

**Using Users:  
The Impact of User Collaborations on Corporate Invention and Product Innovation**

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Prior research on corporate innovation highlights the importance of accessing extramural knowledge from other firms and universities. However, survey evidence indicates that product users are perhaps the most important source of extramural knowledge and crucial in suggesting new projects. Previous studies on corporate knowledge sourcing have not theoretically or empirically considered whether accessing user knowledge enhances a firm's subsequent innovative performance beyond the focal collaboration with a product user. We extend existing theory to explain how firms benefit from collaborations with users, subsequently leading to higher quality inventions and more product innovations. Using a panel dataset of medical device companies and their collaborative efforts with physicians, we find evidence in support of our propositions. We also employ a random parameters model to test for heterogeneity across firms in terms of the benefits gained from collaboration with users. We conclude that the benefits of collaboration depend on the nature of the firm's technological environment and the firm's R&D intensity.

*Keywords: innovation strategy, knowledge sourcing, open innovation, health care strategy, intellectual property strategy, R&D management*

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## **INTRODUCTION**

A considerable amount of academic research has examined how firms manage innovation, focusing on both internal and external sources of new ideas (Arora and Gambardella 1990; Grant 1996; Chesbrough 2003; Karim and Mitchell 2004; Cassiman and Veugelers 2006; Phene et al. 2006; Bercovitz and Feldman 2007; Sampson 2007). Scholars have concluded that internal development of substantial new inventions and products may be constrained by the organization's prior experience (Nelson and Winter 1982), corporate bureaucracy (Thompson 1965), competency traps (Levitt and March 1988), and existing customer preferences (Christensen and Bower 1996). Thus, the importance of extramural knowledge, or knowledge generated outside of the firm, is paramount (Cohen and Levinthal 1994; Almeida and Rosenkopf 2003; Laursen and Salter 2006). While most prior literature focuses on the contributions of extramural knowledge from other firms and universities, Cohen et al. (2002) identify customers as the most important source of information for suggesting new projects. Surprisingly though, there is no existing work examining how user knowledge impacts subsequent firm inventions and innovation outcomes. In this paper, we provide evidence that collaboration with users enhances the subsequent quality and quantity of firm inventions and product innovations.<sup>2</sup>

Explicating the long-term impact of firm-user collaborations addresses a key theoretical gap in prior literature. First, despite significant work on the importance of extramural knowledge in general, we know little about how extramural knowledge sources contribute to new product innovation and when these contributions are more valuable. With regard to product users specifically, the user innovation literature primarily focuses on documenting differences between user-generated and corporate-generated inventions (e.g., Riggs and Von Hippel 1994); only a few studies explore the collaborative outputs of users and firms (Lilien et al. 2002; Chatterji and Fabrizio 2009). Most importantly, the literature offers little theoretical guidance as to whether working with product users will provide benefits beyond the focal collaborative project, and whether these benefits will differ across firms. In this work we develop new theory to explain why collaborations with product users may help firms subsequently develop higher quality inventions and more product innovations.

Our empirical investigation utilizes a new dataset covering an unbalanced panel of 127 publicly owned medical-device firms in the United States in 1985-97. We examine the effect of

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<sup>2</sup> Consistent with Schumpeter (1934), we use the term “invention” to refer to a new technological discovery and “innovation” to refer to the entire process, including discovery, development, manufacture, and marketing.

prior corporate collaborations with physicians, in the form of co-invented patents, on two performance outcomes of the firm: patents, a proxy for inventive outcomes; and new product introductions approved by the Food and Drug Administration (FDA), a proxy for product-market innovations. We find that patents, citation-weighted patents, and product-market introductions all increase in the years following firm-physician collaborations in magnitudes that are economically significant. Importantly, these outcomes occur beyond the initial firm-physician collaboration. Furthermore, results from a random parameters model suggest the benefits of these collaborations will vary substantially across firms. In particular, firm-physician collaborations are associated with a larger effect on innovative outcomes for firms working in newer technology areas and for firms engaged in more internal research and development (R&D).

Our work contributes new theoretical insights to the literature on managing innovation. In particular, we explain how product users provide firms with technical knowledge that enhances subsequent corporate invention, and with market knowledge that improves the likelihood of successful product commercialization. The unique insights that users acquire by using a particular product distinguishes user knowledge from sources of extramural knowledge detailed in earlier studies (e.g., Saxenian 1990; Mowery et al. 1996; Powell et al. 1996; Almeida and Kogut 1999; Stuart 2000; Ahuja and Katila 2001; Cohen et al. 2002; Grant and Baden-Fuller 2004).

We also make four key empirical contributions to the literature. First, to our knowledge this is the first paper to systematically evaluate user contributions to on-going innovation at the corporate level and beyond the focal collaboration.<sup>3</sup> Second, we employ a random parameters model to demonstrate that benefits from collaboration are not universal. Third, we are among the first to look at the impact of extramural knowledge on both inventions and product commercialization, providing a more robust analysis of the innovation process. Finally, we provide large-sample evidence of the value of user insights in the innovation process, confirming the findings of previous smaller-sample studies in the user innovation literature.

In the next section, we review the relevant literature on why and how firms access knowledge beyond their boundaries, explain why user knowledge may be particularly useful for

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<sup>3</sup> This paper seeks to highlight and explore the potential of product users as an additional knowledge source useful for firm innovation. Importantly, we are interested in the subsequent benefits from working with product users at the corporate level, rather than examining the immediate outcomes of user and firm collaborations at the project level as has been done in prior work (Lilien et al. 2002).

firms, and develop novel and testable hypotheses motivated by prior work. We then describe our empirical setting and methods and present our results. We conclude with a discussion of the contributions of this study and open questions meriting further investigation.

### **THEORY & HYPOTHESES**

#### **Importance of Extramural Knowledge**

Incumbent firms face difficult challenges in managing their innovation activities to generate substantial new inventions and commercialize new products (Henderson 1993). Because new ideas are often generated by bringing together diverse knowledge, established firms may struggle to both develop and identify new ideas within their organizational boundaries (Henderson 1993; Dushnitsky and Lenox 2005). Increasingly, scholars and practitioners are recognizing that valuable knowledge may reside outside of the firm (Cohen and Levinthal 1990), and that accessing and integrating this knowledge is critical to a firm's innovative performance (Rosenkopf and Almeida 2003). How firms access extramural ideas and combine knowledge across organizational boundaries, whether drawing from regional networks, other firms, or universities, has been the subject of a substantial recent literature (Saxenian 1990; Mowery et al. 1996; Powell et al. 1996; Almeida and Kogut 1999; Stuart 2000; Ahuja and Katila 2001; Cohen et al. 2002; Grant and Baden-Fuller 2004).

Sourcing ideas from outside the firm poses significant challenges because it can be difficult to value unfamiliar ideas and integrate them into the firm's existing knowledge base. Research-related and experience-based knowledge is often "sticky" and difficult to transfer because it resides within the researcher herself (von Hippel 1994; Ogawa 1998; von Hippel 1998). To overcome this impediment, inter-organizational knowledge transfer often relies upon facilitating mechanisms such as joint ventures (Kogut 1988), alliances (Powell et al. 1996; Rosenkopf and Almeida 2003), research collaborations (Cockburn and Henderson 1998; Stuart 2000; Cohen et al. 2002), hiring employees away from competitors (Almeida and Rosenkopf 2003), consulting arrangements, corporate venture capital (CVC) investments (Hayward 2002; Dushnitsky and Lenox 2005), or acquisitions (Mowery et al. 1996; Cockburn and Henderson 1998; Stuart 2000; Cohen et al. 2002; Hayward 2002; Rosenkopf and Almeida 2003; Dushnitsky and Lenox 2005). In these studies, firms that structured their interactions to promote the identification and transfer of extramural knowledge also enhanced their financial and inventive performance.

### **User Knowledge**

Previous studies of user innovation demonstrate that user inventions developed separately from firms are widespread and significant (von Hippel 1988; 1998). Moreover, survey evidence indicates that customers often provide important insights for new R&D projects, and contribute substantially to the completion of existing R&D projects (Cohen et al. 2002). As Teece (1992:9) points out, “It is often the user that stimulates innovation and comes up with new product concept or product prototype... .” In sum, this body of work demonstrates that a product’s end users often possess valuable knowledge about evolving customer needs, market potential, and product improvements. This implies that users can make unique contributions to the innovative performance of established firms.

