Product-Service Bundling in

Manufacturing Firms

by

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ABSTRACT

Most advanced economies have evolved into service economies with the majority of their activity and jobs being in the service sector. The manufacturing sector is also going through a similar shift towards services. Manufacturers are increasingly complementing their products with new services in order to satisfy a broader array of customer needs and increase the value of their offerings. This shift has offered significant opportunities to the sector and the success of major firms such as IBM, Caterpillar, and Rolls-Royce in competing through services has been remarkable.

Despite the increased importance of services in the manufacturing sector, the academic literature is yet to investigate the many questions that arise under this new manufacturing paradigm. Perhaps for the same reason study of servitization is listed as a research priority in recent publications both in the field of service operations management and in the field services marketing. This dissertation covers three essays aimed at disentangling multiple aspects of the role of services in the manufacturing sector. The literature on the drivers and implications of transition towards services in manufacturing firms is limited. The three studies in this dissertation aim at shedding light on this issue.

Specifically, the first essay looks at the innovation benefits of service transactions with customers. This paper demonstrate the value of services in getting manufacturers closer to customers and allowing them glean useful information from their service interactions. The second essay investigates the antecedents of service strategy adoption. We suggest that the extant diversification theory does not fully explain servitization and this phenomenon represents a unique type of diversification, which is likely driven by

different factors. Through econometric analysis of financial data over a 27-year period, this study explores characteristics of product, firm resources, competition, and industry that encourage adoption of service strategies in manufacturing sector. Finally, the third essay takes a deeper dive and focuses on dealerships, as service centers, in the automobile industry. It investigates the role of dealerships in the success of automakers and explores dealership traits that are critical for market success of an automobile brand.

To Nasim, Maryam, Bahman, Samaneh and Soheil…

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ESSAY I

THE INFLUENCE OF MANUFACTURING SERVICES ON INNOVATION

ABSTRACT

This paper investigates the influence of manufacturer services on innovation. We propose that services in a manufacturing firm provide an additional channel of market intelligence facilitating knowledge transfer and innovation. Further, when the service has a high level of customer contact or knowledge intensity, it is a rich medium for obtaining ethnographic and context-rich knowledge of customers. By analyzing a panel of 1698 U.S. manufacturing firms over a 17-year period we find that as a manufacturer's service sales increase, its number of successful patent applications also increases in subsequent years. This relationship is positively moderated by firm and service-level traits that relate to the likelihood that knowledge is created, captured, and transferred between service and manufacturing. The results are robust across several methodological approaches.

INTRODUCTION

Recent years have witnessed increased service-oriented solutions being offered by product manufacturers (Neely, Benedettini, & Visnjic, 2011). Manufacturers increasingly provide services to accompany their products in order to satisfy a broader array of customer needs and differentiate themselves from the competition (Lusch, Vargo, & O'Brien, 2007). The success of large corporations such as IBM, General Electric, Caterpillar, Xerox and Rolls-Royce in the shift towards services highlights the potential of manufacturing service strategies (Cohen, Agrawal, & Agrawal, 2006; Kastalli & Van

Looy, 2013; Suarez, Cusumano, & Kahl, 2013). Caterpillar's service network, for instance, is at the core of its competitive advantage and has allowed it to fend off competition from Komatsu (Colvin, 2011). Academics and practitioners have promoted the benefits of service transition as a migration from product-centric to customer-centric business models (Fang, Palmatier, & Steenkamp, 2008). We define *manufacturer service offering* as the provision of services by an organization whose primary business activity is manufacturing products. A manufacturing firm (or unit) that has added services to its existing offerings is referred to as a *service-oriented manufacturer* (or unit). Recent studies of this phenomenon has been focused on investigating its financial implications (Fang et al., 2008; Kastalli & Van Looy, 2013; Suarez et al., 2013). In this paper, we advance literature by investigating the spillover effects of services on manufacturer's innovation performance.

Anecdotal evidence suggests that some companies have successfully used their service interactions to obtain market intelligence and improve their products. Information Technology (IT) services, for instance, are increasingly seen as innovation sources rather than cost centers (Nash, 2014). Boston Scientific, a manufacturer of medical devices, sends its IT professionals to customers at healthcare facilities to acquire knowledge and new product ideas. Apple Inc. uses explicit procedures for managing and utilizing the knowledge obtained from service interactions in their Genius Bar, the company's in-store technology support service. Our interview with the Genius Bar staff indicated that the repair crew were the first to discover the faulty camera design in iPhone 6 Plus devices (Apple.com, 2015). In another example, the after-sales service crew from W. L. Gore and Associates learned about a shortcoming in the design of vascular grafts during their interaction with the physicians who used the product. The grafts tended to kink when patients bent their elbows or knees, limiting blood flow. Relaying this information back to the company led to the design of a kink-resistant vascular graft which was subsequently patented and introduced to the market (GoreMedical.com, 2010).

