6.1 Results: External Sourcing of Invention by Innovators

We predict in Proposition 3 that low capability firms will rely more on external inventions than those of high capability, and that this difference will be higher inside clusters as compared to outside them. Looking first at the raw differences, in Figure 2.4, we see that among innovators, low capability firms are 3% more likely to use external inventions. Further, we see this difference is much larger inside clusters (9% or 54%-45%) than outside, where high capability firms actually have a slightly higher likelihood of using external sources (47% for low capability versus 49% for high capability).



(a) Capability

(b) Capability, Inside and Outside Cluster

FIGURE 2.4: Use of External Sources of Invention by Innovating Firms

To explore this further, we distinguish between the sources of external invention as a rough proxy for the value of the innovation. We split external sources into high and low value using a number of measures of potential value. Lacking viable internal alternatives, low capability firms should be amenable even to lower value external inventions, certainly more so that high capability firms. Moreover, this difference is more likely when there is a richer supply of external inventions, that is to say, we expect cluster location to make it more likely for low capability firms, but not high capability firms, to draw upon lower value external inventions.

We use three different measures to categorize external inventions into high and low value. First, *unique* external, which is categorized based on whether the innovating firm indicated that it "could not have acquired a similar invention from another source." The assumption is that if a similar invention could have been acquired from elsewhere, then the resulting new product would likely face competition from similar products, and, therefore, be less valuable. Conversely, if the innovator could only have acquired the required invention from the given external source, the resulting new product is likely more differentiated from competitors, and likely more valuable.A second proxy for value relies upon the channel through which the external invention was acquired. We compare *market channels* (those who acquired the invention via merger and acquisition, licensing or a service contract) to those who acquired the invention *non-market channels*, i.e., through cooperative R&D, joint venture, or informal means. Last, startups may be particularly valuable sources of external inventions that are more novel or unique. We create a variable *start-up* sources =1 if the focal innovator said the source was a start-up (i.e. a new, small company).

Figure 2.5 highlights how, conditional on using external sources of invention, higher capability firms are more likely to use high value sources: unique inventions, those acquired via market channels, and those from startups. In other words, they are more likely to use higher value external inventions even when they do use external inventions to innovate. Similarly to the results for external sourcing as a whole, these differences typically become more pronounced inside clusters as compared to outside them.

These raw tabulations are also reflected in the regression analyses that include firm and industry controls. Table 2.4 presents tests of the relationship between the use of external sources and innovation capability for innovators. We see overall that invention capability is negatively associated with the use of external sources (Column 1). We find this negative relationship is driven by innovating firms in areas with high proximate supply of invention, in line with our predictions. This

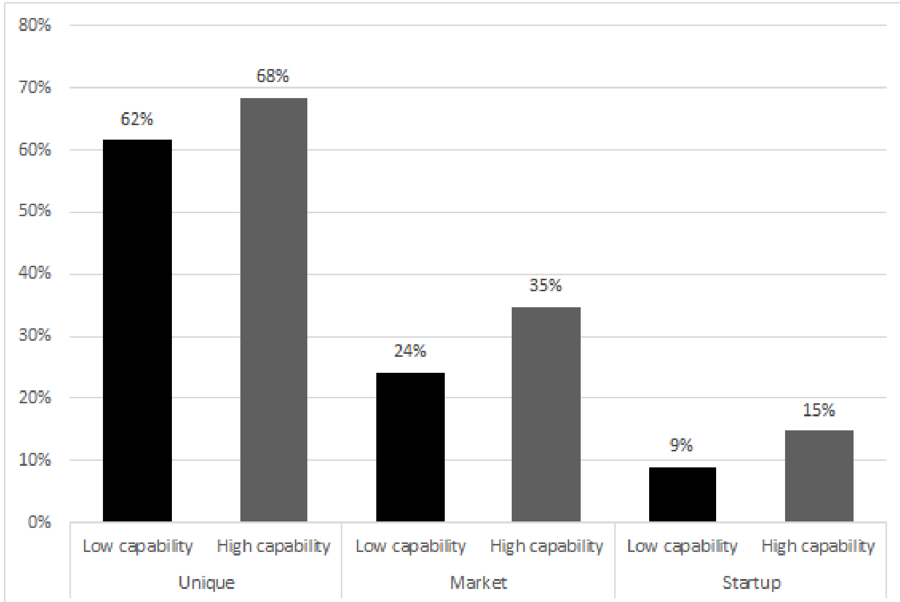


FIGURE 2.5: Use of High and Low Value External Inventions by Innovating Firms Using External Inventions

is consistent with the notion that whereas low capability firms innovate mainly by commercializing inventions made by others, high capability firms can also draw upon internal inventions. Therefore, the latter are less sensitive to the supply of external inventions, in contrast to low capability firms.

Our regressions looking at high and low value external sources include all innovating firms, and compare each external source type to the baseline of internal invention. First, the results in Table 2.5 explore unique external sources. We find that less capable inventors are more likely to use non-unique external sources relative to internal invention (Column 1), but there is no significant invention-capability related difference between use of internal invention and unique external sources (Column 2). Comparing Column 3 to Column 5 shows that the results are driven by firms in clusters.[15] Second, looking at market channels as proxy for value, Table 2.6 indicates that

[15] Note that location in a cluster also provides knowledge inputs that are likely to raise the likelihood of internal invention, particularly for high capability firms. As a result, high capability firms are less likely to acquire low value external inventions as compared to using internal inventions (or high value external inventions).

less capable firms are more likely to acquire via non-market channels (Column 1), but there is no capability related difference external inventions acquired via market channels (Column 2), and the results are driven by firms located in clusters. Third, we find similar invention capability related results for start-up sources (Table 2.7): a negative (although here non-significant) relationship between non start-up sources and capability (Column 1) and no capability related difference between internal and start-up sources (Column 2).

Collectively, these results suggest that being located in a cluster increases the likelihood of new product development for low capability firms more so than for higher capability firms), and this is driven by the use of external inventions, and in particular those of relatively lower value.

Our model suggests that for highly capable firms, clusters provide abundant knowledge inputs that lower the cost of R&D and thereby increase the likelihood they will generate internal inventions. In the above we present evidence consistent with these knowledge inputs by exploring use of 'high value' external sources. Yet, cluster should also be associated with increased likelihood of innovation by high capability firms *if* clusters also provide easier access to knowledge inputs. One reason we do not find such results may be that our location activity measure is based on R&D specialists, which perhaps is a better measure of invention inputs than knowledge inputs. Therefore, we re-ran our latent class analysis using relevant university R&D spending in the local area of the firm (within 100 miles). The results in Table 2.8 highlight that high capability firms are more likely to innovate in areas with relatively high amounts of university R&D, consistent with a knowledge input story.[16]

[16] Because various measures of proximate inventive supply, including R&D specialists and University R&D are highly correlated, we run separate analyses instead of including both in a single regression.

2.7 Discussion and Conclusions

Using data covering the whole of the the U.S. manufacturing sector, we find that being located in an inventive cluster has a positive relationship with innovation and imitation. This overall finding is consistent with prior findings on the geography of innovation, which typically argues that agglomeration allows firms to access knowledge spillovers that help firms to generate inventions. However, in our analysis, the positive relationship between cluster location and innovation is driven by less capable firms, who use cluster location to access the inventions of others. In contrast, clusters provide capable firms with easier access high-value-high-cost external inventive inputs, like those from startups or those that embody unique knowledge. These results highlight the importance of considering both markets for technology, and firms of varying invention capability, to understand the full role of clusters in innovation

Our overall results seemingly contradict current open innovation research, which on the whole suggests absorptive capacity, driven by own inventive ability, increases external innovation inputs (West & Bogers, 2014). We instead find a negative relationship, which is most pronounced in clusters. One fundamental difference in our study is that we include firms across the spectrum of invention capability, which allows us to fully unpack the role of capability in innovation and sourcing of invention. Importantly, our findings are driven by lower capability firms, whereas most prior studies that find complementarity focus on capable innovators using external sourcing to access novel or unique ideas. Prior studies that include low capability firms (e.g. new entrants in developing countries) similarly find that their innovation behavior and outcomes are much more sensitive to environmental conditions than higher capability firms (Arora et al., 2001b).

Our study offers several contributions. Methodologically, we generate a measure of latent invention capability that correlates with but is not determined by prior innovation inputs (like R&D) or prior innovation outcomes (like patenting). Latent measures of invention capability provide a way to measure capabilities in industries where patenting may not be a good measure of invention, and where R&D data may not be systematically available, such as for private firms. Our measure also does not involve detailed measurement of technologies and distance to the cutting edge of the technological trajectory within an industry (as in, e.g. (Franco et al., 2009)) and is therefore measurable and potentially applicable for cross-industry studies. Our measure is also not conditional on the firm actually innovating: firms can have high invention capability and not innovate, or have low invention capability and innovate. A potential extension of this method would be to use new product introductions (perhaps measured using trademarks) alongside firm, industry, and other characteristic variables to similarly estimate commercialization capability, and explore the the influence of both invention and commercialization capability over time.

While our analyses provide a detailed perspective on invention sourcing in the U.S., we also acknowledge several limitations. First, our data are survey-based, and therefore are subject to the caveats associated with such data. Further, because our analysis is cross-sectional, we can only measure associations between innovation capability, innovation, and sourcing of inventions, controlling for industry and firm characteristics. As well, the primary relevant survey questions are based on a single, focal, successful innovation. We don't know about firms' prior external sourcing experience, whether successful or not. While we make an important methodological contribution by measuring a particular type of capability at a point in time, capabilities in general are clearly time dependent and cumulative. Capabilities are shaped by various forms of experience and learning, both pre-entry experience of firm founders, and within industry experience as the firm operates over time. We can see only a single snapshot of attributes and outcomes to build our latent measure of invention capability; further tests would likely provide a more nuanced measure. Research continues to unpack the difficult question of how capabilities evolve, what drives this process, and the independent role of capabilities in choices and performance. We hope future research continues to develop measures of latent capability. Further, location is a strategic choice of the firm. This is important for our results as firms may choose to locate in a cluster to access external inventions.

A cautionary note about extrapolating our findings to describe innovation activities in aggregate is that we only observe the most valuable innovation outcome for each respondent. More capable firms likely have higher rates of innovation and imitation overall compared to those with lower capability (accounting for differences in scale and competition across industries). It is possible, then, that we might find different relationships if we observed all innovative activities of a firm, i.e. the capability-based differences in external sourcing inside clusters may vanish if we were to include the less valuable innovations of highly capable firms.

In conclusion, our results suggest that clusters serve dual roles in innovation: providing knowledge inputs and high value sources to high capability firms and external inventions to lower capability firms.

Table 2.1: Innovation, Imitation or None: Multinomial and Latent Class Logits

	MNL			Latent Class Logit: 2 classes					
				Latent class 1			Latent class 2		
	inno vs none	imi vs none	inno vs imi	inno vs none	imi vs none	inno vs imi	inno vs none	imi vs none	inno vs imi
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Standalone	0.09	0.16	-0.07	-2.37	-3.43*	1.06	-0.71	0.97*	-1.69*
	(0.15)	(0.14)	(0.16)	(1.99)	(1.90)	(0.88)	(0.46)	(0.56)	(0.88)
Multiproduct BU	0.21**	-0.06	0.27**	-0.25	-0.29	0.04	0.71**	-0.07	0.78*
	(0.10)	(0.08)	(0.11)	(0.43)	(0.39)	(0.32)	(0.34)	(0.22)	(0.43)
BU size (log)	1.01***	0.66***	0.35***	4.25***	3.29***	0.96***	0.80***	0.80***	-0.01
	(0.07)	(0.07)	(0.07)	(0.89)	(0.78)	(0.34)	(0.22)	(0.13)	(0.27)
Firm age (years)	-0.004*	-0.003*	-0.001	-0.05***	-0.02***	-0.02***	0.02**	-0.01	0.02***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
High tech industry	1.00***	0.31***	0.70***	1.93***	0.81	1.12***	0.41	0.39	0.02
	(0.10)	(0.09)	(0.11)	(0.50)	(0.53)	(0.35)	(0.35)	(0.25)	(0.48)
Homogeneous industry	0.06	-0.01	0.07	-1.01*	-2.31***	1.30***	-0.77	1.01***	-1.79***
	(0.10)	(0.09)	(0.11)	(0.54)	(0.79)	(0.49)	(0.50)	(0.32)	(0.64)
Cluster	0.13***	0.11***	0.02	-0.23	-0.24	0.01	0.37**	0.24**	0.13
	(0.05)	(0.04)	(0.05)	(0.21)	(0.24)	(0.14)	(0.17)	(0.11)	(0.20)
Constant	-3.37***	-2.04***	-1.33***	-1.4	1.37	-2.77**	-4.29***	-4.15***	-0.14
	(0.24)	(0.21)	(0.25)	(2.05)	(1.74)	(1.22)	(1.17)	(0.81)	(1.59)
Avg class prob					0.35			0.65	
Observations		4692				4692			
LL		-3671.69				-3616.66			

Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1 Regressions predict the likelihood of innovating, imitating, not commercializing a new product, via multinomial logit (columns 1-3) and latent class logit (columns 4-9). Predictors are: firm is standalone (vs multiunit); firm operates in multiple submarkets (multiproduct BU); firm size and age; indicators for high tech or homogeneous industry. Coefficients are change in log odds.

Table 2.2: Innovation, Imitation or None: Average Marginal Effects

	MNL			Latent ClassL: 2 classes					
				Latent class 1			Latent class 2		
	Pr(none) (1)	Pr(imi) (2)	Pr(inno) (3)	Pr(none) (4)	Pr(imi) (5)	Pr(inno) (6)	Pr(none) (7)	Pr(imi) (8)	Pr(inno) (9)
Standalone*	-0.03	0.03	0.00	0.34	-0.36	0.02	-0.07	0.12	-0.05
Multiproduct BU*	-0.01	-0.02	0.03	0.03	-0.02	-0.01	-0.03	-0.01	0.04
High tech industry*	-0.13	0.02	0.10	-0.14	-0.06	0.20	-0.07	0.05	0.02
Homogeneous industry*	0.00	-0.01	0.01	0.20	-0.31	0.11	-0.08	0.13	-0.05
Cluster	-0.03	0.02	0.01	0.03	-0.01	-0.01	-0.05	0.03	0.02
BU size (log)	-0.18	0.08	0.09	-0.40	0.13	0.27	-0.13	0.09	0.04
Firm age (years)	0.001	-0.001	0.00	0.003	0.001	-0.004	0.00	-0.001	0.001

* Indicator variables

Marginal effects represent the increase in probability of an outcome (as compared to any other alternative). For indicator (0/1) variables, it is the increase in probability associate with a change from 0 to 1 (e.g. average increase in probability from being a standalone firm).