The user innovation literature also explores when users are motivated to innovate (Riggs and Von Hippel 1994; Shah 2006) and the particular type of knowledge they possess (von Hippel 1986; Luthje et al. 2005). Other work finds that user-innovators are often motivated by non-pecuniary factors, including their own needs and desires, career concerns or reputational benefits, the urge to reinforce or create a social identity, or simply their interest as a hobbyist (Shah 2006). These motivations result in substantial differences between the inventions generated by users and those generated by established firms. Whereas users frequently innovate to address their own particular needs, for example, manufacturers are more concerned with developing new products for large markets. Users are also more likely to focus on improving product functionality rather than on selecting projects for commercial viability (von Hippel 2005).

Users also possess knowledge that is fundamentally different from the knowledge developed by researchers within firms. Through frequent interaction with a product, users experience its functions and limitations first hand. These experiences may uncover problems that manufacturers did not anticipate and may also suggest potential solutions or improvements. This distinct body of user knowledge influences the inventions that users pursue. Firms with access to user knowledge can gain unique and valuable ideas that are distinct from the knowledge firms are likely to hold or develop internally.

Despite the potential value of user-generated innovation, it can be difficult and costly for firms to access and integrate user knowledge. User knowledge is often tacit, hard to write down,

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based on experience and thus difficult to transfer (von Hippel 1998). Truly free “spillovers” of such knowledge to firms are therefore limited. As with other extramural sources of knowledge, collaborations allow for knowledge transfer that is more fine-grained, tacit, and cooperative than otherwise possible (Uzzi 1996; Uzzi 1997). Accordingly, benefits associated with acquiring user knowledge will most often accrue to firms that actively collaborate with users.

### **The Duality of User Knowledge**

In previous industry studies, Eric von Hippel and his colleagues have found that 20%-80% of important inventions were generated by users (von Hippel 1988). Chatterji and Fabrizio (2008) found that 20% of patented inventions in the medical device industry came from practicing physicians. This important source of extramural knowledge can improve firm performance in at least two ways. First, users can provide knowledge that enhances a firm’s future inventive performance – what we will refer to as “technical” knowledge. Firms with access to user knowledge can also better anticipate the market’s needs, and focus their innovative efforts on products that meet those needs. We call this form of user knowledge "market demand" knowledge.<sup>4</sup>

### **Technical Knowledge**

Prior work demonstrates that user inventions are substantially different from firm inventions, and have several valuable characteristics, including greater importance, breadth, and earlier occurrence in the product life cycle (Chatterji and Fabrizio 2008). Users develop unique insights about the products they use. As a result, users can identify problems and suggest solutions that are relevant to other users. Indeed, Cohen, Nelson, and Walsh (2002) find that customers are the most important source of information suggesting new projects, more so than a firm’s own manufacturing operations. User experience may also suggest different solutions than a firm would develop on its own. User solutions are likely to emphasize practicality, ease of use, and functionality, and will be based upon accumulated experience that is not otherwise available to firm researchers.

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<sup>4</sup> This characterization is similar to the distinction proposed by Nerkar and Roberts (2004:779) to categorize the attributes of firms’ internal knowledge, where technical knowledge is required to “assimilate a range of technological inputs into novel combinations” and market knowledge is required to “facilitate the manufacturing, sales, and distribution of” a particular product. Rather than the firm’s internally developed knowledge, we focus on an extramural source of these two kinds of knowledge, namely product users.

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Although knowledge developed through prior research gives firms an advantage in performing related research, the tendency toward local search limits a firm's ability to identify new problems or solve old problems in a new way. Corporate R&D can utilize user knowledge about problems and potential solutions to embark on novel streams of research. Users can also help rule out unsatisfactory solutions early on – saving the firm lost time, effort and money -- by foreseeing problems that might otherwise remain hidden until an invention is tested or commercialized. While these benefits will vary by firm (a topic we will explore in detail below), we first theorize that, on average, access to users' valuable technical knowledge will enhance the subsequent inventive output of a firm.

*H1: A firm that increases its collaborations with users will subsequently increase its inventive output.*

### **Market Knowledge**

Intuitively, improvements in a firm's inventive output should increase the number of innovative products the firm generates. In addition, we suggest that user-firm collaborations give firms access to another form of valuable knowledge called "market demand" knowledge, which can separately improve product development. Users are uniquely positioned to identify future market needs, evaluate alternative solutions, translate inventions into valuable applications, and provide foresight regarding practical use and potential problems. They can do this because of their accumulated experiences with a particular product and their interactions within the user community (Franke and Shah 2003).

Firms often seek outside knowledge during the inherently uncertain process of product development (Luthje and Herstatt 2004). In many industries, the most crucial information about new products and services resides in a few lead users (von Hippel 1986; Urban and von Hippel 1988). Lead users are defined as those individuals who experience a need that the rest of the population will have later, and who experience significant benefits from finding a solution to their need (von Hippel 1986; Urban and von Hippel 1988). Lead users can provide valuable insights into the market potential of new products for two related reasons. First, lead users are among the select few who can understand what the rest of the market will eventually want, simply by articulating what they need today. Second, because lead users expect to benefit significantly from a solution, they are motivated to collaborate with firms if collaboration will

increase the likelihood of solving their problem. Through collaborations, the knowledge that lead users possess regarding the market potential for new innovations can be transferred to firms.

Lead users can help firms anticipate the difficulties in development and testing, and prioritize more-promising inventions, because of their unique experiences, intensive experimentation, and frequent interactions with other members of the user community (Franke and Shah 2003). Firms able to access user knowledge can focus on developing and testing the inventions with greatest potential to both successfully complete the testing process and meet significant demand in the marketplace. As a result, these firms will generate more inventions that survive the development and testing process and emerge as commercialized product innovations.

Thus, we argue that, all else being equal, users collaborating with firms will provide valuable market demand knowledge, which will lead to an increase in the number of product innovations subsequently generated by those firms. While these benefits will vary by firm (a topic we will explore in detail below), we first theorize that, on average, accessing users' valuable market knowledge will enhance the subsequent innovative output of a firm.

*H2: A firm that increases its collaborations with users will subsequently increase its output of innovative products.*

### **CONTEXT: THE MEDICAL DEVICE INDUSTRY**

The medical device industry is comprised of over 6,000 companies<sup>5</sup> that spend significant sums on R&D (greater than 11% of sales)<sup>6</sup> and produce increasingly rapid product innovations (with product cycles sometimes lasting as little as 18 months)<sup>7</sup>. Intellectual property rights to inventions in the medical device industry tend to be crucial and strong. In fact, R&D managers in medical equipment report the highest degree of appropriability through patents of any industry surveyed – even higher than that reported by R&D managers in the pharmaceutical industry (Cohen et al. 2000).

The medical device industry provides an ideal setting in which to study users' contributions to industrial innovation. First, there is a well-identified set of users (physicians) who are part of a

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<sup>5</sup> Advanced Medical Technological Association, AdvaMed Website, (<http://www.advamed.org/MemberPortal/About/Industry/>) Last accessed June 5, 2007.

<sup>6</sup> Advanced Medical Technological Association, AdvaMed Website, (<http://www.advamed.org/MemberPortal/About/Industry/>) Last accessed June 5, 2007.

<sup>7</sup> The Food and Drug Administration Website, (<http://www.fda.gov/cdrh/ocd/mdii.html>), Last accessed June 5, 2007

professional community of practice. Users in this industry are highly trained, participate interactively in user communities, and develop experience with products through interactive use. These attributes create an environment in which users are keenly aware of existing problems, possess the knowledge to generate potential solutions, and have insights into future market needs that, taken together, can support the generation of potentially valuable inventions and innovations.<sup>8</sup>

The intermediate outcomes of the invention process are clearly defined and identifiable using records of patented inventions. Although patents do not capture all inventions, the high degree of appropriability via patents in the medical device industry strongly supports our use of patent counts as indicators of inventive outcomes. Finally, the data on FDA-approved medical devices provides a reliable record of innovations that are a reasonable approximation of commercialized products.

### **Collaborations Between Physicians and Medical Device Companies**

Innovation in the medical device industry involves interaction between physicians and device companies at all stages of development (Gelijns and Rosenberg 1994). From product conception to clinical testing to dissemination, medical device companies devise strategies to tap the knowledge of their most important customers: practicing physicians (Chatterji et al. 2008).

In this paper, we focus exclusively on physician-industry collaboration at the earlier stages of product research and development, and not on product dissemination. There are two general scenarios through which physicians and companies collaborate on inventions (Carlin 2004). In the first scenario, a physician or team of physicians will patent a new invention that generates interest from a medical device company. If both parties agree, a license or a transfer of patent rights from inventor to company can be arranged. A famous example of this case occurred when Dr. Thomas Fogarty, a prolific medical device inventor, licensed the patent for his revolutionary balloon catheter to Edwards Life Sciences (White 2006). While these arrangements are quite common in the industry, they do not always represent collaborative interactions between physicians and companies, because the physician may have developed the idea independently before engaging the firm.