These examples suggest that services may have a significant spillover effect on innovation. The knowledge gained from services also tends to be different from traditional methods of market learning as it is captured during co-production of the service and through deeper and situated connection with customers in real environment – similar to ethnographic learning. Inspired by this phenomenon, our study is focused on whether services systematically enhance learning and innovation in manufacturing environments.

It is not clear whether the insights obtained from service interactions can add significant value over and above what formal research and development achieves. Nor is it obvious whether this informal route of knowledge acquisition complements research and development or overlaps it, resulting in a substitutive relationship. The information obtained from services is likely unstructured and may not be readily translatable to innovative ideas. Additionally, offering services divides managerial attention and firm resources between products and services. This can increase scope of search for new ideas but will decrease scale and focus. In sum, logic alone cannot determine whether providing services may boost or hamper a manufacturer's innovation performance. Thus, we pose the following research question: *How does offering services influence manufacturer's innovation performance?*

Despite widespread industry adoption and some emerging academic research, there is not sufficient nor unambiguous empirical evidence addressing how services impact manufacturers' business (Bolton, Grewal, & Levy, 2007; Fang et al., 2008; Kastalli & Van Looy, 2013). Considering the costs and risks of migration to a service-oriented business model, further research is required to understand the implications of service offering by manufacturers and factors that "separate winners from losers" (Sawhney, 2006). A nascent stream of research in fields such as management, marketing and operations has begun to empirically investigate the impact of services on financial performance (Fang et al., 2008; Kastalli & Van Looy, 2013; Neely, 2008; Suarez et al., 2013). Yet, more nuanced implications of service strategies and different aspects of the role of services in a manufacturing context remain largely unexplored. Our study advances this literature by shedding light on a different facet of manufacturing services, i.e. their role in generating market and customer knowledge.

Our study also contributes to innovation and organizational learning literatures. In the past few decades, scholars have greatly advanced our understanding of the internal and external factors that influence corporate innovation and generation of new ideas (Cassiman & Veugelers, 2006; Chesbrough, 2003; Damanpour, 1991; Laursen & Salter, 2006; Phene, Fladmoe-Lindquist, & Marsh, 2006; Roy & Cohen, 2016). Scholars have argued that acquiring knowledge from external sources is a requisite for firm's success (Laursen & Salter, 2006; Rosenkopf & Almeida, 2003) and that customers are one of the most important sources external knowledge (Cohen, Nelson, & Walsh, 2002). The literature on user innovation (Chatterji & Fabrizio, 2014; Lilien, Morrison, Searls, Sonnack, & Hippel, 2002; Von Hippel, 1998) also explains why customer knowledge is valuable for firms. However, our understanding of the various mechanisms by which companies can access customer knowledge is limited. By addressing the role that services play in tapping into this source of knowledge, our study builds on and extends user innovation literature. We argue that services interactions with customers provide appropriate context for acquiring “sticky information” from customers (Von Hippel, 1994) and first-hand observation of their activities, mindset, and unarticulated needs. In doing so, we provide rationale and empirical support for why services can provide knowledge that is unique and non-overlapping with other methods of market research. We also demonstrate the conditions under which the service activities are more valuable in providing market knowledge and thereby enhancing organizational innovation.

We first develop a theoretical model, using organizational learning theory (Cohen & Levinthal, 1990; Huber, 1991; Levitt & March, 1988; March, 1991) to derive the our hypothesis linking service activity to innovation performance, and then derive supporting hypotheses involving contingencies with various firm and service-related variables. To test these hypotheses, we combine U.S. patents data with the S&P Capital IQ's Compustat North America database and construct a panel of 1698 publicly held manufacturers for the time period of 1990 to 2006. The data are analyzed using random effects negative binomial regression model. We further evaluate our analyses by a series of robustness and validity checks including the Hybrid method recommended by Allison and Waterman (2002), instrumental variable estimation, and Granger causality test (Granger, 1969, 1988; Wooldridge, 2012). The results indicate that when service sales of a manufacturer increase, its number of awarded patents also increases in subsequent years. We further find that the positive relationship between patents and service sales is greater for high-contact and knowledge-intensive services. We also demonstrate that the patent-service sales relationship is stronger when products and services co-exist in the same business unit within a firm. Finally, we find that the benefit of service activity for innovation is contingent upon environmental dynamism, with more dynamic environments rendering services more beneficial. Our findings imply that services can enhance market intelligence, yielding insights about product performance and helping to identify customer requirements. This enhanced knowledge can, in turn, be used to create new product innovations and associated patents.