Table 2.3: Tests for fit: number of latent classes

Classes	LL	R2 (McF)	AIC	BIC	N	K
4	-3578.9	0.197	7291.8	7724.1	4692	67
3	-3599.0	0.192	7298.0	7620.7	4692	50
2	-3630.3	0.185	7326.5	7539.5	4692	33
1	-3671.7	0.058	7375.4	7478.6	4692	16

This table present the fit statistics across the one, two, three, and four class models which we used to select the number of latent classes. The McFadden R^2 and log likelihood values suggest models with more than one class provide much better fit (i.e. in one class model is 0.06 and is more than 0.18 in the two, three or four class models). Yet, the AIC and BIC are lower in the single class model. Balancing these diagnostics, and aiming for interpretability, we chose a model with two latent classes. Note: BIC=2*LL+K*ln(N)

Table 2.4: Use of external inventions conditional on innovation (linear probability)

External source (Y/N)	All (1)	Outside Cluster (2)	Inside Cluster (3)
Invention capability	-0.25*	0.06	-0.53***
	(0.13)	(0.18)	(0.19)
Vertically integrated	0.13***	0.17**	0.06
	(0.05)	(0.07)	(0.06)
BU size (log)	-0.03	0.02	-0.08***
	(0.02)	(0.04)	(0.03)
Multiproduct BU	-0.11**	-0.05	-0.17***
	(0.05)	(0.08)	(0.06)
Industry FE	Yes(45)	Yes(45)	Yes(45)
Constant	0.72***	0.35*	1.04***
	(0.15)	(0.20)	(0.19)
Observations	1,124	485	639
R-squared	0.08	0.14	0.16

Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1
These regressions predict the likelihood of an innovator firm using an external invention (as compared to internal). The predictors are: firm invention capability, whether is vertically integrated (i.e. has supplier or customers inside the same firm), whether the firm operates in multiple submarkets within their industry (multiproduct BU), firm size, and 45 industry fixed effects. Column (1) is for all firms; Columns (2) and (3) include the regressions run separately for firms outside and inside clusters.

Table 2.5: Use of internal, unique external and non-unique external inventions conditional on innovation (multinomial logit) Ref cat: Internal source

	All		Outside Cluster		Inside Cluster	
	non-unique	unique	non-unique	unique	non-unique	unique
	(1)	(2)	(3)	(4)	(5)	(6)
Invention capability	-1.12	-0.16	-0.03	0.59	-2.27**	-0.92
	(0.71)	(0.57)	(0.84)	(0.81)	(1.07)	(0.80)
Vertically integrated	0.63**	0.48**	0.68*	0.58*	0.63*	0.37
	(0.28)	(0.22)	(0.40)	(0.34)	(0.37)	(0.28)
BU size (log)	-0.16	-0.17	0.11	0.08	-0.41**	-0.36**
	(0.13)	(0.12)	(0.18)	(0.19)	(0.18)	(0.14)
Multiproduct BU	-0.81***	-0.16	-0.46	-0.09	-1.27***	-0.26
	(0.30)	(0.22)	(0.45)	(0.34)	(0.36)	(0.30)
Industry FE	Yes(17)	Yes(17)	Yes(17)	Yes(17)	Yes(17)	Yes(17)
Constant	0.28	-0.35	-1.28	-1.72*	1.88*	0.84
	(0.77)	(0.65)	(1.02)	(0.91)	(1.07)	(0.89)
Observations	1,124		485		639	
LL	-568.3		-266.2		-280.1	

Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1
These regressions predict the likelihood of an innovator firm using non-unique or unique external invention, as compared to internal (the reference category). The predictors are: firm invention capability, whether is vertically integrated (i.e. has supplier or customers inside the same firm), whether the firm operates in multiple submarkets within their industry (multiproduct BU), firm size, and 17 industry fixed effects. Columns (1) and (2) is for all firms; Columns (3), (4), (5), and (6) include the regressions run separately for firms outside and inside clusters.

Table 2.6: Use of internal, market-acquired and non-market acquired external inventions conditional on innovation (multinomial logit) Ref cat: Internal source

	All		Outside Cluster		Inside Cluster	
	non-market	market	non-market	market	non-market	market
	(1)	(2)	(3)	(4)	(5)	(6)
Invention capability	-0.91*	0.54	0.20	0.71	-2.31***	0.89
	(0.55)	(0.75)	(0.75)	(1.09)	(0.77)	(1.19)
Vertically integrated	0.34	0.85***	0.53	0.76*	0.08	1.03***
	(0.23)	(0.26)	(0.33)	(0.41)	(0.31)	(0.33))
BU size (log)	-0.29**	0.10	-0.04	0.36	-0.49***	-0.15
	(0.11)	(0.14)	(0.17)	(0.24)	(0.16)	(0.15)
Multiproduct BU	-0.38*	-0.36	-0.28	-0.11	-0.56*	-0.54
	(0.23)	(0.30)	(0.33)	(0.48)	(0.30)	(0.35)
Industry FE	Yes(17)	Yes(17)	Yes(17)	Yes(17)	Yes(17)	Yes(17)
Constant	0.81	-2.21***	-0.91	-2.78**	2.57***	-2.62**
	(0.63)	(0.81)	(0.88)	(1.22)	(0.84)	(1.30)
Observations	1,124		485		639	
LL	-642.9		-307.1		-313.6	

Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1
These regressions predict the likelihood of an innovator firm using non-market (e.g. cooperative R&D or informal channel) or market (acquisition, licensing) acquired external invention, as compared to internal (the reference category). The predictors are: firm invention capability, whether is vertically integrated (i.e. has supplier or customers inside the same firm), whether the firm operates in multiple submarkets within their industry (multiproduct BU), firm size, and 17 industry fixed effects. Columns (1) and (2) is for all firms; Columns (3), (4), (5), and (6) include the regressions run separately for firms outside and inside clusters.

Table 2.7: Use of internal, startup and non-startup external inventions conditional on innovation (multinomial logit) Ref cat: Internal source

	All		Outside Cluster		Inside Cluster	
	non-startup	startup	non-startup	startup	non-startup	startup
	(1)	(2)	(3)	(4)	(5)	(6)
Invention capability	-0.64	0.88	0.27	1.33	-1.63**	0.64
	(0.52)	(1.32)	(0.66)	(3.32)	(0.79)	(1.34)
Vertically integrated	0.45**	1.14***	0.59*	0.75	0.29	1.54***
	(0.20)	(0.39)	(0.30)	(0.66)	(0.27)	(0.50)
BU size (log)	-0.10	-0.87***	0.13	-0.35	-0.28**	-1.25***
	(0.10)	(0.25)	(0.17)	(0.31)	(0.13)	(0.34)
Multiproduct BU	-0.33	-0.85*	-0.14	-1.09	-0.54*	-0.98**
	(0.21)	(0.48)	(0.31)	(1.03)	(0.28)	(0.49)
Industry FE	Yes(17)	Yes(17)	Yes(17)	Yes(17)	Yes(17)	Yes(17)
Constant	0.25	-0.67	-0.90	-16.46***	1.24	1.11
	(0.59)	(1.24)	(0.78)	(2.64)	(0.85)	(1.38)
Observations	1,124		485		639	
LL	-568.3		-266.2		-280.1	

Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1
These regressions predict the likelihood of an innovator firm using non-startup or startup sourced external invention, as compared to internal (the reference category). The predictors are: firm invention capability, whether is vertically integrated (i.e. has supplier or customers inside the same firm), whether the firm operates in multiple submarkets within their industry (multiproduct BU), firm size, and 17 industry fixed effects. Columns (1) and (2) is for all firms; Columns (3), (4), (5), and (6) include the regressions run separately for firms outside and inside clusters.

Table 2.8: Innovation, Imitation or None: Multinomial and Latent Class Logits, Cluster as University R&D

	MNL			Latent Class Logit: 2 classes					
				Latent class 1			Latent class 2		
	inno vs none (1)	imi vs none (2)	inno vs imi (3)	inno vs none (4)	imi vs none (5)	inno vs imi (6)	inno vs none (7)	imi vs none (8)	inno vs imi (9)
Standalone	0.09	0.16	-0.07	-5.01	-3.59	-1.42	0.77*	-0.18	0.95
	(0.15)	(0.14)	(0.16)	(4.03)	(3.71)	(1.07)	(0.46)	(0.35)	(0.69)
Multiproduct BU	0.22**	-0.06	0.27**	1.27*	-0.14	1.40*	-0.12	0.23	-0.35
	(0.10)	(0.08)	(0.11)	(0.68)	(0.41)	(0.75)	(0.22)	(0.25)	(0.36)
BU size (log)	1.01***	0.65***	0.35***	4.11***	2.87***	1.24**	0.74***	0.71***	0.03
	(0.07)	(0.07)	(0.07)	(1.12)	(0.78)	(0.56)	(0.15)	(0.16)	(0.24)
Firm age (years)	-0.003**	-0.003*	0.00	-0.01	-0.03***	0.01	-0.01*	0.01	-0.01**
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)
High tech industry	1.04***	0.34***	0.70***	0.35	0.34	0.02	1.38***	0.05	1.33***
	(0.10)	(0.09)	(0.11)	(0.62)	(0.44)	(0.63)	(0.22)	(0.34)	(0.46)
Homogeneous industry	0.05	-0.02	0.07	-2.56**	-0.45	-2.11**	0.68**	-0.50	1.18*
	(0.10)	(0.09)	(0.11)	(1.02)	(0.45)	(1.06)	(0.28)	(0.47)	(0.61)
Cluster	0.02*	0.01	0.01	0.17*	-0.03	0.20*	-0.01	0.12***	-0.13**
	(0.01)	(0.01)	(0.01)	(0.09)	(0.05)	(0.11)	(0.02)	(0.04)	(0.05)
Constant	-3.50***	-2.09***	-1.41***	-2.69	1.84	-4.53**	-3.78***	-4.21***	0.43
	(0.26)	(0.23)	(0.28)	(3.38)	(3.71)	(1.83)	(0.60)	(0.92)	(1.11)
Avg class prob				0.30			0.70		
Observations	4692			4692					
LL	-3674.6			-3622.56					

Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1 Regressions predict the likelihood of innovating, imitating, not commercializing a new product, via multinomial logit (columns 1-3) and latent class logit (columns 4-9). Predictors are: firm is standalone (vs multiunit); firm operates in multiple submarkets (multiproduct BU); firm size and age; indicators for high tech or homogeneous industry. Coefficients are change in log odds.

2.8 Supplementary Tables

Table 2.9: Latent Class Prior Probabilities

	class 1 (vs class 2)
Food & Textiles (NAICS 31)	0.35***
	(0.11)
Wood & Chemicals (NAICS 32)	-0.26*
	(0.15)
Pharmaceuticals (NAICS 3254)	0.3
	(0.60)
Machinery & Transport (NAICS 331-3, 37)	-0.40**
	(0.19)
Computers/Electronics (NAICS 334)	0.38
	(0.43)
Semiconductor (NAICS 3344)	-0.12
	(0.37)
Instruments (NAICS 3345)	0.67
	(0.42)
Electrical Equipment (NAICS 335)	-0.11
	(0.32)
Transportation (NAICS 336)	-0.12
	(0.29)
Medical Equipment (NAICS 3391)	-0.67*
	(0.39)
Constant (Ref: Misc Manu (NAICS 339))	-1.31***
	(0.34)

Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1

Table 2.10: Market share growth by innovation outcome, capabilities (linear probability)

	(1) Mkt Inc	(2) Mkt Inc	(3) Mkt Inc	(4) Sales Growth
Invention capability	0.20***	-0.00	-0.11	-0.84
	(0.03)	(0.06)	(0.11)	(0.67)
Innovate		0.18***	0.02	-0.85***
		(0.05)	(0.07)	(0.24)
Imitate		0.13***	0.17***	0.37
		(0.03)	(0.06)	(0.33)
Inv cap * Inno			0.32**	1.98***
			(0.13)	(0.73)
Inv cap * Imi			0.01	0.12
			(0.15)	(0.80)
BU size (log)	0.03**	-0.00	-0.01	0.03
	(0.01)	(0.01)	(0.02)	(0.10)
Start-up BU	0.20***	0.20***	0.19***	1.04
	(0.06)	(0.05)	(0.06)	(0.66)
Constant	0.53***	0.58***	0.60***	0.16
	(0.04)	(0.04)	(0.05)	(0.23)
Industry FE	Yes(45)	Yes(45)	Yes(45)	Yes(45)
Observations	4,316	4,316	4,316	4,575
R-squared	0.04	0.05	0.05	0.01
LL	-3036	-3021	-3016	-12739

Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1

3

When Does Novelty Pay?

When does technological novelty offer new firms competitive advantage? While pioneering new technologies differentiates a startup, novelty also increases uncertainty about whether their idea will prove commercially viable. Added uncertainty can make it more difficult for startups to attract investors and other partners. In this chapter, I examine how the novelty of a startup's invention conditions its likelihood of venture capital (VC) financing. I argue that by increasing uncertainty about commercial viability, novelty requires that startups search more extensively to find willing VCs. Building from prior research, I further contend that prior startup experience will lower the cost of search, especially in clusters. Because novelty requires more search, and experience and cluster location make extensive search easier, I propose novel startups will disproportionately benefit from experience and cluster location. I test these ideas using a hand-collected dataset of 4,700 patenting US medical device startups, following them from birth (first patent), to VC investment (if any), through to eventual success or failure. I find novelty has no impact on funding or success on average. However, firms with novel technologies who also have a lower cost of finding and attracting potential partners are more successful. Specifically, medical device startups with prior experience that are located in industry clusters are more likely to be funded by VCs, especially when they have novel technologies. By contrast, location in clusters is less useful for firms pursuing novel technologies if the founders lack prior startup experience. Similarly, experienced founders are not especially advantaged if they are outside clusters. Advancing theories of innovation and entrepreneurship, this study highlights when, where, and for whom novelty pays.

3.1 Introduction

For new ventures in technology-driven industries, one strategy for success is to offer technologies that are significantly different from current industry offerings. Novel technologies differentiate new ventures both from other startups and from industry incumbents (Tushman & Anderson, 1986). Yet, significantly novel technologies are also more uncertain prospects, adding additional risk of failure to a new inventing venture's already precarious position. For instance, compared to incremental improvements, novel technologies have longer development trajectories (Kerr et al., 2014), meaning any returns on investment will likely come further in their future. For medical devices in particular, novelty is associated with more stringent regulatory approval processes, higher likelihood of regulatory failures, and longer regulatory and insurer coverage time horizons (Neumann et al., 2008; Stern, 2016; U.S. GAO, 2012)). Unsurprisingly, the empirical evidence on the relationship between startup innovativeness at founding and eventual success is mixed (Hyytinen et al., 2015).

In this paper, I explore how novel technologies, as compared to more incremental improvements, shape a key early step in the development of inventing medical device ventures: the acquisition of venture capital (VC) funding. I model VC funding as the outcome of search by startups. Specifically, startups choose how many potential VCs to target, balancing the expected benefit of additional search against the cost of finding and gaining the attention of additional potential VC investors. At the time of investment, all new ventures are of uncertain value, and therefore VCs and other outsiders will vary in how much they value the startup's underlying technology. Driven by these variations, broader search will have expected benefits for all inventing startups, increasing the likelihood of getting at least one VC funding offer. Following from prior research (Fleming, 2001, 2007; Kaplan & Vakili, 2015), I argue that novel technologies are ex ante more uncertain, which will increase variation in valuations across VCs. Hence, startups pursuing novel technologies should expect larger benefit from broader search.