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<sup>8</sup> It is important to note that these conditions are not specific to the medical device industry. Other studies have demonstrated the value of user inventions in industries as diverse as juvenile products (Shah and Tripsas 2007), sports equipment (Shah 2007), and scientific instruments (Riggs and Von Hippel 1994).

Under the second scenario, the physician inventor will consult or co-develop an idea with a medical device company, resulting in a patented invention (Carlin 2004). A common arrangement is a consulting agreement whereby a contracted physician automatically assigns any resulting intellectual property to the firm. In these cases, any resulting patents will list the physician as an inventor but will be assigned to the medical device company. These “co-invented” patents with listed physician inventors represent products of collaboration between innovative physicians and medical device companies. It is this type of collaboration our paper examines.

### **The Regulation of Medical Devices**

To bring a new medical device to market, the FDA’s Center for Devices and Radiological Health (CDRH) must approve an application.<sup>9</sup> CDRH divides products into 3 classes (Class I, II, III) reflecting the risk to patients and the degree of regulatory control that the FDA deems necessary. Class I reflects the lowest level of regulatory control for products that present low risk to patients, such as tongue depressors or bandages. These products are typically simple in design and manufacturing and have a history of safe use.<sup>10</sup>

Class II devices are riskier products that are subject to additional regulation, such as labeling requirements and post-market evaluation. Examples of Class II devices include x-ray systems, pumps, and surgical drapes. Class III devices are the most innovative and riskiest products (Singh 2007), and therefore have the highest level of regulatory oversight. These are devices that are typically used to support or sustain human life or are associated with a very high level of risk to patients, including heart valves, breast implants, and implanted stimulators.

New medical device products are reviewed and approved through one of two processes: pre-market notification and pre-market approval. Approval via pre-market notification, commonly referred to as the 510(k) process, requires demonstration of “substantial equivalence” to a device currently on the market, called a predicate device. This is intended for less risky devices that are similar to other devices that have been proven safe based on a history of sales. The approval process is simplified and often takes less than 3 months (Singh 2007). As a result, products on the 510(k) track can sometimes be brought to market in as little as a year from

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<sup>9</sup> Although it is technically correct to say that the application – rather than the product itself -- has been approved, we will refer to product approvals throughout the paper for simplicity.

<sup>10</sup> “Overview: FDA Regulation of Medical Devices,” [http://www.qrasupport.com/FDA\\_MED\\_DEVICE.html](http://www.qrasupport.com/FDA_MED_DEVICE.html)

conception (Lawyer et al. 2007). Some Class I and most Class II devices are subject to the 510(k) approval process.<sup>11</sup> The total investment required to complete the 510 (k) process ranges between \$10 million and \$20 million.<sup>12</sup>

Some Class II and most Class III devices undergo the much more rigorous pre-market approval (PMA) process which involves animal testing and human clinical trials (Singh 2007). Recent research has found the average review time for a PMA application in 1998-2005 was approximately 409 days, and significantly longer for orthopedic devices (Singh 2007). The total investment required to complete the PMA process ranges from \$30 million to \$100 million.<sup>13</sup>

In 2006, the FDA granted 39 PMAs and 3210 510(k)s, a ratio of PMAs to 510(k)s roughly similar to approvals over the last several years (Lawyer et al. 2007). A recent study by the Government Accountability Office found that in 2003-07, the 510(k) process had a 90% approval rate and the PMA process had a 67% approval rate.

## **DATA & METHOD**

The goal of our empirical analysis is to estimate the impact of firm collaborations with physicians on subsequent inventive performance and new product innovations. Specifically, we explore the variation in levels of firm co-inventions with physicians over time and compare the subsequent rates at which inventions are generated and brought to market. The null hypothesis is that collaborations with physicians in one year will not substantially influence the inventive and innovative outcomes of the firm in the following years. As described in detail below, we make use of patent data commonly used to measure inventive outcomes, and also compile FDA data on products approved through the 510(k) and PMA processes. This approach has the advantage of allowing us to consider separately the impact of user collaboration on both inventive and product-market outcomes. Following Hausman et al. (1984) and Griliches (1990), we employ a production function model to estimate the elasticity of inventive and product-market outcomes to physician co-inventions, controlling for other inputs, including the firm's own R&D and

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<sup>11</sup> Most Class I devices are exempt from premarket notification, and therefore will not be reported in the 510(k) or PMA data used here.

<sup>12</sup> "Drug Eluting Stents: A Paradigm Shift in the Medical Device Industry," Stanford Graduate School of Business Case-OIT-50, 02/13/06, Lyn Denend and Stefanos Zenios.

<sup>13</sup> "Drug Eluting Stents: A Paradigm Shift in the Medical Device Industry," Stanford Graduate School of Business Case-OIT-50, 02/13/06, Lyn Denend and Stefanos Zenios.

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accumulated knowledge stock. As in Jaffe (1989), the Cobb-Douglas production function is as follows:

$$P_i = \beta_1 DrPats_i^{\beta_1} R\&D_i^{\beta_2} KnowL Stock_i^{\beta_3} Employ_i^{\beta_4}$$

where  $P_i$  is the inventive or innovative output of firm  $i$ . Taking the natural log of both sides yields the equation to be estimated:

$$\ln(P_i) = \beta_1 \ln(DrPats_i) + \beta_2 \ln(R\&D_i) + \beta_3 \ln(KnowL Stock_i) + \beta_4 \ln(Employ_i)$$

As discussed below, we estimate this model using Poisson quasi-maximum likelihood estimation.

### Sample

We constructed a large, unbalanced panel of public medical device companies in the United States with data from 1985-97. The sample includes all public firms in the primary medical device Standard Industrial Classification (SIC) code that were granted at least 10 patents between 1980 and 2002. This approach purposefully excludes large conglomerates and firms that are primarily pharmaceutical firms in order to focus on medical device firms. This method also intentionally excludes firms with only rare inventions in order to narrow our study to firms that are pursuing an innovation-based strategy. The resulting dataset includes 127 firms and 767 firm-year observations. In order to observe a five-year window of forward citations for patents in the sample, we are only able to include patents through 1997 in the analysis. Likewise, our identification of physician inventors extends only back to 1980; in order to include lags of up to 5 years, we cannot use data before 1985 in the analysis. The dataset includes information on the firms' FDA-approved products from the CDRH, granted patents from the Hall et al. (2001) dataset, and firm-year level data from the Standard & Poor's Compustat database. In order to identify collaborations with physicians, we rely on the American Medical Association (AMA) Masterfile data, which includes biographical information for all licensed physicians in the U.S.

We constructed our dataset as follows. For the set of firms meeting the criteria described above, we identified all successful U.S. medical device patents applied for between 1980 and 1997 using the NBER patent data (Hall et al. 2001). We used the patent data to identify all of the inventors on each patent, including data on inventors' first, middle, and last names, and their locations by cities and states. The AMA Physician Masterfile contains the name, demographic

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information, address, history of prior locations, type of practice, and medical school information for all licensed U.S. physicians. With this information, we were able to identify which inventors listed on our sample of medical device patents were physicians.

We perform this match in several steps. First, we identified any physicians with the same last name, first name, and state location as an inventor listed on a medical device patent. We used the physicians' historic and current locations in the AMA data and the inventors' addresses in the patent data for this match. After identifying possible matches, we evaluated them more closely to assure a true match. For each record, if there was a middle name or initial available from both sources (the patent data and the AMA data), we verified that these records matched and eliminated any for which they did not match. When one or both of the middle initial observations was missing, we verified that the observations matched by city. Observations lacking sufficient middle name data that did not match exactly based on city were flagged for closer manual evaluation.

## Measures

**Inventive Output.** We capture each firm's rate of inventive output using count of patents, *NumPats*, and the (forward) citation-weighted count of patents in each year, *CiteWtdPats*. We include all patents by sample firms in the 19 technology classes corresponding to medical devices, as per the U.S. Patent and Trademark Office (USPTO 2005). We date the patents according to the application date to more closely approximate the date of invention. Using the Hall et al. (2001) patent database, we count the number of follow-on patents that include a citation to each of the sample patents (forward citations). Patents and citation-weighted patents have been employed consistently as measures of inventive performance in recent literature (Griliches 1990; Trajtenberg 1990; Henderson and Cockburn 1994; Brockhoff et al. 1999; Harhoff et al. 1999). Previous studies have found that the count of citations received by a patent is a good indicator of invention value (Trajtenberg 1990; Harhoff et al. 1999; Hall et al. 2005).