THEORY

Services and Innovation

In this section, we examine the effect of a manufacturer's services on its innovation performance. Innovation is the "engine of economic growth" and the core of competitive advantage (Damanpour, 1991; Nagaoka, Motohashi, & Goto, 2010). It is widely held that a firm's success depends on its ability to acquire and exploit market knowledge (Day & Schoemaker, 2006). We argue that service offering allows manufacturers to connect with their customers in a different way and enhances their ability to acquire market knowledge by revealing hidden aspects of customer behavior. Service interactions are only one of many processes that firms can use to learn about its customers and their needs. We contend, however, that service interactions with customers generate useful knowledge that is different from what traditional methods of market research can produce.

To capture market knowledge, firms rely on various quantitative and qualitative methods such as analyzing sales and consumer behavior data, customer surveys, focus groups, interviews, product returns, and tracking social media. While these methods can provide insight into how to address existing customer needs, they may not be as useful for understanding unarticulated or complex customer needs, since the observation is outside of the contextual complexity of the customer's real world. These methods of market learning use different media for capturing market knowledge. Daft and Lengel (1986), in their seminal study on media richness, argue that performance improves if the complexity of the medium chosen to communicate matches the complexity of the task at hand. For equivocal and more complex tasks, where there are various and potentially conflicting interpretations to the available information, richer media such as face-to-face communication should be used. Conversely, for simpler, explicit and codified tasks, leaner media such as written memos are more suitable (Barnard, 1991; Daft & Lengel, 1986; Gattiker, Huang, & Schwarz, 2007). The theory also argues that media differ in richness depending on their ability to transmit multiple cues (e.g., vocal inflection, emotions, gestures), language versatility, immediacy of feedback, and personalization. Richer media enable transmitting complex information more quickly and effectively. Applying media richness theory to organizational learning, we can infer that learning about a phenomenon of interest (e.g. customer behavior) is affected by the medium used to obtain information about it. Richer media would allow the firm to receive richer and more complex information while leaner media only allow transmission of a limited space of information. For example, use of face-to-face communication with customer, as opposed to emails, allows the firm to receive information beyond words themselves, such as facial cues, emotions and socio-cultural characteristics of the customer. Similarly, field observation would have a larger capacity for capturing complex information, such as unique elements in the customer's environment, actual use of products, the role of a focal product within the broader frame of customer needs, as well as hidden and unspoken needs.

If the firm wants to develop innovative products and services, it has to understand potentially-unarticulated needs, embedded in the complexity of the customer's environment of use. Therefore, it needs to use richer channels of market learning. Most methods of market learning treat customers and their experiences in "solitude" rather than in the real environment where the environment, context, culture and shared understandings, interpersonal relationships and dynamics of events work together to form customer experience. Many interactions and contextual information would have to be ignored in the process of abstraction. Bruner (1991, 2009) refers to this approach to understanding the world as paradigmatic (a.k.a logico-scientific) method of knowing and sets it in contrast to narrative method of knowing. He explains that paradigmatic mode of knowing focuses on establishing universal truth conditions via abstraction of specific example to higher-level hypotheses and paradigms whereas the narrative knowing focuses on the specific conditions in which actions occur. The power of paradigmatic approach comes from its ability to find commonalities between events and aggregate many observations into a single law or theory that can be used to explain the world and make predictions. Having dominated Western intellectual inquiry (Rorty, 1982), paradigmatic approach governs market learning in many firms at the expense of other methods (Cayla & Arnould, 2013).

In making sense of reality, the paradigmatic method seeks to establishes universal truths and theories; and, in this process it would necessarily need to summarize the reality using a set of assumptions about the relevance and importance of different pieces of information. For example, a customer's purchase decision would be treated as "reflecting the behavioral disposition of a general category or as an instance of a general law" (Cayla & Arnould, 2013). In the process of constructing these customer categories the observer would have to ignore details and peculiarities of each customer action or decision to be able to see the commonalities. Though powerful, this approach will be less effective when the phenomenon of interest is complex and arises from interaction among many elements. The nonlinear dynamics in such systems gives rise to the butterfly effect where small differences correspond to large differences in the final outcome (Bar-Yam, 1997; Dooley, 2002; Dooley & Van de Ven, 1999). As a result, ignoring of details and context in paradigmatic methods may "encourage us to rush to conclusions about the whole on the basis of knowing only a few of the parts" (Fuller, 2001: 281).