On the other side, searching for VC funding is costly. I argue search costs are driven by two factors, one internal and one external. First, startup pre-entry experience—specifically, whether the founding inventors have previously founded a medical device startup—will lower search costs for several reasons. Most directly, experienced founding inventors will be more likely to have previously searched for VC funding. They will be more likely to know the set of medical device VCs, have existing ties to some, and more generally, understand the process of seeking investment, collectively lowering the cost of both finding and getting the attention of VCs (Gompers et al., 2010; Hsu, 2007; Zhang, 2009). Further, inventors with prior medical device startup experience will have technical and commercialization knowledge, enabling them to develop more viable inventions. Their demonstrable competence likely also helps to lower the cost of gaining VCs' attention. Second, building from literature on the role of geography in entrepreneurship, I argue that startup location inside an industry cluster will lower the costs of broad VC-related search. Inventive, related entrepreneurial activity clusters geographically (Carlino & Kerr, 2015; Stuart & Sorenson, 2003). As a consequence, certain geographic areas will be relatively abundant in VCs focused on medical technologies, creating economies in investment-related search Chen et al. (2010). Overall, this means that startups in thick VC markets are able to search more extensively.

Building from this logic, I argue that medical device startups with prior experience will be more likely to be funded on average. Since novelty adds uncertainty and hence variance to VC opinions about startup viability, the overall relationship between technological novelty and funding will be mixed. However, because experience enables broader search, the positive relationship between experience and funding will be more significant for novel technologies. Further, I argue that the funding of novel technologies will be much more likely for experienced startups located in clusters who are able to search extensively for the particular VCs who value them.

I explore these ideas using a new, hand-constructed dataset comprised of the population of patenting medical device startups in the U.S. from 1990 to 2005. I follow nearly 4,700 new ventures from birth (first medical device patent) to VC funding, if any, and further, to their eventual success (IPO or M&A), failure (firm closure), or to the end of 2014. The medical device industry provides an ideal setting to explore the relationship between novelty of invention and VC funding, and in particular how an inventor's pre-entry startup experience and location moderate that relationship, for several reasons, including: a focus on technical innovation in the industry, relative homogeneity across inventing founder technical backgrounds and knowledge (inventors are typically surgeons and/or biomedical engineers), and a need for substantial financial capital to develop medical devices (Makower et al., 2010a). Further, the industry is one where inventions are typically patented (Arora et al., 2016; Cohen et al., 2000), allowing me to credibly focus solely on new ventures with patents.

Overall, I find that startup firms pursuing novel inventions are no more likely to receive VC funding and are no more likely to succeed than those pursuing more incremental technologies: funding rates are 14.9% for novel; 14.4% for incremental, and success rates are 11.9% for novel and 11.4% for incremental. Startups whose founding inventors have pre-entry startup experience are more likely to be funded as compared to those without such experience (16.6% versus 13.9%). Further, the role of experience is amplified for those pursuing novel technology, consistent with the argument that experience facilitates VC search, which is especially important for novel technologies. Last, I find these differences are most acute in thick medical device VC markets—specifically, geographic areas with large numbers of active medical-device-investing VCs—supporting the idea that search costs are geographically constrained.

In empirical analyses, I control for other features of the startup firms at entry, including other forms of inventing team experience (e.g. purely technical and experience in incumbent firms), founding inventing team size and composition, and features of the firm at entry associated with intent for growth entrepreneurship and thus the propensity to seek external funding. I further attempt to eliminate alternative interpretations of the results using various supplementary analyses. For example, I find location in clusters plays no role in the receipt of government Small Business Innovation Research (SBIR) and/or Small Business Technology Transfer (STTR) funding, suggesting that the location-related differences in VC funding are not simply driven by location-related differences in startup quality. Further, I find that conditional on funding, startups in thick markets have similar outcomes to those outside, counter to the idea that VCs in thick markets are simply funding more, increasingly marginal, startups. I also investigate whether location-related patterns in financing and performance are driven by "better" or more selective VCs being located inside clusters. To do so, I compare funding by VCs with medical device experience to those without such experience. I find VC experience doesn't appear to be driving the patterns I observe.

My findings contribute to entrepreneurship and strategy research in several ways. First, my paper contributes to our understanding of when novel inventions will help—or potentially hurt—early stage, inventing new ventures. Innovation strategy literature typically depicts startups uniformly as a source of significant invention, in contrast to incumbents who face economic and organizational disincentives in pursing novelty in favor of more incremental invention (Arrow, 1962; Henderson, 1993; Jewkes et al., 1958; Scherer & Ross, 1990; Schumpeter, 1942; Tripsas & Gavetti, 2000). However, in practice, there is wide heterogeneity in the innovation strategies pursued by new ventures, and these variations have consequences for performance. I find, surprisingly, no difference in the likelihood of generation of novel technologies either by startup experience or location. Yet these factors significantly increase the likelihood of receiving VC funding for startups pursuing novel technologies. Understanding what factors influence the commercialization of novel technologies is especially important in industries like medical devices, where novel inventions provide the opportunity both for firm competitive advantage, and where successful novel innovations can expand health care treatment or lower its cost, and consequently improve population health.

This paper also contributes to our understanding of the role of location in innovation and entrepreneurship. Notably, while thick markets offer abundant financial capital—and other specialized resources for new inventing ventures, like skilled managers—the relative benefits of locating in "clusters" vary substantially depending on the novelty of the technologies startups are pursuing.

Further, my paper contributes to the literature linking pre-entry experience to new firm performance. I focus on the particular role that prior related startup experience plays in attracting VC finance, and thereby, the eventual outcomes of startups. While existing research has linked pre-entry experience to success conditional on VC funding (Chatterji, 2009; Gompers et al., 2010) the role of pre-entry experience on the likelihood of VC funding itself—a crucial step in the path towards commercialization for medical device startups and other technology-focused new venture—has received far less attention. My paper suggests an additional mechanism linking pre-entry experience to blockbuster innovation and thereby to increased likelihood of success: by facilitating the selection of startups equipped with novel technologies.

Finally, my paper makes two substantive contributions to theories of innovation that have practical significance for firms and policy. First, significant technological novelty appears to be insufficient on its own for technology-focused startups to gain early advantage. I argue that novelty requires a larger pool of selectors in order to be selected. In other words, in order to be rewarded for novelty, startups need quick access to a broad set of complementary external resources. Second, technological novelty may be under-rewarded, and remain underdeveloped, outside of industry hot-spots. In my setting, medical device industry clusters produce a higher proportion of novel firms not because they are more likely to generate novel ideas—in fact, they aren't—but instead because startups in thick VC markets with novel ideas are funded at a much higher rate. I build a framework that suggests a key driver of this difference are efficiencies in searching for VCs. This implies policies aimed at increasing local production of novel firms and novel innovation, instead of simply focusing on the generation of novel ideas, also would need to focus on attracting more VCs and other complementary resources, and making it quicker and easier for novel startups to find willing early-stage partners.

3.2 Background on VC Funding

An important first step to success for inventing firms the medical device industry is obtaining external financing, most prominently venture capital (VC) finance. VC financing of a startup is the outcome of two parties—startups and VCs—engaging in search, evaluation, and selection processes and agreeing to join together to develop the focal idea or invention conceived by the startup (Gompers et al., 2016; Srensen, 2007). VCs invest funds raised from institutional and individual investors into new ventures with high growth potential, and provide inventing startups with financial capital, managerial expertise and connections to other resources (Da Rin et al., 2013; Gompers & Lerner, 2001; Kaplan & Strmberg, 2004). Conversely, invention-based new ventures need significant financial capital and managerial guidance and expertise to develop their inventions into viable innovations.

Importantly, at the time of the funding decision, there is substantial uncertainty—and typically wide disagreement—about quality of the startup and, in particular, the potential value of the foundational idea or invention (Waldron & Hubbard, 1991). New ventures have no documented track record of performance, in innovation or otherwise, to serve as a direct measure of quality (Stinchcombe, 1965), and therefore potential investors will in general have difficulty assessing the value of new firms (Singh et al., 1986). As prior research has suggested, some of this uncertainty may be related to strategic withholding of information by inventors (Anton & Yao, 1994; Luo, 2014). Further difficulties in assessing value may stem from entrepreneurs' undue optimism about the quality of their own ideas (Berg, 2016; Dushnitsky, 2009; Hmieleski & Baron, 2009), which means that an entrepreneur's observable behavior will be a noisy signal of actual invention quality. Even more fundamentally, at an early stage, inventors themselves may also be highly uncertain about the value their invention will have if commercialized. Hence, the initial selection by VCs is about selecting which experiments to attempt (Kerr et al., 2014). Altogether, this means the value of startups and their underlying inventions will be uncertain when startups are seeking funding and VCs are making investments, leaving room for large variation in evaluations.

A second important feature of the funding process is that searching for and gaining the attention of VCs is costly for startups. Search costs are driven by the need to spend time and money to identify, to evaluate, and to select potential alternatives to attempt to partner with (Gompers et al., 2016). For new, inventing firms, the cost of time spent searching for financial investors is tangible: entrepreneurs often go without pay, while patents move toward expiration and any first mover advantages associated with novelty evaporate as the startup is delayed in their move toward commercialization. Finding VCs is costly because startups do not have complete information about the menu of potential VC investors and their tastes which will shape their assessment of the startup technology (Simon, 1972). Gaining the attention of VCs is costly since new firms generally lack visibility. Concretely, the search process involves activities like networking at industry events, building and accessing relevant social networks, scanning of various public and proprietary information sources, developing and submitting business plans (Teten & Farmer, 2010), and more broadly may involve building of assets to demonstrate quality (e.g. patenting and prototyping (Hoenig & Henkel, 2015; Hsu & Ziedonis, 2013)), all of which cost money and take time.

3.3 Theoretical Framework

To understand what determines whether a startup, and in particular a startup pursuing a novel technology, will receive VC funding, I build a framework where the likelihood of being selected depends on the choice of a new venture to seek out potential VCs to fund them. New ventures choose the number of VCs to solicit based on their expected value from searching for (and soliciting the attention of) additional VCs balanced against their cost of continued or additional search. Seeking out more VCs increases the likelihood of getting any funding offer, as there is uncertainty—and hence difference in opinions—about the value of the startup's invention. Because there is variation across VCs, as a first point I assume the marginal benefit of additional search is positive: the more VCs a startup seeks, the more likely they are to get at least one funding offer.

To unpack the role of novelty in VC funding I make three main arguments, developed in the sections below, and reflected in the stylized model depicted in Figure 3.1

and formalized in the Model Appendix. First, I contend that novel technologies will have higher variance in expected outcomes, and, relatedly, larger variation across VCs in opinions about funding. Additional search will therefore have a larger benefit for startups pursuing novel technologies over those pursuing incremental technologies (as depicted by differing marginal benefit (V) curves in Figure 3.1). Second, building from existing entrepreneurship research (e.g. Agarwal & Shah (2014)), I argue that pre-entry experience of the founding inventors—specifically, whether or not they have been a founding inventor on a prior medical device startup—will decrease the costs for the focal startup of searching for VCs ($c_{exp} < c_{inexp}$). Last, placing the funding decision in geographic context, I argue startups' search costs will be higher outside of clusters of industry inventive activity, where the set of potential VCs a startup can solicit and gain attention from locally (and therefore affordably) is smaller. Figure 3.1 highlights the limits of search in thin markets). In other words, whereas inside clusters new inventing firms can, if they choose, seek out many different VCs, outside clusters, there are far fewer potential options. Overall, because novelty adds variability to evaluations and thereby requires that startups search more extensively to find willing partners, this suggests that novelty will (only) pay for experienced startups located in close proximity to a relatively large number of potential investors.

3.3.1 Technological Novelty

Inventing startups vary in the degree of technological novelty of their inventions. Novel inventions are markedly dissimilar from the suite of all prior inventions at the time they are conceived (Dahlin & Behrens, 2005; Ettlie et al., 1984). They embed new technical knowledge (Dewar & Dutton, 1986) typically by marrying together previously distinct sources of knowledge or separate technologies (Fleming, 2001; Strumsky & Lobo, 2015; Verhoeven et al., 2016). The first spinal disc implant to add in an embedded microprocessor intended to capture and relay diagnostic information to surgeons, patented in 2004, exemplifies a novel medical device invention.[1]

In contrast, incremental inventions typically refine, rather than replace or recombine, established, successful technologies (Abernathy & Clark, 1985; Henderson, 1993; Henderson & Clark, 1990; Tushman & Anderson, 1986). Novel inventions therefore have a higher likelihood of abject failure as compared to more incremental technological changes (Fleming, 2001, 2007). Yet, conditional on success, the potential for value from novel invention—for a breakthrough innovation—is also increased (Ahuja & Lampert, 2001; Gatignon et al., 2002; Gelijns et al., 1998).

Overall, novel inventions are more uncertain in terms of their expected outcomes. This increased variability will be reflected in wider variability in VC funding choices: for incremental technologies, most VCs, or other potential external stakeholders, will have similar ideas of what an idea will be worth once developed into a product, in contrast, some will see significant promise in novel technologies while others will see little. An inventing startup will be funded if, through their search, they find at least one VC that privately values investing in them. Technological novelty therefore requires more search by funding-seeking startups, all else equal. However, novelty also increases expected value conditional on success. This means there is no clear main prediction for the role of novelty in the likelihood of venture capital funding.

3.3.2 Search Costs & Prior Startup Experience

Startups will vary in their costs of finding and gaining the attention of VCs. A particularly important factor that will drive VC search costs will be the prior startup

[1] USPTO patent 7794499 Prosthetic intervertebral spinal disc with integral microprocessor. Original assignee is Theken Disc. Abstract: A device for storing data related to movement of a prosthetic implant includes at least one transducer for generating at least one real time movement signal responsive to movement within the prosthetic implant. A processor generates movement data parameters and associated time stamps in response to the real time movement signal. The generated data parameters and time stamps are stored within a memory associated with the processor. A communications link may be used to selectively access the movement data parameters and the time stamps in the memory from an external source.

experience of the founding team. Theories of strategic entrepreneurship relate—through various mechanisms—pre-entry experience of entrepreneurs to better startup performance (Agarwal & Shah, 2014; Delmar & Shane, 2006; Helfat & Lieberman, 2002; Jovanovic, 1982; Klepper, 2007). In particular, pre-entry experience in the focal industry, either within a startup firm or as an employee of an incumbent, has been linked to commercial knowledge and startup success (Chatterji, 2009; Gompers et al., 2006).

Pre-entry startup experience provides two benefits that I argue will lower the cost of searching for VCs. First, prior startup experience imparts awareness of VCs, visibility to VCs, and, potentially, prior connections within the existing set of potential VC funders (Hsu, 2007). Serial inventor-entrepreneurs know industry-specific innovation processes and, further, may have continuing ties into industry-specific networks of suppliers and customers which can help them more easily find and connect with VC investors (Delmar & Shane, 2006). Beyond other types of industry experience, experience inside an inventing startup represents prior involvement in identifying and evaluating opportunities (Shane, 2000), and the development of entrepreneurship-specific human capital (Elfenbein et al., 2010). In short, experienced inventors will know where to look, and will be more easily found by VCs.