We also employ a modified measure to deal with two concerns. First, one might be concerned that firms that co-invent with physicians in the recent past are likely to do so again, and that physician co-invented patents receive more citations, as demonstrated by Chatterji and Fabrizio (2008). Second, one might be concerned that physician co-invention might be correlated with the firm's propensity to generate future patents citing their own work, artificially inflating

the forward citation count. To alleviate these concerns, we develop a modified count of forward citations excluding physician co-invented patents from the current year and excluding forward citations from patents generated by the focal company (self citations), *ModifiedCiteWtd*.

**Product-Market Innovations.** Many studies of innovation rely on counts of patents or citation-weighted patents because they lack information on actual product introductions. We are fortunate to also have data on product innovations. We construct a firm-year count of the number of FDA-approvals (*NumInnov*) based on the CDRH data. To date the product innovations, we use the year that the application is received by the FDA. Our base measure is the aggregated count of product approvals via the 510(k) and PMA process, including all classes of products. We also consider separately the count of Class I, Class II, and Class III product approvals.

**Physician Co-invention.** Our primary independent variables of interest are firm-physician collaborations in the last five years, which we proxy for with the count of patents assigned to the firm that are co-invented with a physician in a firm-year observation. If at least one inventor on a firm's patent is a physician, we count this as a physician co-invented patent. In our base specification, we include the one year lagged value of physician co-invention (*DrPats<sub>t-1</sub>*). As discussed below, we also test for robustness to including five years of lags.

### Controls

Control variables include the firm's R&D expenditures in millions of dollars (*R&D*) and the firm size, measured by the number of employees in thousands (*Employ*). We expect that more R&D expenditures will lead to more inventive output and more product innovations. We include a control for the firm's accumulated technical knowledge stock (*KnowledgeStock*), measured with the depreciated stock of patents over the prior five-year period using a depreciation rate of 20%. We also include a control for the firm's accumulated product-market knowledge (*ProductStock*), measured analogously with the depreciated stock of FDA-approved innovations over the prior five-year period. These measures control for time varying heterogeneity in firms' knowledge bases. Importantly, by including the count of the firm's recent patents, we control for the degree of "successful" research effort by the firm.

### Method

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The dependent variables (*NumPats*, *CiteWtdPats* and *NumInnovs*) take on integer values and are bounded at zero. OLS estimation would provide inefficient and potentially biased estimates. We adopt a Poisson quasi-maximum likelihood estimation procedure to account for the discrete nature of these outcome variables. This estimation procedure is similar to the familiar Poisson model, but does not depend on the (oft-violated) assumption of constant dispersion (i.e., variance equal to the mean) (Wooldridge 1999). This method also allows for conditional firm fixed effects and the calculation of robust standard errors with clustered correlation structures to generate appropriate test statistics.

In general, we include the natural logs of the explanatory variables with a one-year lag. Thus, we are estimating the relationship between, for example, last year's R&D expenditures and this year's inventive and product innovation outcomes. This approach is consistent with prior literature (Jaffe 1989; Dushnitsky and Lenox 2005). Since we do not have strong priors regarding when the benefits of user collaborations will be evident in the firm's inventive outcomes, we test two alternative specifications. Our base models include only the one-year-lagged count of physician co-inventions. The alternative is the most flexible specification: We include each of the prior five-year lags as a separate variable. This approach has the advantage of not imposing an assumed pattern of depreciation.

### **Empirical Concerns**

As in any study of firm strategy, we have important empirical concerns to address. First, there is likely to be considerable firm heterogeneity in the production of invention and product innovation not captured by the variables in our model. To explicitly account for unobserved heterogeneity, we include firm-level (conditional) fixed effects. To the extent that there are inherent differences between firms' inventive performances that are constant across the period studied, the fixed effects will condition these differences out of the estimation.

Second, the choice and opportunity to engage in co-invention with physicians is potentially endogenous to the inventive performance outcomes studied here. This issue is more difficult to account for. Including firm-level fixed effects helps alleviate this potential source of bias to the extent that the drivers of endogeneity are constant across the time period studied. For example, if "better" firms attract physicians interested in engaging in collaborative research, and this is a permanent characteristic of the firm, then exploiting changes over time for each firm avoids bias

associated with endogeneity. In addition, to the extent that firm-physician co-inventions represent ideas that physicians bring to firms, the timing of such inventions is not likely to be endogenous to the inventive activities of the firm. This scenario appears to be the most common, according to our discussions with physicians. However, it is also likely that medical device companies seek out consulting physicians to participate in firm R&D activities. If the drivers of collaboration change over time in a way that is correlated with our outcome measures, estimation that fails to account for this may produce biased estimates.

### **ANALYSIS & RESULTS**

Sample summary statistics are presented in Tables 1-3. There is considerable variation across variables in the model. Physician co-invention was common for the sample firms, representing 24% of firm patents, but the degree of co-invention varied considerably across firms. Table 3 provides summary statistics for selected companies in the sample in order to provide additional insight into the data. Medtronic, a well-known medical device company, is one of the largest firms in our sample. This firm co-invented 15% of its patents with physicians. Some smaller firms, such as Biomagnetic Tech., developed more of their patented inventions with physicians; others, such as Luther Medical Products, developed fewer patents with physicians. It is important to note that the identification in our empirical analysis does not depend on the substantial differences across firms – these differences are conditioned out in the fixed-effect estimation. Instead, our estimation makes use of within-firm variation over time to identify the effects of physician collaborations on inventive outcomes.

In order to provide more quantitative evidence about the physician-firm collaborations represented by co-invention activity in our sample, Tables 4a and 4b summarize the primary employment settings and specialties of the doctor co-inventors in our data. Note that many of the doctor co-inventors are employed in group practice (38%) or solo practice (24%). Only 5% are in medical schools. The physician co-inventors come from a diverse set of specialties. Physicians in various surgery specialties are well represented, collectively forming the largest contingent in the data (about 15%).

#### **Impact of Physician Collaborations**

Results of estimates testing our two hypotheses are presented in Table 5 (for the patent count and citation-weighted patent count) and Table 6 (for the number of approved product innovations).

For each dependent variable, we report our base specification, using the one-year-lagged value of physician collaborations, and also an extended model including five lags of physician collaborations in order to examine the time profile of the effects. Note that the use of the Poisson quasi-maximum likelihood fixed-effects model necessitates dropping firms with one observation (i.e., one year of data, which is the case for 26 firms) or with all zero outcomes (i.e., firms with no patents during the sample period, no cited patents, and no new FDA-approved products). For this reason, the number of observations and firms included varies across the dependent variables.

In all cases, prior physician collaborations are associated with an increase in the inventive performance outcome variable. The one-year-lagged physician collaboration measure is significant and positive in all estimations. Firms that collaborated with physicians in the recent past generated more patents, more citation-weighted patents, and more new approved products. Holding every other variable at its mean, an increase from the mean (1.15) to the mean-plus-one standard deviation (4.51) physician co-inventions is associated with an increase of 5 citation-weighted patents (based on Model 3 in Table 5) and an increase of 0.66 in the number of innovations (based on Model 1 in Table 6).<sup>14</sup> This provides evidence consistent with hypotheses 1 and 2. In the models including five years of lags, joint tests for significance in each case support the joint significance of the five measures at the 1% level. Importantly, in all cases, it is collaborations in the most recent two years that have an effect on firms' innovative outcomes, a reasonable result given that product cycles in the industry can be as short as 18 months.<sup>15</sup>

It is interesting to note that the control for firms' accumulated technical knowledge stock (*KnowledgeStock*), measured by the depreciated stock of patents in the prior five-year period, is a significant predictor of new inventions generated by the firm (Table 5), but is not a significant predictor of new product innovations.<sup>16</sup> Likewise, firms' product-market knowledge stock (*ProductStock*), measured by the depreciated stock of approved innovations in the prior five-year period, is a significant predictor of new product innovations, but not of new inventions. These results provide confirmatory evidence that technical and product-market knowledge are in fact

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<sup>14</sup> The calculation of the implied changes in the dependent variable are calculated using the Clarify software (King et al. 2000; Tomz et al. 2003).

<sup>15</sup> The positive and significant coefficient on the five-year-lagged doctor collaborations is most likely picking up the underlying knowledge stock of the firm. We do not view this as an indication that collaborations from five years ago are a significant driver of current inventive outcomes.

<sup>16</sup> Note that the accumulated stock of technical knowledge is not significant in the equations including five years of lagged doctor collaborations because it is highly correlated with the five-year-lagged value.

distinct and contribute differently to the discovery (i.e., invention) and development and commercialization (i.e., innovation) processes.