Realizing these shortcomings, many researchers have concluded that understanding markets and customers, as complex phenomena, are not possible by entirely relying on paradigmatic methods of learning (Arnould & Price, 2006; Cayla & Arnould, 2013; Elliott & Jankel-Elliott, 2003). For example, Cayla and Arnould (2013) note the difficulty of the paradigmatic approach in challenging the preexisting mental models, and argue that the conventional methods of market research have failed to stimulate creativity in organizations and open up new avenues for innovation. This stream of research advocates the use of ethnographic approaches to market learning as an alternative founded upon the narrative mode of knowing. Ethnography is based on observing how people live their lives with no prior hypothesis or attempt to make logical conclusions (Anderson, 2009). Ethnographic market research tries to understand markets from the perspective of customers. In doing so, researchers would visit customers in the real environment and capture narratives of their daily experiences.

We argue that services have an ethnographic component, providing a new perspective into customer behavior above and beyond the traditional methods of market learning. Ethnography have been described as “observing people in naturally occurring settings” (Randall & Rouncefield, 2012). In many respects, observations made during service interactions with customers resemble ethnographic learning. Service interactions are powerful ways of understanding customers because the service provider and the customer engage in co-production, allowing the service provider to observe customers’ behavior, needs and experiences in the real environment – something that is difficult via conventional methods of market research. The service provider does not directly attempt to make logical conclusions about and abstractions of the customer behavior, but rather makes direct observations of people and things while performing the service. Corporate ethnography is founded upon the idea that events do not map to fixed meanings or experiences for customers. Rather, meanings are dependent on the context, culture, history and how events unfold over time. Therefore, it is necessary to observe markets from within, before an accurate conclusion could be made. Similarly, observations made during service interactions are situated and allows the provider to observe customers “in action”. For example, once a service engineer is dispatched to a customer site, they can observe the customer’s work environment, including the physical conditions, work behaviors, competencies or lack thereof, corporate culture, social interactions, and the context in which failures or successes occur. Swan and Bowers (1998) notes that shared meanings of things arise from the interactions between people as they work together, and act toward objects. Shared understandings are formed as people interpret and reinterpret events while they unfold over time. Examining individuals out of context, as is the case with conventional market research, will not paint a complete picture of customer behavior.

Services, in a manufacturing firm, facilitate learning by allowing the firm to access rich and situated knowledge of the customers that is not easily obtainable through conventional methods of market research. While the conventional methods seek understanding of the market by establishing universal rules and searching for conformity with a paradigm (Cayla & Arnould, 2013), the knowledge obtained from service is unique and can challenge the accepted paradigms.

Service transactions are ideal opportunities for customer interaction. The intangibility of service necessitates stronger interaction between the provider and the receiver (Jacobs, Chase, & Lummus, 2014). Hill (1977) conceptualizes services as a previously agreed-upon change in the condition of the service receiver or their belonging. From this perspective, services often involve significant customer input and reciprocal transfer of information between the customer and the provider (Karmarkar, 2015; Roels, 2014). Therefore, offering services could be a means for product manufacturers to strengthen contact with customers and tap into their sticky knowledge. Acting as an efficient market listening mechanism, services provide insights into the customers' mindset and preferences, unmet demands, and opportunities for new value proposition (Rothwell et al., 1974). Von Hippel (1998) explains that customer interaction contributes to the innovation process because customers have incentive to share knowledge with the firm in order to benefit from the resulting innovations, and have sticky knowledge that can only be transferred via close interaction. Often the users of a technology possess deep experience with and insight about it, which makes them key sources of feedback. Through services, firms can get closely in touch with their customers, engage them in the dialogue, and utilize their ideas and feedback for developing new product ideas (Foss, Laursen, & Pedersen, 2011).

In a competitive market, satisfying customers and meeting their explicit requirements are not enough for retaining market share. However, as noted by Leonard and Rayport (1997) customers' ability to provide new product ideas is constrained by their prior experiences and ability to imagine and describe potential innovations. Market researchers often find contradictions between what people say and what they do. Revealing these hidden demands requires richer contact with customers. For example, in an observation of operating rooms the researchers found that surgeons frequently moved their head, struggling for better visibility, while, they had asserted previously that light was sufficient in the room (Burrows, 2014).