Second, and more indirectly, prior startup experience of the founding inventors will lower search costs by increasing the expected quality of the startup's inventions. For technology-focused startups, choices made during the invention stage—e.g. component specifications, initial target indications, the choice of materials—can have significant consequences for innovative success (Eggers, 2012). Technically experienced inventors are more likely to have developed relevant inventive capabilities (Argote et al., 1990; Franco et al., 2009) and conduct focused technological search that produces more feasible options (Katila & Ahuja, 2002; Katila, 2002). Further, prior startup experience also provides inventors with intuition for building a functioning invention that will become a viable innovation (Hoye & Pries, 2009; Shane, 2004). In the medical device industry, startup experience helps the inventor to know what will pass regulatory hurdles, be cost effective to manufacture, and be most appealing for physicians and hospital systems. In sum, inventors with prior startup experience are more likely to generate inventions that are both technically sound and commercially viable. An expected quality bump from prior startup experience may make it easier to gain attention of VCs.

Building from these two arguments, I contend that the cost of VC search for startups with prior startup experience will be lower ($c_{exp} < c_{inexp}$), as in Figure 3.1. This implies that, all else equal, more experienced startups will search across a larger number of VCs ($VC_{exp} > VC_{inexp}$) for both novel and incremental Figure 3.1. In terms of likelihood of funding, because they have lower costs of search, *experienced startups will be more likely to be funded than inexperienced startups (Hypothesis 1).*

Further, while there is no clear main prediction for the role of novelty in the likelihood of venture capital, novel inventions are more uncertain and hence opinions across VCs will be more variable. Therefore, experience will increase search activity more for startups pursuing novel technologies than for those pursuing incremental technologies ($VC_{n,exp} - VC_{n,inexp} > VC_{i,exp} - VC_{i,inexp}$ in Figure 3.1). Presuming the expected values and incremental and novel technologies are such that increased search has a proportional effect on likelihood of funding, *the relationship between experience and likelihood of funding will be stronger for firms pursuing novel technologies (Hypothesis 2).*

3.3.3 Thick and Thin VC Markets

The above reasoning presumes that startups can search for as many VCs as is optimal for them, given their experience and the novelty of their foundational technology. However, the costs of searching for VCs also varies based on startup location. Industries cluster geographically (Carlino & Kerr, 2015; Delgado et al., 2014b; Stuart & Sorenson, 2003), creating hotspots of related inventive and entrepreneurial activity. For example, medical device inventive entrepreneurship proliferates in locations like Boston and Minneapolis, where, in my sample, 10-25 patenting medical device startups entered every year throughout the 1990s and 2000s. VC firms also cluster geographically, and tend to invest in co-located startups (Cumming & Dai, 2010; Gompers & Lerner, 2001; Powell et al., 2002). Part of the reason for startup and VC clustering is agglomeration externalities: having a large number of potential investments nearby lowers the costs for a startup in searching for VCs, and other necessary complementary resources, and conversely, lowers the costs for VCs in searching for new ventures to invest in (Chen et al., 2010; Saxenian, 1996). Relatedly, recent research has argued that large numbers of small firms facilitate inventive new firm formation and innovation by thickening the market for complementary inputs (Agrawal et al., 2014). Empirically, I see that the VC firms that invest in medical device firms tend to be located in medical device entrepreneurship clusters, and tend to invest locally,[2] a pattern reflected in other VC-heavy industries, like computing or biotechnology (Chen et al., 2010; Kolympiris et al., 2011). Hence, industry clusters are thick markets for entrepreneurial invention and finance—they are dense with both startups and potential VC investors—whereas areas outside clusters are comparatively thin in both.

Comparatively, in thin markets, there are fewer potential VC investors at a given point in time and therefore startups face a steep increase in costs of continuing to search past a certain threshold, i.e. beyond the few local VCs. Figure 3.1 highlights

[2] Of the medical device startups in my sample, 77% of those who receive VC funding are funded by a VC in the same MSA, where VC MSA is defined by the first funding round. (The share rises to 82% if we consider VCs in the same CSA). The share is higher inside clusters versus outside: 78% of startups in clusters are funded by VCs in the same MSA, whereas 75% of startups outside clusters are funded by VCs in the same MSA. If we broaden to CSAs, this difference is 84% versus 76% (difference p=0.014).

this constraint in its starkest form: startups outside clusters effectively face an upper threshold in the number of VCs they can solicit, which dampens the searching differences between experienced and inexperienced firms, and further those related to novelty and experience.[3] Having a large number of potential VCs is especially important for startups pursuing novel technology as there is larger variation across VCs in the value assessed at the time of evaluation. Following from this, I expect the *experience and novelty related differences in likelihood of funding to be relatively more pronounced in industry clusters (Hypothesis 3)*, where startups are able search for more VCs on the margin.

3.4 Empirics

3.4.1 Setting

I explore these ideas using a large, hand-collected sample of nearly 4,700 patenting U.S. medical device startups. Startup firms in the U.S. medical device industry invent surgical devices, prosthetics, implants, and diagnostics used to improve the health and health care. Medical devices are regulated pre-market and sold to health care providers (physicians and hospital systems) who are reimbursed by insurers when the devices are used in health care treatment. For new firms and incumbents alike, the process of developing new medical devices involves clinical trials, and liaising with regulatory bodies (e.g. the US FDA, European approval agencies) and reimbursement panels (e.g. the U.S. Centers for Medicare and Medicaid Services) in order to bring devices to market (Herzlinger, 2006). Pre-market regulatory processes typically require substantial funding: \$30 to \$90 million by one 2010 estimate (Makower et al., 2010a). Hence, new device firms need substantial, long-term outside finance in order to successfully develop devices. VC financing is a typical mode of obtaining

[3] Depending on where the n cutoff lies (e.g. n=1), there could even be no difference in the amount of search by experienced and inexperienced startups.

these necessary financial resources.[4]

3.4.2 Data

My dataset comprises the population of new, patenting medical device firms in the US from 1990 through 2005. Creating a sample of nascent, inventing medical device startup firms using patent data was a multi-step process. First, for all utility patents 1975-2010, I identified and isolated medical device patents using the USPTO classification grouping.[5] Then, I used assignee categories and assignee names to identify medical device patents filed by U.S. startup firms. Startup firms are defined as company assignees who: (1) have not filed a patent in the 15 years prior to 1990 up until the data of first patent filing, and (2) are neither simply a new affiliate or division of an existing firm, nor a non-startup-firm entity (i.e. a hospital, research institute or university). The second step involved first excluding any foreign or non-company assignees, then using external datasets (BvD Orbis, Capital IQ) to identify and eliminate subsidiaries of incumbent firms, and string matching-based cleaning to exclude any remaining non-companies (e.g. "hospital"). These semi-automated exclusion processes identified about 7,500 potential U.S. medical device startups, which were then hand-cleaned to eliminate any remaining affiliates of incumbents (typically misspellings, e.g. Bausch & Lamb) or other non-startup entities. The final sample of nascent, patenting U.S. medical device startup firms is approximately 4,700 new ventures.

A feature of the medical device industry is the near-universal use of patents as a

[4] A related quote about VC financing and the medical device industry from Paul LaViolette, a former Boston Scientific executive and VC with SV Life Sciences: "I like to say that the hardest thing in the world is to open a restaurant in New York and have it succeed for six months." Building a radical new medical device and then commercializing it "is not as hard as that, but it's second." (Gertner, 2013).

[5] USPTO medical device list available at:
http://www.uspto.gov/web/offices/ac/ido/oeip/taf/data/meddev.htm.
I used the US patent files available via the Harvard US Patent dataverse (Lai et al., 2011).

means of value appropriation from invention (Arora et al., 2016; Cohen et al., 2000). I rely on this fact to justify focusing on *patenting* medical device startups.

After building my startup sample using patent data, I then linked to several other datasets using firm name,[6] including: Thomson VentureXpert as a source of venture capital funding, VC fund characteristics, and IPO exits; SDC Platinum for data on both M&A and IPO events; Capital IQ for supplementary data on M&A and IPO, product approvals, firm name changes and bankruptcy filings; USPTO trademark data for any trademarks filed by startup firms; data from the NIH to flag firms receiving SBIR and STTR funding (via ExPorter); FDA data on US approvals; Lexis Nexis press release information for CE mark (European) market clearances; and alliance information from Recap IQ. I used patent maintenance fee payment data to identify pre-term patent expiry events, which I use as a proxy measure of startup firm failure.

3.4.3 Main Dependent Variable: Venture Capital Funding

I identify firms that receive venture capital funding using the VentureXpert data to build an indicator variable of VC funding. VentureXpert has been used extensively in strategy and entrepreneurial finance research to identify and study VC funded firms (e.g. Da Rin et al. (2013); Park & Steensma (2012)). I also identify the timing of first VC funding.

3.4.4 Key Independent Variables

Pre-Entry Startup Experience

I measure the experience of each nascent startup using firm's founding inventors' U.S. patenting histories. To track individuals over time I rely on the inventor identification

[6] Cleaning of startup firm names for linking across datasets relied in part on the user-generated STATA command *stnd_compname* and on hand-cleaning via explorative linking using *reclink*2 (Wasi & Flaaen, 2015).

tags from the Harvard US Patent Inventor Database (Lai et al., 2011). For all founding inventors, I have at least a 15-year, pre-startup patenting window, starting from 1975. I collect all prior patents on which they are listed as an inventor. The focal startup is flagged as having "pre-entry startup experience" (a 0/1 indicator variable) if any founding inventor of the focal startup was an inventor on a medical device patent assigned to a prior medical device startup. An example is Transvascular, a cardiovascular device company founded in 1996: founder-inventor Joshua Makower previously was a founding inventor of medical device startup EndoMatrix.[7]

In the main analysis, I also control for other types of pre-entry experience in medical device inventing, including solely pre-entry inventing experience, where the startup inventors have previously filed for a medical device patent outside of the firm context (e.g. through a university or as an independent inventor). One example is NuVasive, a minimally invasive spinal surgery startup, founded in 1997 by orthopedic surgeon James Marino, previously an independent inventor.[8] I also separate out firms with founders that have solely pre-entry incumbent experience, for example, as an inventor with Medtronic or Boston Scientific. The omitted category, no experience, consists of inventors without a medical device patent prior to the focal invention. An example of this is Coapt Systems a maker of bioabsorbable implants whose founding inventors are a plastic surgeon and internist.[9]

[7] Transvascular's founding patent was US 6190353 Methods and apparatus for bypassing arterial obstructions and/or performing other transvascular procedures (a novel technology).

[8] NuVasive's first patent was: US 6030401; "A device for removing cortical tissue from a vertebral endplate". Marino's prior invention was filed in 1986: US 4733654; "Intramedullar nailing assembly".

[9] Their first patent was US 6645226 Multi-point tension distribution system device and method of tissue approximation using that device to improve wound healing.

Technological Novelty

I follow Fleming (2001) and Strumsky & Lobo (2015) to classify a patent as novel if: (1) it is the first instance of a (new) technology (USPTO subclass) on a patent, or (2) it is the first instance of a particular pairwise combination of existing technologies on patents. In other words, a patent is considered novel if it is either a new technology or the first pairwise combination of existing, but never before combined, technologies. As mentioned above, an example of a novel medical device patent in my sample is US patent 7794499, applied for in 2004 by startup Theken Disc, for a *Prosthetic intervertebral spinal disc with integral microprocessor.*[10] This patent is a novel combination of existing technologies. Concretely, it is a spinal disc implant with an embedded microprocessor to collect diagnostic information, the first to do so. Building from this patent-based measure of novelty, a nascent startup is considered to be pursuing novel invention if their first patent application is novel.[11]

Ideally a measure of novelty accounts for the state of the world at the time the invention is generated: novel technologies are different from the stock of prior technologies at the time they are developed (Dahlin & Behrens, 2005). Crucially, a measure of novelty should also be independent of later success or failure. My measure has both features: (1) novel technologies are those markedly different from the stock of prior patents at the time of filing (as close to the time of invention generation as possible), and, (2) patents can be novel without ever resulting in a commercialized product or without ever being cited by future patenting inventors.

For my theory, a key feature of novel technologies is that they are more uncertain ex ante, compared to more incremental technologies. To investigate this assumption

[10] The section entitled "Additional Examples of Startups with Novel Technologies" lists some examples of other startups pursuing novel medical device technologies.

[11] All findings are robust to measuring startup novelty based on if any patent of the startup is for a novel technology combination.

at the technology level, I compared patent-level outcomes for all U.S. medical device patents (137,116) filed from 1981-2005. Consistent with my assumptions, I find that novel patents are higher value: conditional on being cited, they accumulate more forward citations on average, and are more likely to be "breakthrough" inventions (i.e. 2 standard deviations above mean citations for patents filed in the same class-year). I also find that novel patents are more likely to expire early due to lack of maintenance fee payments (see Table 3.7).

Thick VC market

In my theory, the thickness of the local market for VC funding of inventive medical device startups lowers search costs. To capture this, I build a proxy measure for VC market thickness by counting the number of unique VC funds that initiated funding of a medical device startup in the in the local area (the Metropolitan Statistical Area, or MSA) of the startup firm in the five years prior to focal startup first filing year. In the empirical analyses, I distinguish thick from thin markets using an indicator variable cut at the median by MSAs for each year. I also use counts (and alternative lagging structures) in alternative specifications with no qualitative differences in results. After creating the thick market indicator variable, I vetted the list of MSAs flagged as thick markets to ensure well-known medical device industry hotspots—Minneapolis-St Paul and Boston, for example—are captured as being thick markets (they are). Table 3.14 provides list of cluster-MSAs and some descriptive information.

I also built a measure on the startup side of the market: the number of new patenting medical device ventures started in the MSA of the focal firm in the 2 years prior to focal firm entry. I found similar results using that measure. Other potential measures of market thickness of the focal MSA, based on: (1) the number of large medical device establishments and (2) volume of medical device patenting by non-firm actors, yield similar categorization of thicker market locales and therefore qualitatively similar results.[12]

3.4.5 Control Variables

The *number of inventors* has been highlighted both as a potential driver of novelty (via knowledge recombination) and of innovation performance (Fleming, 2001; Singh & Fleming, 2009). Hence, I control for the number of inventors listed on the patent. I also control for the number of patents filed by the firm in the year of their first patent, or their *initial patents*, as a proxy for size of the startup at entry.

Female inventor flags if there are any women on the founding inventing team, where inventor gender is categorized using the U.S. social security birth name data. Prior research suggests that female-led ventures are less likely to receive VC funding even when controlling for quality (Coleman & Robb, 2009; Guzman & Kacperczyk, 2016; Robb & Coleman, 2010).

Controlling for the non-technical quality of the startup firm and the choice to actually pursue funding by the inventor-entrepreneurs, is difficult. A recent stream of research suggests several features of firms at or near the time of entry are associated with the pursuit of high growth entrepreneurship and eventual success (Guzman & Stern, 2015). I include two such variables to help to control for variations in the likelihood to seek funding across startup experience and locations: (1) firm *name length* (with longer names being associated with lower quality) which takes the form of an indicator variable for firm names that are 3 words or longer, and (2) *early trademark* filing (i.e. in the year of patent filing) as a measure of commercialization intent.[13] Further, by including solely patenting firms, my analysis includes only inventor-entrepreneurs who invested in protecting their intellectual property under

[12] The clustering together of all facets of inventive activity—including patenting, firm formation, VCs, and established incumbent firms—in the same geographic areas is not surprising if we think that agglomeration economies play a substantive role in location decisions for VCs, firms and other relevant actors (Alcacer & Chung, 2007; Carlino & Kerr, 2015).