### **Robustness Check**

Since the two focal outcome measures -- counts of citation-weighted patents and approved product innovations -- are expected to be related, we pursued further analysis to examine the potential that the increase in product innovations was due to the increase in inventive outcomes, rather than being separately attributable to physician collaboration. In other words, we tested for the mediating role of citation-weighted patents in the analysis of product innovations. Results reported in Model 3 of Table 6 demonstrate that although citation-weighted patents do positively predict product innovations, as expected, the effect of physician collaborations on innovative outcomes is not substantially diminished with the inclusion of this control. This finding is consistent with medical device companies gaining two different types of knowledge from physicians: technical knowledge that is most useful for creating new inventions, and product-market knowledge that helps firms develop inventions into commercial product innovations.

As an additional robustness check, we estimated equations for our focal dependent variables (Modified Citation Weighted Patents and Number of Innovations) together in a system of equations using Zeller (1962) seemingly unrelated regressions to account for possible correlation in the error terms across the two equations. Coefficient estimates confirm the results reported here, and significance levels are greater due to gains in efficiency from joint estimation. A Breusch-Pagan test of independence rejects the null of independent equations.

To further explore the effect of physician collaborations on new product innovations, we exploit an additional aspect of the FDA approval data. Each approved device is assigned to a product category by the FDA, and each product category is classified into Class 1, 2, or 3 depending on the risk level and regulatory oversight required, as described above. We are therefore able to create three separate dependent variables representing the count of innovations in each of the three regulatory classes generated by a firm in a given year. Using these separate counts of innovations, we can investigate which types of innovations are influenced the most by physician collaborations. Although this analysis is limited by the fact that each estimation includes only firms that generate at least one innovation in the relevant class during our sample period -- which amounts to 40 firms for Class I, 82 firms for Class II, and 27 firms for Class III

devices -- the results are still informative. Results reported in Table 7 indicate that collaboration with physicians is significantly and positively associated with product innovations in Classes II and III, but not in Class I (the simple devices like tongue depressors). Increasing both the one-year and two-year-lagged number of physician collaborations from 1 to 2 is associated with an increase in Class II devices of 0.28 and an increase of Class III devices of 0.14, holding all other variables at their (sub-sample appropriate) means. As expected, physicians appear to contribute to the more complex and substantial product innovations, where accumulated experience can provide superior knowledge based on learning by using. Longer lags of collaborations are more significant for Class III devices, consistent with the expectation that these more complicated devices take longer to develop.

### **Empirical Extensions: Exploring the Differential Benefits of User Collaborations**

The results of our main analysis support the argument that collaborations with physicians positively influence firms' subsequent inventive and innovative performances. As an extension, we also explore which firms benefit the most from these collaborations and why. After all, the foundation of strategic management lies in explaining heterogeneity in performance across firms (Barney 2001), and theories such as the resource-based view of the firm argue that firm performance varies due to underlying differences in the resources and capabilities of the firm (Wernerfelt 1984; Dierickx and Cool 1989; Amit and Schoemaker 1993; Barney 2001). The question that remains unanswered by our analysis so far is: If working with users is valuable, then why do only select firms develop capabilities to collaborate with physicians?

A more nuanced theory of competitive advantage recognizes that particular capabilities and strategies, even those that provide competitive advantage to some firms, are not equally valuable in all industry contexts or to all firms. The value of a given strategy to a particular firm depends on both the competitive environment in which the firm operates and on the firm's set of existing capabilities and resources. While a comprehensive test of this assertion is beyond the scope of the paper, we briefly consider two important firm-level variables that may influence the benefits of collaborations with users: (1) the novelty of the technology areas in which the firm works; and (2) the firm's internal research and development expenditures.

First, the novelty of the technologies that the firm is working with is one important aspect of the firm's competitive environment. User insights regarding the desirable characteristics of

technology and the anticipated size of market demand are expected to be more valuable, and more difficult for firms to develop internally, especially for products in less-established markets (Shah and Tripsas 2007; Tripsas 2008; Chatterji and Fabrizio 2009). In order to measure the degree to which an area of technology is more established or more uncertain, we use data from the USPTO to establish the age of the technology areas in which the firm is inventing. The USPTO evaluates the classification system used for patents on a quarterly basis. When a new technology emerges, patents are initially allocated to existing classes. When the new technology area becomes sufficiently significant, the USPTO recognizes it with a separate class. Pre-existing patents that belong in the new class are re-assigned to reflect the new classification scheme. The establishment date of a technology area therefore may post-date the application (and even grant) date of patents within that area. We use establishment dates at the primary and subclass level to determine the age of each technology area in each year. Our firm level measure is the weighted average (with weights equal to the number of patents) of the ages of technology classes in which the firm patents (*CLASSAGE*). This measure reflects whether the firm is working in more or less established areas of technology.

Next, the firm's own R&D intensity provides a rough measure of the firm's existing capabilities in developing new ideas and integrating knowledge from outside of the firm. We might expect that firms that perform more R&D will benefit more from collaborations with users since these companies are better able to identify and access valuable extramural knowledge. On the other hand, firms that do little internal R&D might rely on collaborations to generate new ideas, substituting user collaborations for internal R&D investment.

**Testing for Differential Benefits -- Random Parameters Model.** To empirically investigate these sources of firm heterogeneity, we build on a nascent literature in empirical strategic management research (Chung and Alcácer 2002; Knott 2008; Pacheco-de-Almeida et al. 2009) and estimate a random parameters Poisson model, using the LimDep 9.0 software package created by William Greene. Conceptually, the random parameters model is a generalization of a fixed-effects model. While the fixed-effects model allows the coefficient on the constant term to differ across subjects, the random parameters model allows for a subject-specific coefficient on any or all of the explanatory variables. In our context, this allows the

exponents in the Cobb-Douglas production function (presented above) to differ across firms. The parameter vector in the random parameter model is:

$$\beta_i = \beta^0 + \Delta z_i + \Gamma v_i$$

Where  $\beta_i$  is the random parameter vector for subject  $i$ ,  $\beta^0$  is the vector of means of the distributions for the random parameters,  $\Delta z_i$  captures the effect of subject-specific variables contained in  $z$  on the coefficients, and  $\Gamma v_i$  is the covariance matrix of the random parameters ( $\Gamma$ ) multiplied by the vector of unobservable latent random terms ( $v_i$ ), which are mean zero and assumed to be normally distributed (Greene 2007).

This model allows us to perform several empirical analyses that are useful in this study and in empirical strategy research more generally. First, one can test for the significance of variance in the firm-specific components of each coefficient to determine whether there is in fact a heterogeneous relationship between that variable and the outcome measure. Second, one can specify observed variables ( $z_i$ ) expected to be correlated with the firm-specific coefficients, and thereby test for the underlying drivers of the heterogeneity across firms.<sup>17</sup> Finally, and of critical importance in the management of innovation literature, the random parameters model explicitly allows for differences in productivity across firms and thereby avoids bias associated with imposing a common coefficient for all firms. This is particularly relevant for testing the interaction of R&D and other variables, such as the “spillover pool” created by universities or other firms’ R&D, when evaluating the “absorptive capacity” hypothesis. For example, in Knott (2008), firms differ in their marginal productivity of R&D, and, as one would expect, more productive firms invest more in R&D. In a random parameter model of sales on R&D expenditures, the coefficient for R&D differs across firms. However, in a typical regression model where the coefficient for R&D is constrained to be constant across subjects, an included regressor that is correlated with the level of R&D investment will generate a biased coefficient.

To the extent that firms which benefit more from user collaborations engage in more collaborations (as we would expect, assuming that the marginal costs of physician collaboration are not correspondingly greater for these firms), an empirical model including the interaction of physician collaborations with other conditioning variables without allowing for firm-specific coefficients will bias the coefficients on the interaction terms upward. For example, an

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<sup>17</sup> Random parameter models are also useful for testing predicted correlations across firm-specific coefficients. See for example Pacheco-de-Almeida et al. (2009).

interaction of physician collaborations with the firm's R&D intensity might result in a significant and positive coefficient that would appear to indicate complementarities between these two activities. This result could, however, be a product of the varying marginal benefits of physician collaboration (or firm R&D). Employing a random parameter model avoids this problem.

We estimate a model allowing firm heterogeneity in both the effect of physician collaborations and the productivity of the firm's own R&D. The results from the random parameters model provide estimates for both the means and standard deviations (across firms) of the parameter estimates.<sup>18</sup> Tables 8 and 9 report these estimates for the number of patented inventions and the number of FDA approved innovations, respectively, generated by the firm.<sup>19</sup> Column 1 reports the estimated means of the coefficients, and their standard errors. Column 2 reports the standard deviations of the coefficient estimates and the standard errors for these estimates. We first note that our primary finding that inventions and innovations increase with physician collaboration is robust to estimation with this much more flexible model. The advantage of this method is that we can also see that the standard deviation (i.e., the variance in the estimated parameter across firms) is also significant for both physician collaborations and the firm's R&D expenditures, indicating significant heterogeneity across firms. Figures 1 and 2 provide graphical depictions of the firm-specific coefficients on physician collaborations for each firm, as well as their 95% confidence interval. While on average firms benefit from these collaborations, the impact varies across firms and some firms do not benefit at all.

We estimate each model again to include measures of the average age of the technology classes in which a firm patents and firm R&D intensity in the  $z_i$  vector, and test for the significance of these variables as predictors of the firm-specific coefficients on physician collaborations.

Consistent with (Greene 2007), we use firm means for the variables in  $z_i$ . Referring back to the equation above, this process generates estimates of parameters in the vector  $\Delta$ , including in this case the relevant coefficient for each observable characteristic for each of the random parameters. Columns 3 through 5 in Tables 8 and 9 report the results of these estimates. Note that column 5 in each table reports the estimates for the  $\Delta$  parameters.

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<sup>18</sup> Following standard practice, we allowed 100 iterations.

<sup>19</sup> Attempts to estimate a Poisson random parameters model for the citation-weighted patents failed to converge, possibly because this variable has a substantial range. This variable is similar to a continuous variable with a significant number of zeros. Due to the similarity of results using the simple patent count and the citation-weighted patent measure (as reported in Table 5), we are comfortable reporting only the results for the patent count in this section.

For the number of inventions (Table 8), both the technology-class age and the firm's R&D intensity are negatively correlated with the firm-specific beta on physician collaborations. This result is consistent with the expectation that physician collaborations have a larger positive effect on inventions in newer technology areas, where firms' accumulated knowledge is less relevant. It also suggests that physician collaborations have a larger positive effect for firms that conduct less of their own R&D, suggesting potential substitution between internally developed and externally sourced invention-generating knowledge. For the number of innovations (Table 9), the effect of physician collaboration is more pronounced for firms focusing their innovative efforts in newer technology areas and for firms with higher R&D intensity. We discuss these results in the following section.

## **DISCUSSION**

In light of the existing work on the value of extramural knowledge sources and the substantial importance attributed to users as sources of innovative knowledge, understanding the impact of corporate strategies to tap this unique resource is particularly important. We find that companies benefit from collaborating with users, in terms of both their subsequent inventive and innovative outputs. Furthermore, we find that the benefits derived from collaboration depend on the technological environment and firm capabilities. The effect of user collaboration is greatest for firms that are focusing their research efforts in areas of new, rather than established, technologies. This finding is consistent with the expectation that users help firms overcome the constraints of local search by contributing new ideas outside of established research areas, and that users can provide market knowledge that is particularly valuable in new and uncertain technology areas.

The evidence also suggests that firm research is complementary to users' market demand knowledge in developing commercialized innovations. This finding is consistent with users assisting in product development by providing feedback and input on market needs and desirable product characteristics, which in turn allow a firm to more effectively craft innovative products from their set of inventions. Interestingly, the opposite relationship is found for the development of new inventions, suggesting that users' technical knowledge is a substitute for the firm's own research in terms of identifying novel inventions. While further research will be required to understand this finding, potential gains from absorptive capacity are outweighed by the

substitution of knowledge. This may be due to the nature of extramural knowledge in this case. The product ideas contributed by physicians are typically technical and codified rather than based on a deep understanding of scientific knowledge.

This research makes several important contributions to the existing literature on managing innovation and sourcing extramural knowledge. Our results support the notion that users should be included in a broader conception of “open innovation” (Chesbrough 2003), whereby firms take advantage of a variety of extramural sources of knowledge, including other firms and universities. Future research might consider whether firms benefit more and for a longer period of time from accessing several extramural sources with equal intensity or from concentrating on a specific source, for example other firms, universities, or users.

We find that collaboration with product users can benefit firms beyond the project level (Lilien et al. 2002), and influence longer term corporate invention and innovation. The prior work on extramural knowledge has rarely documented the long-term impacts of knowledge sourcing, and previous work on user innovation has not documented the long-term impacts of corporate-user interactions. Thus, our results imply that collaborations with users might be even more valuable to firms than the previous literature indicated. We also demonstrate that these benefits will not be equal across firms and will depend on firm-level characteristics, an important insight for future work on corporate-user interactions and on the impact of extramural knowledge sourcing more generally.

Next, we explicate two contributions of user knowledge that benefit firms: (1) technical knowledge leading to enhanced inventive performance and (2) market knowledge leading to improved product-market innovation outcomes. As Schumpeter (1934) first pointed out, there is a crucial distinction between invention and innovation, and we find that user knowledge can be helpful in supporting both. This is an important theoretical distinction between users and other sources of extramural knowledge (Saxenian 1990; Mowery et al. 1996; Powell et al. 1996; Almeida and Kogut 1999; Stuart 2000; Ahuja and Katila 2001; Cohen et al. 2002; Grant and Baden-Fuller 2004) and is driven by the unique knowledge acquired by users through experience using a particular product.

Furthermore, the literature on innovation has focused more on the “technology push” drivers of innovation, and less on the “demand pull” drivers (Mowery and Rosenberg 1979). Part of this emphasis on the technological inputs has been the dual recognition that (a) important

technical knowledge often resides outside the boundaries of the firm, and (b) a firm's ability to access and exploit this knowledge is enhanced by firm investments in collaborative research activities. Our work suggests that knowledge about market demand also shares these two characteristics. First, knowledge about complex demand characteristics, including predicting market needs and anticipating optimal innovation characteristics, often resides outside of the firm. In fact, firms are unlikely to develop this knowledge via internal research activities precisely because such knowledge is based on the sort of experiential learning that most often occurs during the intensive use of a product and participation in the user community. Users are therefore a critical source of the knowledge needed to guide "demand pull" innovation. Furthermore, accessing this knowledge through research collaborations with users provides the firm with a competitive advantage in their inventive and innovation processes.

### **LIMITATIONS**

There are important limitations to our work. First, FDA approval is not necessarily the best measure of market success for new product innovations. Future research should consider whether collaboration with users leads to increased sales or profits related to a particular product. Such an effect, if demonstrated, could be due to both improvements in the quality of product innovations and the potential exploitation of physicians as a marketing mechanism, regardless of the innovation quality.

In addition, while most of the prior literature on user innovation has emphasized the importance of lead users and their interactions with firms (von Hippel 1986; Urban and von Hippel 1988), we do not explicitly identify lead users in our study. It is reasonable to assume that physicians that patent with medical device firms (our entire sample of users) might be an important set of lead users, but there are likely many other lead users who do not patent and likewise many users who do not offer particularly valuable insights to firms. Further research could identify lead users in this industry and demonstrate the differential benefits of collaborations with these individuals as opposed to generic users.

Next, it is important to test these ideas beyond the medical device industry, where users are likely to be especially important. For example, it would be interesting to test for heterogeneity across industries in the degree to which firms can benefit from collaboration with users. Additionally, we are unable to separately measure the components of user knowledge that are

related to invention versus innovation. Rather, we are only able to observe the distinct impact on subsequent firm patents and products. Future research, likely based on field interviews, might uncover methods to classify various aspects of user knowledge at a micro level.

Furthermore, we do not have data on the costs of collaborating with users, which would be a useful counterweight against which to measure the benefits described in this paper. Future work might estimate these costs by surveying firms and physicians and examining the regulatory oversight of firm-physician relationships. Recent pending legislation has the potential to raise the costs of collaboration in the hopes of guarding against conflicts of interest (Chatterji et al. 2008).

Finally, there are two potential issues with our measure of firm-physician collaborations. The first is that we cannot measure the underlying degree of collaboration or effort expended in collaborating with physicians. The co-inventing measure that we do have represents *successful* collaborations with physicians, at least to the degree that a patentable invention resulted. We do control for the level of successful invention by the firm using the firm's own patented inventions, and therefore the coefficient on physician collaboration indicates the benefits of involving a physician in successful research projects, above and beyond the firm's own level of success. Second, firm-physician collaborations likely represent an endogenous choice of the firm. To the extent that the drivers of this choice vary over time and are correlated with the subsequent inventive outcomes studied here, our estimates may be biased. While prior work has suggested that some firms may value extramural knowledge more highly than internal knowledge (Argote et al. 2003), there may be other reasons for the patterns of collaboration observed in our data. Future research should explore why some firms draw on more extramural knowledge than others and whether the determinants of this strategic choice are primarily permanent aspects of the firm (such as location) or characteristics that change over time (such as research productivity).