[13] I specifically count filings of medical apparatus trademarks (US class 10).

a company assignee, another sign of self-selection for commercial intent. One potential way to control for differences in the technological quality of patents would be via forward citations, which are known to measure economic value of patents, e.g. Trajtenberg (1990); however, since early success and funding typically precede citations, forward citations are caused, in part, by VC funding. Because of this, I do not include forward citations as a predictor of VC funding.

To control for variations in the technological and entrepreneurial environment at the time of invention and startup entry, I include *year fixed effects.* I also control for the main *technological class* of the firm's founding patent (e.g. imaging, dentistry) to ensure I account for any overall differences in funding likelihood and success at the technology-market level.[14].

In hazard models, I also control for events that signify some level of invention success and growth of the startup which may occur as the startup moves through the development process, as such events are likely to increase the likelihood of funding. These controls help to account for any experience-related differences in the likelihood of achieving intermediate outcomes. These include: (1) *CE mark* clearance which allows sale of products in the European Union,[15] (2) US FDA *pre-market approvals* (PMA) which allow for sale of products in the US, (3) *SBIR/STTR funding* which enables prototyping and proof of concept work and has been shown to positively affect VC funding (Howell, 2017), (4) *trademark* filing, which is meant to proxy for a precursor measure for market entry, and (5) patent application for *later patents* which signifies startup growth. All of these events will reduce the uncertainty associated with the startup invention. I expect all will increase the hazard of VC funding.

[14] There are 19 medical device patent classes (per the USPTO classification). Because some classes contain < 10 startups, I group small classes into similar classes, and therefore include 13 dummies. The categories used in the analysis are listed in the Table 3.8

[15] CE marking is a less demanding process as compared to FDA approval. Firms often target CE marks first, and perform clinical trials required for FDA approval in Europe; a trend known as device flight by those in the industry.

3.4.6 Additional Outcome Variables

SBIR/STTR Funding

Using the ExPorter data, I collect all research projects funded by the Small Business Innovation Research (SBIR) and Small Business Technology Transfer (STTR) programs and document whether and when the firms in my sample receive such funding. The federal government supports early-stage technology commercialization through the SBIR/STTR grant program, which is managed by various departments including the Department of Health and Human Services. Unlike private VCs, program funders take no equity in the firm, and hence the funding is non-dilutive. Firms self-select into applying and the related granting agency makes funding decisions. Here, SBIR/STTR funding is intended to serve as a placebo test against an argument that the cluster-related patterns are driven by quality sorting and not by differential VC (i.e. selection) search costs. If variations across location are simply driven by quality, I would expect to see the same patterns for SBIR/STTR as in the VC results: alternatively, if search costs are driving VC funding patterns, I would not expect to see similar patterns for SBIR/STTR.

Technology Alliances

I also use SDC and RECAP IQ data to document technology alliances with as an alternative outcome to VC funding. Following (Schilling, 2009) from SDC, I selected R&D alliances, cross-licensing, cross-technology transfer, and joint ventures, and from RECAP IQ I selected co-development agreements, cross-licensing agreements, research agreements and joint ventures. Similar to VC financing, alliances involve a partner taking a stake in the technology of the startup firm; however, geographically determined search costs likely play less of a role in selection by alliance partners (Mccann et al., 2016).

3.4.7 Outcomes Conditional on VC Funding: Firm Success and Failure

Exploring success and failure conditional on VC funding helps us to better understand the role of experience, novelty, and location in the search and selection process. For example, if startup experience represents social connections absent invention quality, then the conditional results should show a negative relationship between experience and success. To further explore the mechanisms driving VC funding, I examine the conditional (on VC funding) likelihood of startup success and failure. *Firm success* is measured as a completed IPO or M&A (e.g. a technology acquisition), using data from SDC Platinum and Capital IQ. Given the goals of the VCs, positive liquidity events are successful outcomes for VC-backed startups. In contrast to success, *firm failure*, specifically business shutdown, is harder to observe. Unlike IPOs or M&A exits, there is not a comprehensive source for the timing or occurrence of a failed exit. Since my sample includes exclusively patenting firms, I use lapses in the payment of patent maintenance fees as a proxy for startup firm failure (Khanna et al., 2015). Firms must pay maintenance fees to keep patents alive at the 4th, 8th, and 12th year after issuance during their 20-year term; the relatively low associated cost means that this is likely a somewhat conservative estimate of firm-level failure.[16]

3.5 Empirical Strategy

To test my main predictions, I use two types of analyses. First, I run firm-level regressions predicting the likelihood that a startup receives VC funding from founding until the end of 2014. For this, I employ both linear probability models (for ease of interpretation of interactions between key variables: *technological novelty,*

[16] Note that patents in force on June 8, 1995 or earlier have a term that is the greater of 20 years from application or 17 years from patent grant (see: https://www.uspto.gov/web/offices/pac/mpep/s2701.html). Fees (as of August 2016) range from $400 to $3400 for small firms. See: http://www.uspto.gov/learning-and-resources/fees-and-payment/uspto-fee-schedule.

experience, and market thickness), and logit models.

Second, I run discrete event history analysis to predict the hazard of VC funding at a given point in time. Event history models predict the likelihood that a startup receives VC funding in a given period conditional both on not yet receiving funding and, further, on still being at risk of funding, and accounting for exits of unfunded firms due to acquisition or failure.[17] Event history models explicitly model how the likelihood of funding changes, and differs by startup characteristics, over the life of the venture. Further, event history models allow the inclusion of time varying covariate control variables (e.g. receipt of a CE mark approval, SBIR funding, etc., described above) that may confound key predictors in simple probability models. I employ discrete event hazard models using a logit specification for ease of inclusion of time-varying predictors, although continuous time models (Cox proportional hazard) generate qualitatively identical results (Allison, 2010). In all regressions I cluster standard errors at the MSA level as market thickness is a MSA-year level measure. I explore alternative dependent variables (SBIR/STTR and alliances) using linear probability and logit models. Last, I explore firm outcomes, which are: (1) success (IPO or M&A), (2) failure (patent expiry), or (3) continued existence as a private, standalone firm, using a multinomial logit model.

3.6 Results

Table 3.1 contains descriptive statistics of the sample of 4,663 medical device startup firms, of which a third (33%) pursue novel technology. Overall, 23% have pre-entry commercialization experience. By construction, about half of startups form within a thick market; the average density of VC firm activity is 18 total new investments in the MSA of the respondent firm in the five years prior to entry. On average, 15% of patenting medical device startups eventually receive VC funding. Novel technology-

[17] The discrete hazard rate function is: $P_{it} = P_r[T_i = t | T_i \geqslant t, x_{it}]$

pursuing-startups (Panel B) are no more likely to get VC funding as compared to those pursing more incremental technology.

Notably, Table 3.1 highlights that neither pre-entry startup experience nor market thickness is associated with the likelihood of a startup pursuing novel technology. This (lack of a) relationship holds across categorizations of pre-entry experience (e.g. incumbent firm, university) and if I measure industry clusters in terms of medical device patenting rates, or other measures of inventive activity. This surprising finding highlights that any differences in startup novelty by experience or cluster-location emerge as a function of the commercialization stage—including VC funding—and not at the generation and firm formation stage in the innovation process.

Table 3.1 also highlights the association between VC funding for startup firm outcomes. For VC funded firms, 14% IPO, 27% M&A (or 41% successfully exit) and 22% fail, as compared to 0.2% IPO, 6% M&A (or 6% successfully exit) and 43% fail for non-VC funded firms. In other words, VC funded medical device firms are seven times as likely to have a successful exit, and half as likely to fail, consistent with VC being highly significant in the success of patenting medical device startups.

Figure 3.2a tabulates the main results of the paper, building from covariate-adjusted estimates of the likelihood of VC funding. First, the pursuit of novel technology has no association with the likelihood of VC funding on average, but for startups in which inventors have prior startup experience, novelty is positively associated with VC funding. Finally, these are results driven by firms in thicker markets, where the pursuit of novelty for experienced startups nearly doubles likelihood of VC funding. Tables 3.2 and 3.3 contain the main regression analyses on predictors of VC funding, with Table 3.3 underpinning the results in Figure 3.2a. I include logit as well as simple linear probability regression results for ease of interpretability of interaction coefficients. As expected, prior startup experience increases the likelihood of VC funding from 13.8% to 17.1%, whereas there is no difference on average between novel (14.9%) and incremental (14.4%).[18] In line with predictions, however, firms with novel technologies who also have a lower cost of finding and attracting potential partners are more likely to get funding. Specifically, the startup-experience-related increase is larger for those pursuing novel inventions (1.6x, or from 13% to 21%) as compared to those pursuing incremental inventions (1.1x, or 14% to 15%). Further, the positive association between startup experience and funding among novel startups is much stronger inside thick VC markets (2.4x, or 16% to 28%) as compared to thin VC markets (1.3x, or 9% to 11%).Comparatively, for incremental startups the experience-related increase in the likelihood of funding does not vary across VC market thickness. And, notably, startup experience provides little benefit in terms of funding either for incremental technologies or for startups in thin VC markets.

Table 3.4 outlines the discrete event history models of funding likelihood. Discrete event history models further incorporate the element of time until funding, and include uncertainty-reducing events that are correlated with experience and location—e.g. CE marking, signifying approval to enter the EU market, or a second patent application—that can occur during the development process and influence funding outcomes. I find these events are associated with an increase in the hazard of funding, but the main results reflect those from the simple likelihood models in Table 3.3.

To drill into the mechanisms behind the relationships between experience and cluster-location and funding outcomes, I also run some supplementary analyses (Tables 3.12 and 3.13). First, I split prior startup experience into (1) prior experience in a VC-funded startup and (2) prior experience inside a startup that did not receive VC funding. I find experience within a VC-funded startup to be largely driving the main results, suggesting that connections into the VC network are a key factor in lowering

[18] All predicted probabilities listed here are based on adjusted average marginal effects analysis run using the relevant logistic regression model in Table 3.3.

search costs. Second, I split out (1) startups located in thick markets with founders that moved to the cluster since their last startup (*movers*) from (2) all other thick market startups (*stayers*). This analysis is intended to parse out whether location in thick markets is measuring local network connections (or other pre-existing benefits of location) or the search-related benefits of market thickness. I find that movers are highly similar to stayers (or slightly better) in terms of the relationship with funding, and how that relationship is moderated by novelty and startup experience, suggesting the value of market thickness itself driving the results.

Table 3.5 presents results for the placebo test using SBIR/STTR funding in place of VC funding. As described above, SBIR/STTR funding is federally mandated to support the technological commercialization of inventions by small business, is awarded based on invention and inventor quality, is non-dilutive, and is often a part of early stage funding for medical device and life science companies (Bigelow, 2015). Hence, to the extent that my above results simply reflect quality sorting, I would expect to see the same patterns by novelty and thick markets as in the VC funding results. Instead, while prior startup experience is positively related to funding, there is no appreciable difference in SBIR/STTR funding likelihood for novel as compared to incremental technologies by experience or across market thickness. This supports the contention that the significant increase in likelihood of funding inside clusters, and for clusters interacted with experience and novelty, is related to VC search costs.

Table 3.6 predicts success (IPO, M&A) and failure, conditional on funding, using a multinomial logit framework. Conditional on VC funding there is little evidence of a relationship either way between novelty and success. Novel startups inside clusters that receive VC funding are more likely to fail than incremental startups, which would not be predicted by the above reasoning. In general, there are no patterns between firm level cluster location, experience, and likelihood of success or failure, which suggests VCs in clusters are no better or worse in selecting startups to fund.

3.7 Alternative Interpretations

My theory argues for particular mechanisms that drive the relationships between novelty, experience, startup location, and likelihood of VC finance. However, there are alternative interpretations based on other mechanisms and grounded in prior research that deserve discussion.

First, I argue the relationships between cluster location and VC funding are driven by lower VC search costs that enable novel startups to find a viable partner. However, there are several alternative mechanisms by which cluster location may increase the likelihood of VC funding. First, if there are simply more or more active VCs in clusters, and they select firms to fund based mainly on co-location, then likelihood of funding in clusters should be higher overall. However, I would then expect that funded firms in clusters would be of worse quality on the margin than those outside clusters, and therefore perform worse conditional on funding. The results of outcomes conditional on funding in fact show the opposite pattern (Table 3.6), which help to rule out this simple story. Further, simple locational preferences would not explain the experience and novelty-related patterns in financing in clusters I observe.

A more nuanced counter-argument is that VCs in thick markets are better, either at selecting startups to fund or at developing startup ideas into successful ventures, and these better VCs tend to fund co-located startups (Chen et al., 2010). Better selection capabilities would predict both an increased likelihood of funding of higher-potential startups (e.g. those with prior experience) in thicker markets, and non-negative performance effects conditional on funding; further, better VC management capabilities inside clusters would similarly predict positive performance effects conditional on funding. Collectively, the VC-quality-clustering story is difficult to disentangle from my argument about search costs in the main analyses, especially since more experienced VCs do tend to locate in thick markets and fund startup firms nearby. To investigate if this is driving the results I separate out the likelihood of funding by inexperienced and experienced VCs (Table 3.11), where VC experience in funding medical device startups acts as a proxy measure of VC quality. I find the patterns across likelihood of funding by inexperienced and experienced VCs to highly similar. This provides some suggestive evidence that geographic variations in VC quality are not driving the main results.

Similar to quality clustering of VCs in thick markets, one might argue that the source of differential across thick and thin markets is related to geographic differences in startup quality. For example, because of quality differences in source firms and the firms they spawn locally, experienced inventors in thick markets may be more capable than those outside in thin markets (Boschma, 2015; Klepper, 2010). Similarly, one might argue that because thick markets as "industry clusters" are comparatively rich in knowledge spillovers (Audretsch & Feldman, 2004; Carlino & Kerr, 2015) and startup-experienced inventors are have the absorptive capacity to effectively use the valuable external knowledge (Cohen & Levinthal, 1990), experienced inventors in "industry clusters" may generate better quality inventions than experienced inventors outside clusters. Such an argument is consistent with my main results. However, the SBIR/STTR results are not consistent with better quality startups being located in thick VC markets: there is no evidence of location-related differences either overall or by novelty and experience in SBIR/STTR funding (Table 3.5).

3.8 Discussion and Conclusion

Do new firms in technology-driven industries pursuing novel technologies benefit from being novel? In this paper, I explore how technological novelty relates to the likelihood of venture capital funding, a crucial early stage resource in the path to success for medical devices startups, and for growth entrepreneurs in other technology-driven industries. To do so, I model novelty as a risky but potentially promising endeavor, and explore how the key features of new firms—specifically pre-entry experience and location—interact with novelty to predict startup selection by VCs. In my framing, the startup experience of inventors lowers the cost of searching for potential VC funders, which I predict will be especially valuable for novel inventions. Further, because marginal search costs are lower in thicker markets, I argue that thick VC markets should amplify the role of experience, especially for firms pursuing novel technologies.