## CONCLUSION

Our work extends the literature on the benefits of accessing extramural knowledge sources by suggesting that firms may experience long-term benefits from tapping into the knowledge of product users. The benefits are evident in both creating novel inventions and bringing new innovations to market. Importantly, users contribute different types of knowledge associated with invention (technical knowledge) and product innovation (market demand knowledge). As firms develop capabilities in combining insights from users with complementary knowledge generated

internally, the result may be a substantial competitive advantage in generating superior innovations.

However, we have also demonstrated that all firms will not benefit equally from open innovation strategies, even if these activities are beneficial on average. This point is often overlooked in empirical strategic management research. Some firms, whether due to their research focus or complementary activities, may find it more beneficial than others to collaborate with users and develop capabilities in doing so. The challenge for future scholarship will be to evaluate the contextual value of these capabilities (Barney 2001, Peteraf 1993), and their influence on sustained competitive advantage.

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**Table 1:** Summary statistics

N=767 firm-year level

	Mean	St Dev	Min	Max
Cite Weighted Patents	102.92	237.57	0	1893
Modified Cite Weighted Patents	70.14	164.46	0	1232
Number Innovations	3.94	7.71	0	70
Lagged Doctor Collaborations	1.15	3.42	0	40
Class Age	4.41	6.28	-19	54
Knowledge Stock	10.52	27.49	0	291.58
Product Stock	9.38	17.89	0	17.76
Lagged Employees ('000)	2.12	7.52	0.01	65.9
Lagged R&D (M)	16.42	42.20	0.01	345.00
% Company Patents w/ DR	24%	33.25	0	100%

**Table 2:** Correlations

		1	2	3	4	5	6	7	8
1	Cite-Weighted Patents								
2	Modified Cite Weighted Patents	.96							
3	Number Innovations	.57	.55						
4	Lagged Doctor Collaborations	.50	.43	.40					
5	Class Age	-.11	-.10	.00	.01				
6	Knowledge Stock	.61	.60	.54	.79	.03			
7	Product Stock	.45	.46	.78	.42	.05	.62		
8	Lagged Employees	.35	.35	.72	.25	.05	.44	.71	
9	Lagged R&D	.40	.38	.68	.41	.06	.63	.78	.84

**Table 3:** Statistics for select sample companies

	Avg Annual # employees ('000)	Avg Annual # Patents	Avg Annual # FDA approved Product	Avg Annual # Doctor Patents	Avg Annual % Pats w/ Doctor
Medtronic	8.92	63.46	15.46	11.23	15.81%
Stryker	2.80	4.31	6.92	1.00	17.79%
Biomagnetic Tech	0.10	1.67	0.56	0.44	25%
Luther Medical Prods.	0.04	2	0.92	0.08	9%

**Table 4a**

Doctor co-inventor primary employment

<b>Present Employment</b>	<b>% Doctor Co-inventors</b>
Group Practice	38
Self-Employed Solo Practice	24
No Classification	13
Medical School	5
Other Non-Patient Care	5
Non-Gov't Hospital	4
Two Physician Practice - Owner	3
Locum Tenens	2
City/County/State Hospital	2
City/County/State Other	1
Vet Admin (Fed Gov't Hospital)	0.5
Fed Gov't Hospital Other	0.5
HMO	0.4
Other Patient Care	0.2
Army (Fed Gov't Hospital)	0.1

**Table 4b**

Doctor co-inventor specialty

<b>Specialty</b>	<b>% Doctor Co-inventors</b>
Emergency Medicine	12
Internal Medicine	11
Cardiovascular Disease	9
Diagnostic Radiology	8
Anesthesiology	6
Family Practice	6
Orthopedic Surgery	5
General Practice	3
General Surgery	3
Unspecified	3
Thoracic Surgery	3
Psychiatry	3
Public Health & Gen Preventive Med.	2
Cardiac Electrophysiology	2
Allergy	2
Obstetrics & Gynecology	2
Ophthalmology	2
Gastroenterology	2
Pediatrics	1
Plastic Surgery	1
Vascular Surgery	1
Other Specialty	1
Neurological Surgery	1
ALL OTHERS	10 total

**Table 5:** Firm patents as a function of doctor collaborations\*\*\*

	(1)	(2)	(3)	(4)	(3)	(4)
	Count of Patents		Citation Weighted Patents		Modified Citation Weighted Patents	
<b>ln_DrPats<sub>t-1</sub></b>	<b>0.174</b>	<b>0.183</b>	<b>0.206</b>	<b>0.209</b>	<b>0.174</b>	<b>0.182</b>
	<b>(0.084)*</b>	<b>(0.085)*</b>	<b>(0.067)**</b>	<b>(0.064)**</b>	<b>(0.070)*</b>	<b>(0.066)**</b>
<b>ln_DrPats<sub>t-2</sub></b>		0.043		<b>0.151</b>		<b>0.174</b>
		(0.069)		<b>(0.065)*</b>		<b>(0.088)*</b>
<b>ln_DrPats<sub>t-3</sub></b>		-0.005		-0.013		0.025
		(0.051)		(0.055)		(0.064)
<b>ln_DrPats<sub>t-4</sub></b>		0.097		-0.009		0.067
		(0.067)		(0.088)		(0.086)
<b>ln_DrPats<sub>t-5</sub></b>		0.007		0.168		0.190
		(0.064)		(0.074)*		(0.075)*
<b>ln_KnowledgeStock<sub>t-1</sub></b>	<b>0.385</b>	<b>0.322</b>	<b>0.234</b>	0.136	<b>0.336</b>	0.170
	<b>(0.124)**</b>	<b>(0.148)*</b>	<b>(0.104)*</b>	(0.138)	<b>(0.102)**</b>	(0.134)
<b>ln_ProductStock<sub>t-1</sub></b>	0.030	-0.016	0.031	-0.025	0.015	-0.079
	(0.106)	(0.113)	(0.119)	(0.113)	(0.124)	(0.110)
<b>ln_Employ<sub>t-1</sub></b>	<b>0.394</b>	<b>0.425</b>	0.192	0.242	0.210	0.280
	<b>(0.123)**</b>	<b>(0.125)**</b>	(0.160)	(0.164)	(0.197)	(0.206)
<b>ln_R&amp;D<sub>t-1</sub></b>	0.052	0.058	0.111	0.135	0.159	0.214
	(0.102)	(0.109)	(0.115)	(0.120)	(0.137)	(0.148)
Year indicators	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	739	739	739	739	733	733
Number of firms	100	100	100	100	99	99

Standard errors in parentheses; \* significant at 5%; \*\* significant at 1%

\*\*\* Results show that inventive performance increases following doctor collaborations.

**Table 6:** New product approvals as a function of doctor collaborations\*\*\*

	(1)	(2)	(3)
<b>ln_DrPats<sub>t-1</sub></b>	<b>0.215</b>	<b>0.182</b>	<b>0.157</b>
	<b>(0.076)**</b>	<b>(0.075)*</b>	<b>(0.071)*</b>
<b>ln_DrPats<sub>t-2</sub></b>		<b>0.126</b>	0.045
		<b>(0.063)*</b>	(0.074)
<b>ln_DrPats<sub>t-3</sub></b>		-0.069	
		(0.090)	
<b>ln_DrPats<sub>t-4</sub></b>		-0.144	
		(0.078)	
<b>ln_DrPats<sub>t-5</sub></b>		-0.081	
		(0.090)	
<b>ln_KnowledgeStock<sub>t-1</sub></b>	-0.004	0.046	-0.030
	(0.094)	(0.109)	(0.094)
<b>ln_ProductStock<sub>t-1</sub></b>	<b>0.236</b>	<b>0.258</b>	<b>0.222</b>
	<b>(0.057)**</b>	<b>(0.065)**</b>	<b>(0.076)**</b>
<b>ln_Employ<sub>t-1</sub></b>	0.375	0.329	0.266
	(0.156)*	(0.150)*	(0.153)
<b>ln_R&amp;D<sub>t-1</sub></b>	0.123	0.125	0.144
	(0.126)	(0.124)	(0.122)
<b>Modified CTWD Patents</b>			<b>0.001</b>
			<b>(0.000)**</b>
Year indicators	Yes	Yes	Yes
Firm Fixed effects	Yes	Yes	Yes
Observations	698	698	698
Number of firms	88	88	88

Standard errors in parentheses; \* significant at 5%; \*\* significant at 1%  
 \*\*\* Results show that innovative performance increases following doctor collaborations.