Using a comprehensive, unique, and hand-collected sample of nearly 4,700 patenting medical device startup firms to test these ideas, I find novelty pays in terms of early stage selection only for those startups with pre-entry startup experience in firms that are situated in clusters. While my results are not causally identified, I attempt to address alternative explanations through alternative specifications and various other tests. Further, while the results relating to thick VC markets leave some room for alternative explanations, I offer a theory of startup development that is both plausible and builds from core ideas about agglomeration economies. My theory suggests that it need not be true that either startups or VCs in thick markets are better quality for the likelihood of funding and of eventual commercial success of novel startups in clusters to be higher. Instead, simply by allowing for more efficient search for complementary resources, clusters may disproportionately produce novel startups.

My findings contribute to the innovation literature that links new venture novelty to performance. Broadly, my study fits within the growing literature in the evolutionary economics tradition that looks at how features of the selection environment affect when and whether novel ideas are selected (Berg, 2016; Boudreau et al., 2016; Criscuolo et al., 2016; Piezunka & Dahlander, 2015). I theorize and document when novelty is associated with increased likelihood of funding, and when its less likely to improve funding chances. In doing so, I provide one explanation for the mixed findings on the effect of novelty on performance (Hyytinen et al., 2015): that is, variations in the thickness of the market for complementary resources and in new firms' ability to access to those markets. Unlike much of the prior work that links novelty to funding, I measure novelty at the time of invention and hence I am neither conflating innovation success (e.g. realized technological breakthroughs) with novelty, nor relying on ex post recollections by founders of their founding strategy (as in, e.g. Hellmann & Puri (2000)). A further advantage is that I construct a sample that varies geographically, in contrast to work based on samples from one, typically resource-dense, geographic location (e.g. MIT-spawned startups as in Katila & Shane (2005)).

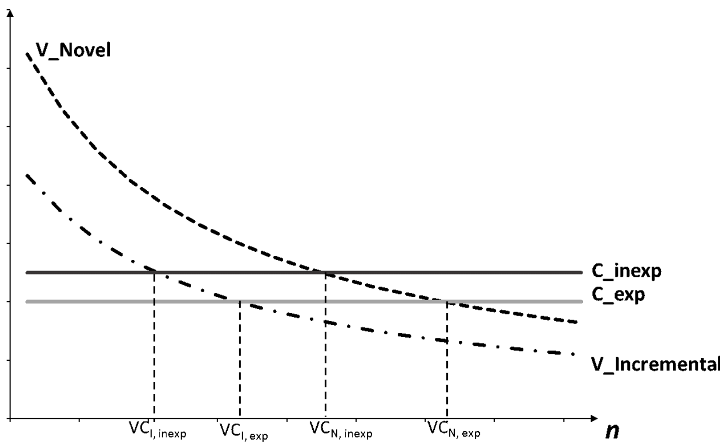
My findings also contribute another layer into the expansive entrepreneurship literature linking pre-entry firm experience to (better) startup performance. I argue and find evidence supporting the idea that pre-entry experience of founding inventors is associated with higher likelihood of funding for novel startups in particular, and, through funding, to firm-level success. In that same tradition, my results are somewhat in contrast with prior work suggesting the competitive advantages based on pre-entry resource differences fade over time as new firms establish their own track record (Hallen, 2008). However, this may signify an important distinction based on the necessity of early-stage external funding for success: when VC funding is necessary, pre-entry experience may play a significant role in who gets to establish their own track record, reinforcing the advantages that pre-entry experience provides.

Last, I also contribute to the growing literature that looks at the heterogeneous role of industry clusters in innovation and firm performance across different types of firms (Alcacer & Chung, 2007; Gambardella & Giarratana, 2010). While these studies, and broader strategy research typically focuses on the knowledge spillover effects of clusters in invention, I instead focus on the post-invention role of clusters (in particular, as thick markets for complementary resources to invention) in shaping innovative success through efficiencies in search and matching that are especially important for novel inventions and novelty-pursuing startup firms.

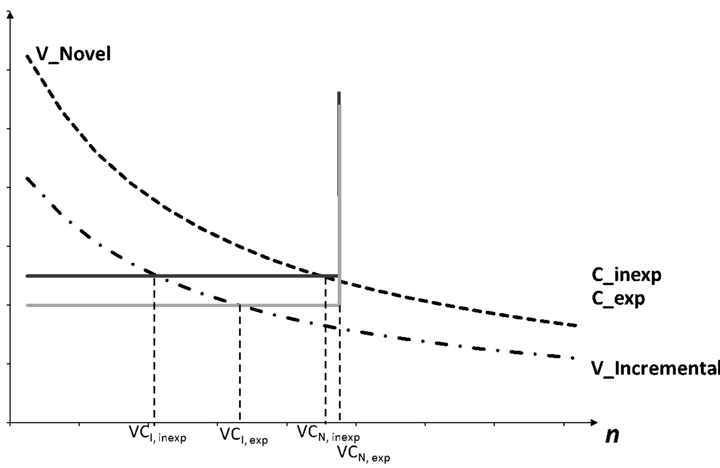
An interesting extension of the analyses in this paper would be to look at how experience and novelty interact in thick and thin markets in the acquisition of other early stage resources for startup firms. For example, similar to VCs, early employees choose and are chosen by firms, and managerial talent is known to be relatively geographically bounded (Dahl & Sorenson, 2012). Hence a similar model—whereby novel startups search for managerial expertise and match with managers based on their unique skills and preferences—could be used to explore the how market thickness affects the acquisition of skilled human capital for inventing startups.

My paper has several empirical limitations. First, most notably, inventions are not randomly assigned to startup firms, and firms are not randomly allocated to locations, and therefore I cannot isolate the causal effect of novelty, experience, or locational attributes on funding. This leaves room for the alternative explanation that differences in quality of the inventions across these dimensions are responsible for the results. I have attempted to rule out this explanation by using alternative dependent variables (e.g. SBIR/STTR funding), and by exploring firm level outcomes conditional on VC funding, which collectively suggest quality differences are not solely driving the patterns I observe. Further, I attempted to rule out that differences in VC quality or selection preferences as an alternative explanation by location using conditional outcomes and by separately analyzing firms funded by experienced VCs, and found little support for such explanations. Second, while my measure of technological novelty has many strengths—it is characterized at the time of invention and isn't subject to success or recall bias—a remaining limitation is that it is based on eventually-granted patents, and so nascent startups that never seek (or get) U.S. patents are not captured. Prior research suggests that patents are used extensively in the medical device industry, more so than any other industry (Arora et al., 2016). Therefore, using patents to define inventing entrants is of less a concern in my context than it would be in others. A final note is that my measure is of technological novelty and not novel market segments or novel business models. Both other types of novelty likely influence the ex-ante risk and eventual performance of startups, and deserve exploration—including the development of systematic measures of such novelty—in future research.

In conclusion, I find that the pursuit of technological novelty may be under-rewarded—offering inventing startups no advantage in terms of resource acquisition or eventual performance—when gaining attention of potential partners takes comparatively large effort and increased time. Medical device industry clusters produce novel ideas and novel startups at a higher rate than non-cluster locations. However, interestingly, the difference emerges in the commercialization stage due to selection, and not in the invention stage. Therefore, startups and policy makers outside such locations may benefit from expanding access to VCs and other complementary commercialization resources, which can increase the likelihood of success for startups pursing novel technologies, and thereby the locally-produced, novel innovation.

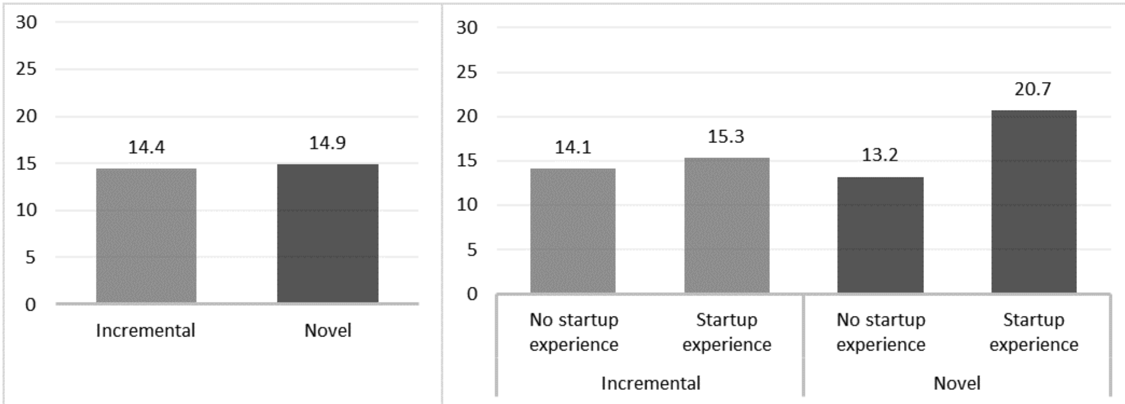


(a) Stylized search model: thick markets

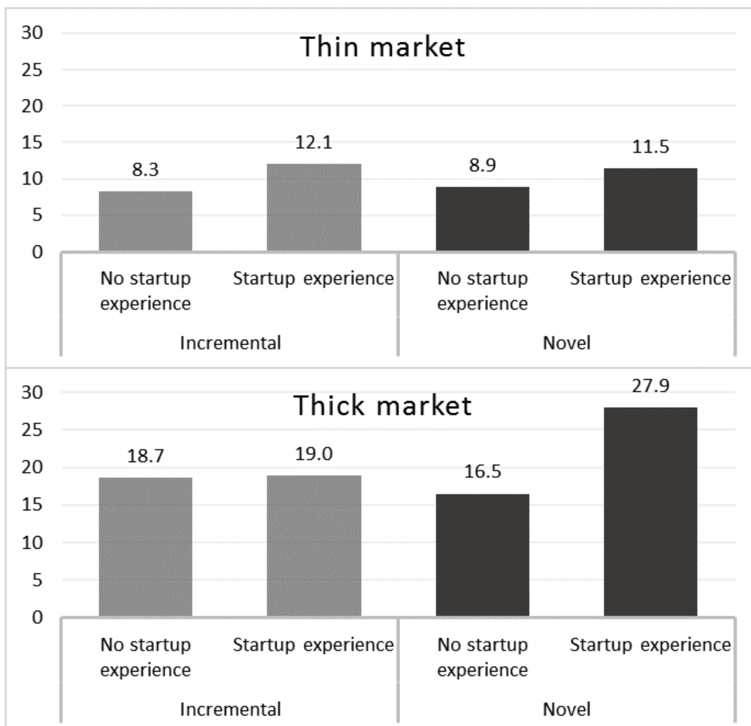


(b) Stylized search model: thin markets

FIGURE 3.1: Stylized model of startup search for potential VC funders
These figures provide a simple, highly stylized structure to explore how novelty, startup experience, and cluster location interact and shape how extensively startups seek out VC funding (i.e. how many VCs they solicit). I assume that startup experience lowers cost, which will increase the equilibrium amount of search. I also assume that novel technologies benefit more from additional search, which implies that the increase in equilibrium search from prior experience will be larger for novel startups. Last, I assume that outside of clusters, search costs will increase starkly above some threshold (e.g. beyond the number of local VCs), as depicted in Figure 3.1b. In this particular setup, this implies that experience related efficiencies in search will have limited consequences on the level of search outside clusters as compared to inside them. This further implies that novelty pursuing firms will search less outside of clusters.



(a) Likelihood of funding, by novelty and experience



(b) Likelihood of funding in Thin (top) and Thick (bottom) markets, by novelty and experience

FIGURE 3.2: Funding, by market thickness, novelty and experience
These figures plot the likelihood of a startup receiving VC funding at any point from founding until the end of 2014, adjusting for startup year, tech class of first patent, number of founding inventors and initial patents, female inventor, and several measures of startup quality. Novelty is defined based on a firm's first patent, and startup experience is based on the patenting history of the founding inventor(s).

Table 3.1: Descriptive Statistics

	(A)	(B)		(C)		(D)	
	All	Incre-mental	Novel	No Startup Exp	Startup Exp	Thin Mkt	Thick Mkt
N	4663	3113	1550	3602	1061	2189	2474
Main Variables							
Novel Technology	0.33	**0**	**1**	0.33	0.34	0.33	0.33
Startup Experience	0.23	0.23	0.23	**0**	**1**	0.21	0.24
Thick market (y/n)	0.53	0.53	0.54	**0.52**	**0.57**	**0**	**1**
VCs in MSA (#)	18	19	17	**18**	**20**	**1**	**33**
Controls							
Female	0.14	0.13	0.14	0.14	0.13	0.12	0.15
Inventors (#)	2.12	2.14	2.17	**2.10**	**2.32**	**2.09**	**2.21**
Initial Patents (#)	1.07	1.07	1.06	1.06	1.08	**1.05**	**1.08**
Long name	0.28	0.29	0.28	0.28	0.27	**0.31**	**0.26**
Entry Trademark	0.13	0.12	0.15	0.14	0.11	0.13	0.13
Year (First Filing)	1998	1998	1997	1998	1998	1998	1998
Outcomes							
VC Funded	0.15	0.14	0.15	0.14	0.17	**0.08**	**0.20**
IPO Exit	0.02	0.02	0.03	0.02	0.03	**0.01**	**0.04**
M&A Exit	0.09	0.09	0.09	0.09	0.10	**0.08**	**0.11**
Failure	0.40	**0.38**	**0.43**	0.40	0.37	0.42	0.38
VC Conditional Outcomes							
N	680	451	229	504	176	185	495
IPO Exit	0.14	0.12	0.17	0.14	0.14	**0.08**	**0.16**
M&A Exit	0.27	0.27	0.27	0.27	0.25	0.30	0.25
Failure	0.22	**0.18**	**0.29**	0.20	0.26	0.20	0.22

The table reports variable means for the full sample (panel A), by invention novelty (panel B), by founding inventor prior medical device startup experience (panel C), and market thickness (panel D) of the startup firm. **Bolded** numbers signify statistically significant differences (at $p < 0.05$) between means inside that panel. For example, the likelihood of failure is significantly higher for novel startups versus incremental (43% versus 38%).

Table 3.2: Likelihood of VC Funding (linear probability)

	(1)	(2)	(3)	(4)
Novel	0.00	-0.01	0.00	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Startup Exp	0.03**	0.01	0.03**	0.04*
	(0.02)	(0.02)	(0.02)	(0.02)
Thick Market	0.10***	0.10***	0.10***	0.11***
	(0.03)	(0.03)	(0.03)	(0.03)
Novel * Startup Exp		0.06**		-0.01
		(0.03)		(0.03)
Novel * Thick Mkt				-0.03
				(0.02)
Thick Mkt * Startup Exp			0.00	-0.04
			(0.03)	(0.03)
Novel * Startup Exp * Thick Mkt				0.13***
				(0.04)
Incumbent Exp	0.08***	0.08***	0.08***	0.08***
	(0.02)	(0.02)	(0.02)	(0.02)
Tech Exp	0.02	0.02	0.02	0.02
	(0.01)	(0.01)	(0.01)	(0.01)
Inventors (#)	0.01***	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)
Initial Patents (#)	0.07***	0.07***	0.07***	0.07***
	(0.02)	(0.02)	(0.02)	(0.02)
Female	-0.02	-0.02	-0.02	-0.02
	(0.01)	(0.01)	(0.01)	(0.01)
Long Name	-0.08***	-0.08***	-0.08***	-0.08***
	(0.01)	(0.01)	(0.01)	(0.01)
Entry Trademark	0.07***	0.07***	0.07***	0.06***
	(0.02)	(0.02)	(0.02)	(0.02)
Entry Year FE	Yes(15)	Yes(15)	Yes(15)	Yes(15)
Tech Class FE	Yes(13)	Yes(13)	Yes(13)	Yes(13)
Observations	4,663	4,663	4,663	4,663
R-squared	0.09	0.09	0.09	0.09

This table presents the linear probability estimates of the likelihood of VC funding of a patenting medical device startup. An observation is a startup ($n = 4663$). Both types of regressions include coefficient estimates. The interpretation of the linear coefficient is percentage point increases in probability of funding.
Standard errors (clustered at the MSA level) are in parentheses.
p<0.01,p<0.05,*p<0.1

Table 3.3: Likelihood of VC Funding (logistic)

	(1)	(2)	(3)	(4)
Novel	0.04	-0.08	0.04	0.08
	(0.09)	(0.11)	(0.09)	(0.19)
Startup Exp	0.32***	0.16	0.40**	0.45**
	(0.12)	(0.16)	(0.17)	(0.22)
Thick Market	0.89***	0.89***	0.92***	1.00***
	(0.20)	(0.20)	(0.20)	(0.20)
Novel * Startup Exp		0.46**		-0.15
		(0.22)		(0.40)
Novel * Thick Mkt				-0.24
				(0.22)
Thick Mkt * Startup Exp			-0.12	-0.43
			(0.23)	(0.29)
Novel * Startup Exp * Thick Mkt				0.87**
				(0.40)
Incumbent Exp	0.56***	0.55***	0.56***	0.55***
	(0.11)	(0.11)	(0.11)	(0.11)
Tech Exp	0.16*	0.17*	0.16*	0.17*
	(0.10)	(0.10)	(0.10)	(0.09)
Inventors (#)	0.10***	0.10***	0.10***	0.10***
	(0.03)	(0.03)	(0.03)	(0.03)
Initial Patents (#)	0.39***	0.40***	0.39***	0.40***
	(0.14)	(0.14)	(0.14)	(0.14)
Female	-0.19	-0.18	-0.19	-0.17
	(0.14)	(0.14)	(0.13)	(0.14)
Long Name	-0.91***	-0.90***	-0.91***	-0.91***
	(0.13)	(0.13)	(0.13)	(0.13)
Entry Trademark	0.55***	0.55***	0.55***	0.55***
	(0.12)	(0.12)	(0.12)	(0.12)
Entry Year FE	Yes(15)	Yes(15)	Yes(15)	Yes(15)
Tech Class FE	Yes(13)	Yes(13)	Yes(13)	Yes(13)
Observations	4,663	4,663	4,663	4,663
Psuedo R-squared	0.114	0.115	0.114	0.116
LL -1716	-1714	-1716	-1712	

This table presents the logit estimates of the likelihood of VC funding of a patenting medical device startup. An observation is a startup ($n = 4663$). The interpretation of the logit coefficient is in terms of log-odds: a one unit increase in x is associated with a β increase in the log-odds that y is 1. Marginal effects interpretations of the coefficients are included in the results section.
Standard errors (clustered at the MSA level) are in parentheses.
p<0.01,p<0.05,*p<0.1

Table 3.4: Hazard of VC Funding (Discrete Event History)

	(1)	(2)	(3)	(4)
Novel	1.05	0.94	1.05	1.20
	(0.08)	(0.09)	(0.08)	(0.23)
Startup Exp	1.24*	1.08	1.26	1.39
	(0.15)	(0.15)	(0.22)	(0.30)
Thick Market	2.20***	2.21***	2.21***	2.48***
	(0.44)	(0.44)	(0.44)	(0.50)
Novel * Startup Exp		1.50**		0.73
		(0.30)		(0.30)
Novel * Thick Mkt				0.70
				(0.15)
Thick Mkt * Startup Exp			0.98	0.71
			(0.22)	(0.19)
Novel * Startup Exp * Thick Mkt				2.63**
				(1.09)
Post SBIR/STTR	1.36*	1.35*	1.36*	1.34*
	(0.24)	(0.24)	(0.24)	(0.24)
Post CE Mark	3.36***	3.35***	3.36***	3.31***
	(0.79)	(0.78)	(0.79)	(0.77)
Post Trademark	1.18	1.18	1.18	1.18
	(0.15)	(0.15)	(0.15)	(0.15)
Post 2nd Patent App	2.97***	2.99***	2.97***	2.99***
	(0.32)	(0.32)	(0.32)	(0.32)
Post PMA Approval	1.16	1.20	1.16	1.22
	(0.82)	(0.83)	(0.82)	(0.82)
Entry controls	Y	Y	Y	Y
Entry Year FE	Yes(15)	Yes(15)	Yes(15)	Yes(15)
Tech Class FE	Yes(13)	Yes(13)	Yes(13)	Yes(13)
Observations	64,630	64,630	64,630	64,630
LL	-2926	-2924	-2926	-2921

This table predicts the hazard of VC funding, taking into account different time at risk across various startup types. The dependent variable is 1 if the startup received VC funding in a given year, and 0 otherwise. Startups are dropped from the sample either when they receive funding or when they otherwise exit. The table reports hazard-odds ratios: > 1 represents increases in hazard over the reference category, whereas < 1 represents decreases in hazard rates. Time since entry is specified as quadratic function of years since first patent filing ($year$, $year^2$).
Entry controls are: Incumbent exp, Tech exp, Inventors (n), Initial patents, Female, and Long Name. Standard errors (clustered at the MSA level) are in parentheses.
p<0.01,p<0.05,*p<0.1

Table 3.5: Alternative Dependent Variable: Likelihood of SBIR/STTR funding (linear probability)

	(1)	(2)	(3)	(4)
Novel	0.02	0.02	0.02	0.03*
	(0.01)	(0.01)	(0.02)	(0.02)
Startup Exp	0.02	0.02	0.02	0.03*
	(0.01)	(0.01)	(0.02)	(0.02)
Thick Market	-0.01	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Novel * Startup Exp		-0.01		-0.03
		(0.02)		(0.03)
Novel * Thick Mkt				0.02
				(0.02)
Thick Mkt * Startup Exp			-0.02	-0.03
			(0.02)	(0.02)
Novel * Startup Exp * Thick Mkt				0.03
				(0.03)
Incumbent Exp	-0.02*	-0.02*	-0.02*	-0.02*
	(0.01)	(0.01)	(0.01)	(0.01)
Tech Exp	0.02*	0.02*	0.02*	0.02*
	(0.01)	(0.01)	(0.01)	(0.01)
Inventors (#)	0.01**	0.01**	0.01**	0.01**
	(0.00)	(0.00)	(0.00)	(0.00)
Initial Patents (#)	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Female	-0.01	-0.02	-0.02	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Long Name	-0.02***	-0.02***	-0.02***	-0.02***
	(0.01)	(0.01)	(0.01)	(0.01)
Entry Trademark	-0.00	-0.00	-0.00	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)
Entry Year FE	Yes(15)	Yes(15)	Yes(15)	Yes(15)
Tech Class FE	Yes(13)	Yes(13)	Yes(13)	Yes(13)
Observations	4,663	4,663	4,663	4,663
R-squared	0.03	0.03	0.03	0.03

This table presents the linear probability estimates of the likelihood of SBIR funding of a patenting medical device startup. An observation is a startup ($n = 4663$). Standard errors (clustered at the MSA level) are in parentheses.
p<0.01,p<0.05,*p<0.1

Table 3.6: Likelihood of Successful and Failed Exit, versus No Exit, Conditional on VC funding (multinomial logit)

	(1)		(2)		(3)		(4)	
	Succeed	Fail	Succeed	Fail	Succeed	Fail	Succeed	Fail
Novel	0.11	0.51***	0.09	0.36	0.12	0.52***	-0.06	-0.89*
	(0.21)	(0.20)	(0.22)	(0.24)	(0.21)	(0.20)	(0.43)	(0.51)
Startup Exp	0.14	0.10	0.11	-0.12	0.44	0.39	0.56	0.04
	(0.23)	(0.34)	(0.33)	(0.48)	(0.49)	(0.52)	(0.52)	(0.61)
Thick Market	0.27	0.29	0.26	0.28	0.38	0.40	0.30	-0.23
	(0.22)	(0.22)	(0.21)	(0.23)	(0.24)	(0.31)	(0.28)	(0.38)
Novel * Startup Exp			0.09	0.50			-0.43	0.96
			(0.64)	(0.62)			(0.94)	(0.90)
Novel * Thick Mkt							0.27	1.74***
							(0.45)	(0.55)
Thick Mkt * Startup Exp					-0.43	-0.41	-0.65	-0.25
					(0.48)	(0.60)	(0.57)	(0.82)
Novel * Startup Exp * Thick Mkt							0.68	-0.63
							(1.13)	(1.18)
Entry Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Entry Year FE	Yes(15)	Yes(15)	Yes(15)	Yes(15)	Yes(15)	Yes(15)	Yes(15)	Yes(15)
Tech Class FE	Yes(13)	Yes(13)	Yes(13)	Yes(13)	Yes(13)	Yes(13)	Yes(13)	Yes(13)
Observations	680		680		680		680	
LL	-642.3		-641.8		-641.9		-636.4	

This table predicts the likelihood of successful exit (IPO/M&A), or failure (patent non-renewal), as compared to not exiting. The DV is 0 if a startup lives on at the end of 2014, 1 if the startup exited by IPO or M&A, and 2 if the startup failed. The table reports logistic coefficients: a 1-unit increase in x would be associated with an increase of β in the log-odds of the outcome relative to not exiting. Entry Controls: Incumbent exp, Tech exp, Inventors(#), Initial patents, Female, Entry Trademark. Standard errors (clustered at the MSA level) are in parentheses.***p<0.01,**p<0.05,*p<0.1

3.9 Model Appendix

A nascent startup firm has an inventive idea, i, that requires external investment from a VC, j, to develop. Both the startup and the VC are risk neutral. The value of an idea i to a specific VC j at the time of the funding choice is $V_{ij} = w_i + \epsilon_{ij}$ where w_i represents the common value of the idea i across VCs and ϵ_{ij} is the opinion of the j^{th} VC of the value of i, or the "fit" between the idea and the VC.

For tractability, I assume that ϵ are independently and identically type I extreme value distributed (mean 0 and variance $\frac{\sigma^2\pi^2}{6}$, the standard multinomial logit structure). Startups know VC opinions are distributed as such, but don't know a particular VC opinion until they pay (in time and effort) c to solicit the opinion of VC_j (e.g. by making a pitch).

Building from the logic developed in the paper, startups vary in terms of the novelty of their invention, which I assume increases the variation in the opinion of VCs about its value ($\sigma_N > \sigma_I$) and thus increases the benefit seeking more opinions. Startups also vary in terms of their prior startup experience, which lowers the marginal cost of soliciting an additional VC ($c_{exp} < c_{inexp}$), and based on their location, which effectively places an upward bound on the number of VCs a startup can solicit (or, if n is the maximum number of potential VCs a firm can solicit, then $n_K > n_T$ where K represents thick markets and T thin).

Startups choose how many VCs to solicit (s) out of a maximum possible n based on their expected net surplus, which, based on the assumptions on ϵ and as shown in (Anderson et al., 1992), is:

$$U(s; \sigma, c) = \alpha w + \sigma ln(s) - cs \tag{3.1}$$

where αw is the share of expected value captured by the startup. Solving for s^* gives:

$$s^* = min[n, max[1, \frac{\sigma}{c}]] \tag{3.2}$$

If we assume that $\sigma > c$ (and therefore $s^* > 1$), then provided $\frac{\sigma}{c} < n$, I find that $s^* = \frac{\sigma}{c}$. This implies: (1) firms with prior experience will have a higher $s^*(\frac{\partial s*}{\partial c} < 0)$; (2) firms with novel technologies will have a higher $s^*(\frac{\partial s^*}{\partial \sigma} > 0)$; and (3) the effect of experience will be higher for firms with novel technologies ($\frac{\partial^2 s}{\partial c \partial \sigma} < 0$). This presumes $\frac{\sigma}{c} < n$, which is more likely to be true in thicker markets (for example, since $n_K > n_T$, it is feasible that in a thin market $\frac{\sigma}{c} > n_T$, and so s^* is simply n_T, but in a thick market $\frac{\sigma}{c} < n_K$). Hence, on average, the difference in s^* by novelty and experience will be diminished in thin VC markets vis-à-vis thicker markets.

3.10 Additional Examples of Startups with Novel Technologies

OrthoHelix Surgical Designs was founded in 2003 in Medina, Ohio by inventor and founder David B. Kay, MD (an Orthopaedic Surgeon specializing in foot/ankle). The founding patent of the firm was *US: 07189251 Open helical organic tissue anchor having recessible head and method of making the organic tissue anchor*, a novel combination of technologies. The startup was first funded in January 2006 by Mutual Capital Partners (Fund I), alongside River Cities Capital (Fund IV) in later rounds: both are local (Ohio) VCs. OrthoHelix received more than $30M in total VC investment. The company was acquired for more than $135 million by Tornier in 2012.

Veralight was founded in 2004 and is based in Albuquerque, New Mexico. VeraLight develops noninvasive technologies for the disease detection and health monitoring of diabetes. Their founding patent was: *US 7725144 Determination of disease state using raman spectroscopy of tissue*. This patent provided the foundation for the SCOUT DS system, a noninvasive diabetes screening system designed to provide a method for screening prediabetes and Type 2 diabetes based on the presence of diabetes-related biomarkers found in skin. The founding inventing team, Marwood Ediger, Craig Gardner, and Edward Hull, had no inventing experience prior to Veralight. The first round of VC was led by a new VC vSpring Capital in September 2005 for $5M. Veralight received their last round of funding in December 2012, and was acquired in August 2013 by of Luminor Medical Technologies (pka Miraculins).

Theracardia was founded in 1997 in San Clemente, California and went out of business in 2002. It was a developer of minimally invasive medical devices to treat sudden cardiac arrest (namely, the inPULSE Device and System). Minimally Invasive Direct Cardiac Massage procedure is intended to generate cardiac outputs similar to open-chest massage but without the need for a major thoracotomy (a middle ground between CPR and open-chest massage). TheraCardia, received approximately $30 million in VC funding from 1998 through 2001. Their founding patent was novel: *US 6200280 Cardiac massage apparatus and method.*

3.11 Supplementary Tables

Table 3.7: Patent Level Outcomes by Patent Novelty, for All US Medical Device Patents, 1981-2005

	Novel	Incremental	Difference	p (diff)
N	45,070	92,046		
Breakthrough patent*	0.05	0.04	0.01	0.00
Forward citations**	11.59	10.85	0.74	0.00
No forward citations	0.13	0.20	-0.07	0.00
Expire within 4 years of grant	0.14	0.12	0.02	0.00
Expire before full term	0.42	0.35	0.07	0.00

*$>$ 2 standard deviations above mean of forward citations in tech class-filing year
** non-self citations within 5 yrs post-grant, conditional on > 0 citations

Table 3.8: Tech Group Controls and Relevant Patent Classes

	Class(es)	N	Share novel	VC Funded	Description
1	422, 424, 436	208	0.50	26	Chemistry
2	705	130	0.32	19	Data
3	433	236	0.17	12	Dental
4	362, 378, 382	70	0.46	15	Imaging
5	351, 356	68	0.17	6	Optics
6	623, 227	343	0.32	80	Prosthesis
7	128	393	0.32	36	Surgery: truss, reproduction, rests & restraints, respiratory
8	600	1106	0.32	158	Surgery: diagnostic, cardiac, hearing, urological, endoscopic
9	601	112	0.49	15	Surgery: kinesitherapy (e.g. vibration devices)
10	602	193	0.30	6	Surgery: orthopedic
11	604	730	0.40	101	Surgery: blood, fluid, material
12	606	805	0.28	168	Surgery: instruments & stabilizers
13	607	269	0.31	38	Surgery: light, thermal, & electrical

This table outlines some descriptive statistics on each of the technological classes that make up the set of 13 indicator variable controls used in the regressions.