**Table 7: New product approvals by class as a function of doctor collaborations \*\*\***

	Class 1	Class 2	Class 3
	(1)	(2)	(3)
ln_DrPats <sub>t-1</sub>	-0.247 (0.206)	<b>0.185</b> <b>(0.070)**</b>	<b>0.370</b> <b>(0.218)^</b>
ln_DrPats <sub>t-2</sub>	-0.270 (0.219)	0.063 (0.078)	<b>0.362</b> <b>(0.254)^</b>
ln_KnowledgeStock <sub>t-1</sub>	-0.504 (0.315)	-0.011 (0.099)	-0.104 (0.170)
ln_ProductStock <sub>t-1</sub>	<b>0.683</b> <b>(0.167)**</b>	<b>0.188</b> <b>(0.082)*</b>	-0.042 (0.225)
ln_Employ <sub>t-1</sub>	0.418 (0.327)	0.224 (0.176)	0.494 (0.399)
ln_R&D <sub>t-1</sub>	<b>0.770</b> <b>(0.307)*</b>	0.130 (0.134)	0.066 (0.309)
Modified CTWTD Patents	0.001 (0.001)	0.001 (0.000)**	0.001 (0.000)
Year indicators	Yes	Yes	Yes
Firm Fixed effects	Yes	Yes	Yes
Observations	398	665	265
Number of firms	40	82	27

Standard errors in parentheses; \* significant at 5%; \*\* significant at 1%; ^ jointly significant at 5%

\*\*\* Results show that innovation performance gains from working with doctors are greatest for devices in Classes 2 and 3.

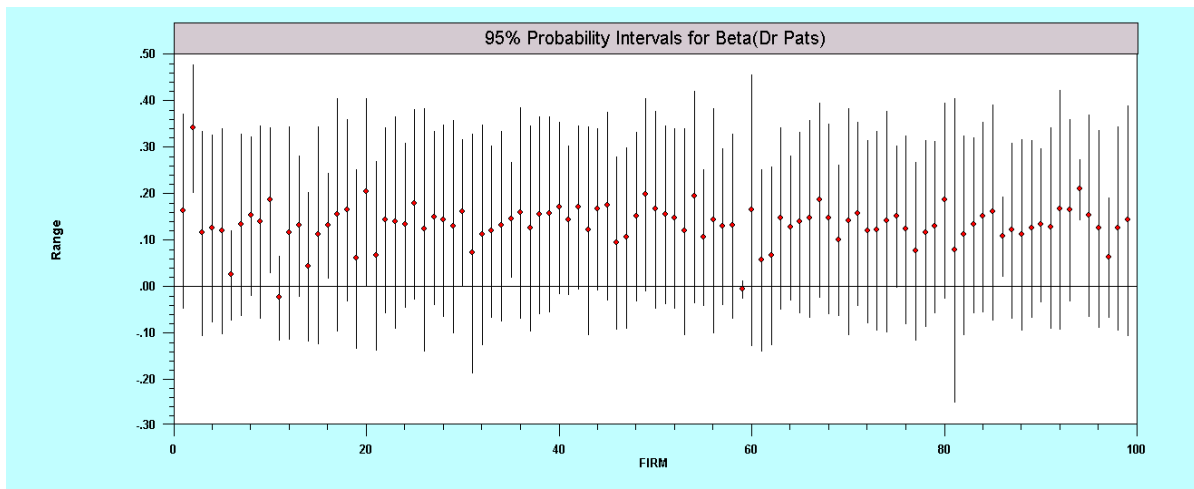


Figure 1: Firm-Specific coefficient on doctor collaborations – count of patents

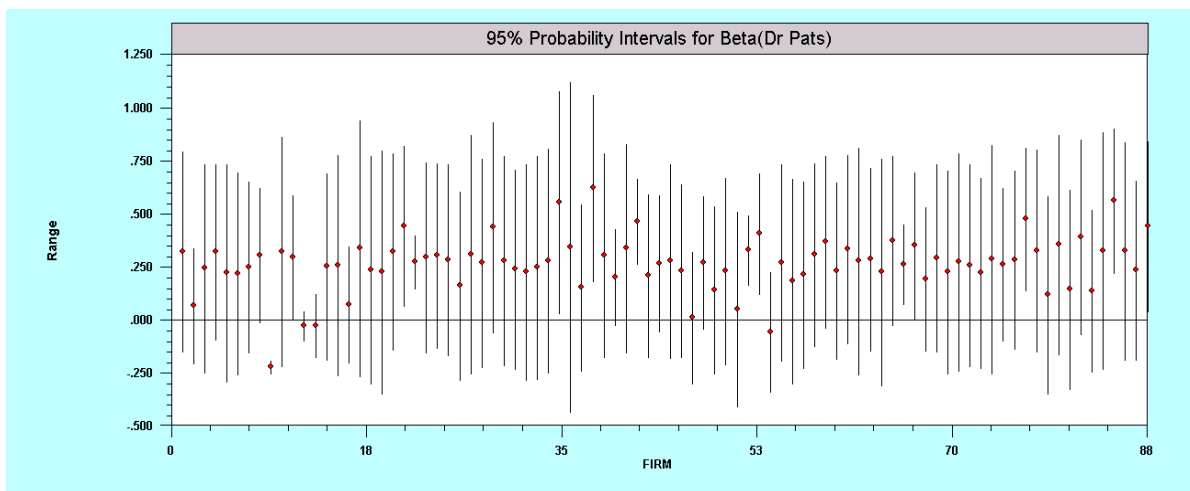


Figure 2: Firm-Specific coefficient on doctor collaborations – number of innovations

**Table 8:** Firm inventions as a function of doctor collaborations, random parameter model \*\*\*

	(1) mean	(2) s.d.	(3) mean	(4) s.d.	(5) z variables
<b>RANDOM PARAMETERS</b>					
ln_DrPats <sub>t-1</sub>	0.142	0.111	0.389	0.588	
	(0.023)**	(0.012)**	(0.042)**	(0.036)**	
ln_R&D <sub>t-1</sub>	0.165	0.371	0.220	0.124	
	(0.026)**	(0.017)**	(0.041)**	(0.008)**	
<b>NONRANDOM PARAMETERS</b>					
ln_KnowledgeStock <sub>t-1</sub>	0.369		0.394		
	(0.027)**		(0.027)**		
ln_ProductStock <sub>t-1</sub>	-0.023		-0.001		
	(0.020)		(0.024)		
ln_Employ <sub>t-1</sub>	0.274		0.233		
	(0.026)**		(0.035)**		
<b>Z PARAMETERS: DrPat</b>					
Technology Class Age					-0.044
					(0.008)**
Firm R&D Intensity					-0.006
					(0.001)**
<b>Z PARAMETERS: R&amp;D</b>					
Technology Class Age					-0.026
					(0.004)**
Firm R&D Intensity					-0.003
					(0.001)**
Year indicators	Yes		Yes		
Firm Fixed effects	Yes		Yes		
Observations	739		739		
Number of firms	100		100		

Standard errors in parentheses; \* significant at 5%; \*\* significant at 1%

\*\*\* Results show that invention performance gains from working with doctors are heterogeneous across firms, and greater for firms in newer technology areas and that are less R&D intensive.

**Table 9:** Firm innovations as a function of doctor collaborations, random parameter model \*\*\*

	(1) mean	(2) s.d.	(3) mean	(4) s.d.	(5) z variables
<b>RANDOM PARAMETERS</b>					
ln_DrPats <sub>t-1</sub>	0.289	0.247**	0.207	0.389	
	(0.037)**	(0.024)	(0.048)**	(0.033)**	
ln_R&D <sub>t-1</sub>	0.067	0.377**	0.136	0.203	
	(0.028)*	(0.020)	(0.044)**	(0.013)**	
<b>NONRANDOM PARAMETERS</b>					
ln_KnowledgeStock <sub>t-1</sub>	-0.062		-0.026		
	(0.036)^		(0.035)		
ln_ProductStock <sub>t-1</sub>	0.318		0.309		
	(0.039)**		(0.039)**		
ln_Employ <sub>t-1</sub>	0.246		0.187		
	(0.031)**		(0.041)**		
Modified CTWTD Patents	0.001		0.001		
	(0.000)**		(0.000)**		
<b>Z PARAMETERS: DrPat</b>					
Technology Class Age					-0.030
					(0.008)**
Firm R&D Intensity					0.008
					(0.002)**
<b>Z PARAMETERS: R&amp;D</b>					
Technology Class Age					-0.016
					(0.004)**
Firm R&D Intensity					-0.001
					(0.001)
Year indicators	Yes		Yes		
Firm Fixed effects	Yes		Yes		
Observations	698		698		
Number of firms	88		88		

Standard errors in parentheses; ^ significant at 10%; \* significant at 5%; \*\* significant at 1%

\*\*\* Results show that innovation performance gains from working with doctors are heterogeneous across firms, and greater for firms in newer technology areas and that are more R&D intensive.