Table 3.9: Hazard of VC Funding (cox proportional hazard)

	(1)	(2)	(3)	(4)
Novel	1.05	0.94	1.05	1.20
	(0.08)	(0.09)	(0.08)	(0.22)
Startup Exp	1.24*	1.08	1.25	1.37
	(0.15)	(0.15)	(0.21)	(0.29)
Thick Market	2.16***	2.17***	2.17***	2.42***
	(0.41)	(0.41)	(0.42)	(0.48)
Novel * Startup Exp		1.47**		0.75
		(0.28)		(0.30)
Novel * Thick Mkt				0.72
				(0.15)
Thick Mkt * Startup Exp			0.98	0.72
			(0.22)	(0.19)
Novel * Startup Exp* Thick Mkt				2.50**
				(1.02)
Post SBIR/STTR	1.34*	1.33	1.34*	1.33
	(0.23)	(0.23)	(0.23)	(0.23)
Post CE Mark	3.54***	3.53***	3.54***	3.49***
	(0.74)	(0.74)	(0.74)	(0.73)
Post Trademark	1.17	1.17	1.17	1.17
	(0.15)	(0.15)	(0.15)	(0.14)
Post 2nd Patent App	3.00***	3.01***	3.00***	3.01***
	1.05	0.94	1.05	1.20
Entry controls	Y	Y	Y	Y
Entry Year FE	Yes(15)	Yes(15)	Yes(15)	Yes(15)
Tech Class FE	Yes(13)	Yes(13)	Yes(13)	Yes(13)
Observations	64,630	64,630	64,630	64,630
LL	-4707	-4705	-4707	-4703

Standard errors (clustered at the MSA level) are in parentheses.
p<0.01,p<0.05,*p<0.1

Table 3.10: Alternative Dependent Variable: Likelihood of Technology Alliance (linear probability)

	(1)	(2)	(3)	(4)
Novel	0.01	0.01	0.01	0.00
	(0.01)	(0.01)	(0.01)	(0.01)
Startup Exp	0.02**	0.02*	0.02**	0.02**
	(0.01)	(0.01)	(0.01)	(0.01)
Thick Market	0.01***	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)
Novel * Startup Exp		-0.01		-0.00
		(0.02)		(0.02)
Novel * Thick Mkt				0.01
				(0.01)
Thick Mkt * Startup Exp			-0.01	-0.01
			(0.01)	(0.02)
Novel * Startup Exp * Thick Mkt				-0.00
				(0.03)
Incumbent Exp	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.01)	(0.01)
Tech Exp	-0.00	-0.00	-0.00	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)
Inventors (#)	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Initial Patents (#)	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Female	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Long Name	-0.02***	-0.02***	-0.02***	-0.02***
	(0.00)	(0.00)	(0.00)	(0.00)
Entry Trademark	0.02***	0.02***	0.02***	0.02***
	(0.01)	(0.01)	(0.01)	(0.01)
Entry Year FE	Yes(15)	Yes(15)	Yes(15)	Yes(15)
Tech Class FE	Yes(13)	Yes(13)	Yes(13)	Yes(13)
Observations	4,663	4,663	4,663	4,663
R-squared	0.02	0.02	0.02	0.02

Standard errors (clustered at the MSA level) are in parentheses.
p<0.01,p<0.05,*p<0.1

Table 3.11: Likelihood of Experienced VC Funding versus Inexperienced VC Funding or No VC Funding (multinomial logit)

	(1)		(2)		(3)		(4)	
	No VC	Inexp VC	No VC	Inexp VC	No VC	Inexp VC	No VC	Inexp VC
Novel	0.05	0.15	0.28**	0.32*	0.05	0.15	-0.16	-0.13
	(0.10)	(0.14)	(0.12)	(0.16)	(0.10)	(0.14)	(0.31)	(0.40)
Startup Exp	-0.47***	-0.24	-0.19	-0.06	-0.49*	-0.12	-0.53	-0.13
	(0.11)	(0.19)	(0.14)	(0.19)	(0.30)	(0.35)	(0.36)	(0.41)
Thick Market	-1.17***	-0.45*	-1.17***	-0.45*	-1.18***	-0.41	-1.36***	-0.59*
	(0.29)	(0.24)	(0.29)	(0.24)	(0.30)	(0.25)	(0.32)	(0.30)
Novel * Startup Exp			-0.79***	-0.54*			0.15	0.01
			(0.25)	(0.30)			(0.65)	(0.77)
Novel * Thick Mkt					0.03	-0.18	0.46	0.04
					(0.33)	(0.39)	(0.41)	(0.47)
Thick Mkt * Startup Exp							0.61*	0.59
							(0.33)	(0.44)
Novel * Startup Exp * Thick Mkt							-1.26*	-0.65
							(0.69)	(0.85)
Entry Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Entry Year FE	Yes(15)	Yes(15)	Yes(15)	Yes(15)	Yes(15)	Yes(15)	Yes(15)	Yes(15)
Tech Class FE	Yes(13)	Yes(13)	Yes(13)	Yes(13)	Yes(13)	Yes(13)	Yes(13)	Yes(13)
Observations	4,663		4,663		4,663		4,663	
LL	-2148		-2144		-2147		-2141	

This table predicts the likelihood of VC funding, splitting VCs into "Experienced" (the reference category) and "Inexperienced" to see how this relates to selection.The table reports logistic coefficients. Other Entry Controls: Incumbent exp, Tech exp, Inventors(#), Female, Entry Trademark. Standard errors (clustered at the MSA level) are in parentheses.***p<0.01,**p<0.05,*p<0.1

Table 3.12: Likelihood of VC Funding: splitting up experience (linear probability)

	(1)	(2)	(3)	(4)
Novel	0.01	-0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Startup Exp **(VC)**	0.10***	0.05	0.00	-0.01
	(0.04)	(0.03)	(0.03)	(0.04)
Startup Exp **(No VC)**	0.01	0.00	0.04**	0.05**
	(0.01)	(0.02)	(0.02)	(0.02)
Thick Market	0.09***	0.09***	0.10***	0.11***
	(0.03)	(0.03)	(0.03)	(0.03)
Novel * Startup **(VC)**		0.15***		0.04
		(0.05)		(0.08)
Novel * Startup **(No VC)**		0.03		-0.03
		(0.03)		(0.04)
Novel * Thick Mkt				-0.03*
				(0.02)
Thick Mkt * Startup **(VC)**			0.13**	0.08
			(0.06)	(0.06)
Thick Mkt * Startup **(No VC)**			-0.06**	-0.10***
			(0.03)	(0.03)
Novel * Startup **(VC)** * Thick Mkt				0.14
				(0.10)
Novel * Startup **(No VC)** * Thick Mkt				0.13***
				(0.04)
Entry Controls	Y	Y	Y	Y
Entry Year FE	Yes(15)	Yes(15)	Yes(15)	Yes(15)
Tech Class FE	Yes(13)	Yes(13)	Yes(13)	Yes(13)
Observations	4,663	4,663	4,663	4,663
R-squared	0.09	0.10	0.10	0.10

Standard errors (clustered at the MSA level) are in parentheses.
p<0.01,p<0.05,*p<0.1

Table 3.13: Likelihood of VC Funding: splitting up cluster (linear probability)

	(1)	(2)	(3)	(4)
Novel	0.01	-0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Startup Exp	0.03*	0.01	0.03**	0.04**
	(0.01)	(0.02)	(0.01)	(0.02)
Thick Market **Mover**	0.16***	0.16***	0.16***	0.17***
	(0.04)	(0.04)	(0.05)	(0.06)
Thick Market **Stayer**	0.08***	0.08***	0.09***	0.10***
	(0.03)	(0.03)	(0.02)	(0.03)
Novel * Startup		0.06**		-0.02
		(0.03)		(0.03)
Novel * Thick Mkt **Mover**				-0.03
				(0.07)
Novel * Thick Mkt **Stayer**				-0.03
				(0.02)
Thick Mkt **Mover** * Startup			-0.01	-0.06
			(0.07)	(0.09)
Thick Mkt **Stayer** * Startup			-0.01	-0.06**
			(0.03)	(0.03)
Novel * Startup * Thick Mkt **Mover**				0.16*
				(0.09)
Novel * Startup * Thick Mkt **Stayer**				0.14***
				(0.05)
Firm Entry Controls	Y	Y	Y	Y
Entry Year FE	Yes(15)	Yes(15)	Yes(15)	Yes(15)
Tech Class FE	Yes(13)	Yes(13)	Yes(13)	Yes(13)
Observations	4,663	4,663	4,663	4,663
R-squared	0.10	0.10	0.10	0.10

Standard errors (clustered at the MSA level) are in parentheses.
p<0.01,p<0.05,*p<0.1

Table 3.14: Descriptive Statistics of Cluster MSAs

	Years	VCs per year (mean)	Total Start-ups	Total Clstr Start-ups
San Francisco-Oakland-Fremont, CA	16	22.32	312	312
New York-New Jersey-Long Island, NY-NJ-PA	16	9.85	375	375
Boston-Cambridge-Quincy, MA-NH	16	8.90	270	270
San Jose-Sunnyvale-Santa Clara, CA	16	6.45	205	205
Minneapolis-St.Paul-Bloomington, MN-WI	16	3.06	234	234
Chicago-Naperville-Joliet, IL-IN-WI	16	2.34	137	137
San Diego-Carlsbad-San Marcos, CA	16	2.24	181	181
Los Angeles-Long Beach-Santa Ana, CA	16	1.54	369	369
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	15	2.32	162	151
Bridgeport-Stamford-Norwalk, CT	14	2.50	30	30
Trenton-Ewing, NJ	8	2.17	18	18
Seattle-Tacoma-Bellevue, WA	8	1.46	96	50
Houston-Sugar Land-Baytown, TX	6	0.52	64	22
Washington-Arlington-Alexandria, DC-VA-MD-WV	5	0.72	58	14
Dallas-Fort Worth-Arlington, TX	5	0.69	61	15
Denver-Aurora, CO	5	0.30	66	20
Pittsburgh, PA	4	1.20	25	9
Nashville-Davidson-Murfreesboro-Franklin, TN	4	1.13	15	7
Boulder, CO	4	0.70	37	11
Raleigh-Cary, NC	3	1.30	27	6
Atlanta-Sandy Springs-Marietta, GA	3	0.75	60	11
St. Louis, MO-IL	3	0.69	35	9
Baltimore-Towson, MD	2	1.31	42	4
Ann Arbor, MI	2	0.71	17	3
Portland-Vancouver-Beaverton, OR-WA	2	0.07	54	9
Hartford-West Hartford-East Hartford, CT	1	0.30	10	2

This table outlines descriptive information at the MSA level for cluster MSAs. Cluster (0/1) is defined at the MSA-year; however, most MSAs are either VC clusters or not throughout the study period (16 max years). Some either become less active (e.g. Dallas, Houston) or emerge towards the end of the period (e.g. Seattle, Boulder). VCs per year is the count of VC firms who made at least one first-round investment in a medical device firm in a year: a single VC firm made multiple investments in a year is counted as 1 firm.

Table 3.15: VC Firms Investing in 5 or More Medical Device Startup Firms

VC Firm	Lead on n firms	MSA
Three Arch Partners	26	San Francisco-Oakland-Fremont, CA
Versant Ventures	21	San Francisco-Oakland-Fremont, CA
New Entreprise Associates	17	San Francisco-Oakland-Fremont, CA
Delphi Ventures	16	San Francisco-Oakland-Fremont, CA
Domain Associates	16	Trenton-Ewing, NJ
Frazier Healthcare	13	Seattle-Tacoma-Bellevue, WA
Alta Partners	11	San Francisco-Oakland-Fremont, CA
Spray Venture Partners	11	Boston-Cambridge-Quincy, MA-NA
St Paul Venture Capital	11	Minneapolis-St.Paul-Bloomington, MN-WI
Medventure Associates	10	San Francisco-Oakland-Fremont, CA
Morgenthaler	10	San Francisco-Oakland-Fremont, CA
Interwest Partners	9	San Francisco-Oakland-Fremont, CA
Charter	8	San Jose-Sunnyvale-Santa Clara, CA
Canaan Partners	7	San Francisco-Oakland-Fremont, CA
De Novo	7	San Jose-Sunnyvale-Santa Clara, CA
EDF Ventures	7	Ann Arbor, MI
Kleiner Perkins	7	San Francisco-Oakland-Fremont, CA
Mayfield Fund	7	San Francisco-Oakland-Fremont, CA
Menlo Ventures	7	San Francisco-Oakland-Fremont, CA
Mohr Davidow Ventures	7	San Francisco-Oakland-Fremont, CA
Onset Ventures	7	San Francisco-Oakland-Fremont, CA
Sprout Group	7	Ny-N. New Jersey-Long Island, NY-NJ-PA
US Venture Partners	7	San Francisco-Oakland-Fremont, CA
Affinity Capital	6	Minneapolis-St.Paul-Bloomington, MN-WI
MPM Capital	6	Boston-Cambridge-Quincy, MA-NH
Prism Venture	6	Boston-Cambridge-Quincy, MA-NH
Sanderling Venture	6	San Francisco-Oakland-Fremont, CA
Atlas Venture	5	Boston-Cambridge-Quincy, MA-NH
Galen Associates	5	Bridgeport-Stamford-Norwalk, CT
Latterell Venture Partners	5	San Francisco-Oakland-Fremont, CA
Polaris Partners	5	Boston-Cambridge-Quincy, MA-NH
Psilos Group	5	Ny-N. New Jersey-Long Island, NY-NJ-PA

This table lists all VC firms that were lead investors for 5 or more medical device startups (and the number of sample companies for which they were lead VC) . The main location MSA is based on the main office as listed in VentureXpert.

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Biography

Colleen Mary Cunningham was born in Prince George, British Columbia, Canada. A first generation university graduate, she holds a B.A. (Economics) from the University of British Columbia, 2007, a M.A. (Economics) from Simon Fraser University, 2008, and studied for her Ph.D. (Business Administration) at the Fuqua School of Business, Duke University.

Colleen was awarded a 2016/17 Kauffman Dissertation Fellowship, as well as a receiving a Duke Graduate Student Fellowship throughout her Ph.D. studies. She also won a 2011/12 Fulbright Student award. For her M.A. studies at Simon Fraser University, she was awarded a Special Graduate Entrance Scholarship as well as receiving a Graduate Fellowship.

Colleen will start as an Assistant Professor in the Strategy and Entrepreneurship department of London Business School, London UK, in July 2017.