Studies on manufacturing services also find links between service offering and knowledge generation. Kastalli and Van Looy (2013) argue that offering services significantly improves manufacturer's understanding of the customer's broader needs, which can be leveraged for designing new products and services. Customer interaction, achieved through services, facilitates the learning process and generation of ideas for filling the gaps between the existing offerings and ultimate market needs.

Services can also act as a medium for knowledge transfer in manufacturing firms. Suarez et al. (2013) point out that services can facilitate the transfer of product-related knowledge to customers, and knowledge of customers to corporate innovators. Moreover, service provision involves significant acquisition of new knowledge and resources, which can spill over from the service area to the product area. Kastalli and Van Looy (2013) assert that services in product firms can generate market and product knowledge, which can be utilized to enhance new product or service development. Gries et al. (2005) surveyed 173 German manufacturers in order to identify the sources through which manufacturers discover design flaws. The study indicates that a significant portion of the design flaws in product firms are discovered during service activities. The authors report that processing warranty claims and performing maintenance and repair services accounted for 43 percent of discoveries of design flaws, together, compared to only 25 percent being discovered during manufacturing and assembly processes. The study also highlights the role of customers in design improvement. Unsolicited customer feedback accounted for 36 percent of flaw discoveries, while customer surveys only revealed 5 percent of the flaws. Gebauer (2007) finds that the manufacturers who center their business strategy around customer support services also create a culture of innovation. These findings indicate that services and the resulting customer interaction can be particularly useful for acquiring knowledge and enhancing innovation.

Through these interactions firms gain a better understanding of how their offerings are performing under real-world conditions, to what extent they meet customer requirements, and what improvements are needed (Chatterji & Fabrizio, 2014). Services performed on products have a strong potential for uncovering design flaws and incompatibilities. Each used product is one that is tested by customers free of charge under real conditions. Product-related services, such as repair and maintenance, are an effective channel for obtaining used products and examining their performance. Sundin et al. (2009) support this argument contending that offering product services teaches the manufacturer how its products perform throughout their life-cycle. Services can also prompt development of other new services. Once a manufacturer adopts a service-oriented strategy it gradually discovers new avenues for serving customers and expands its services.

Services such as product consultation tap into the customers' complex behavior and mindset, i.e., how they make decisions and value products. Tuli et al. (2007) report that business counseling services accelerate organizational learning by providing a deeper knowledge of customer's operational environment and their specific needs. Similarly, installation and training services provide a better understanding of customers' operating conditions, capabilities, and shortcomings. This knowledge would lay the foundation for development of new services or products in future. Repair services help shed light on a product's performance in the field and its durability. Likewise offering other types of service can generate knowledge that can be leveraged for improving the product itself or developing totally new services. Sundin et al. (2009) provide multiple examples of how the reprocessing of used products, e.g. maintenance, repair and remanufacturing, has generated innovation ideas leading to significant product enhancement. These improvements encompassed product performance, ease of use, safety, ease of repair, maintainability and recyclability. To summarize, the experience and knowledge gained from developing and performing services can be leveraged to boost future innovation.

Hypothesis 1. For a manufacturer, increases (decreases) in the level of service offering are followed by increases (decreases) in the level of innovation.

We next present a series of hypotheses that act as moderators for Hypothesis 1. As illustrated in Figure 1.1, we conceptualize organizational learning as a process by which firms expose themselves to useful customer information, receive and make sense of the information, transfer the information within the organization and finally convert them to inventions (Cohen & Levinthal, 1990; Huber, 1991; Hurley & Hult, 1998; Zahra & George, 2002). Using this framework, we are able to analyze the boundary conditions for the main hypothesized relationship and derive factors that may enhance or weaken it. Service is viewed as a medium for customer interaction that exposes the firm to customer information. Consequently, service's contact intensity influences the level of exposure. Knowledge intensity of service will in turn influence the ability to capture useful and rich information and understand it. Understanding of customers, then, must be shared within the organization which is influenced by organizational structure. This learning process, however, depends on the organization's motivation to scan its environment and commitment to learning, which is hypothesized to differ across dynamic and stable environments. Finally, knowledge cannot drive invention unless the firm has the infrastructure and capability to innovate, which is controlled for via a variety of measures as it is out of study scope.

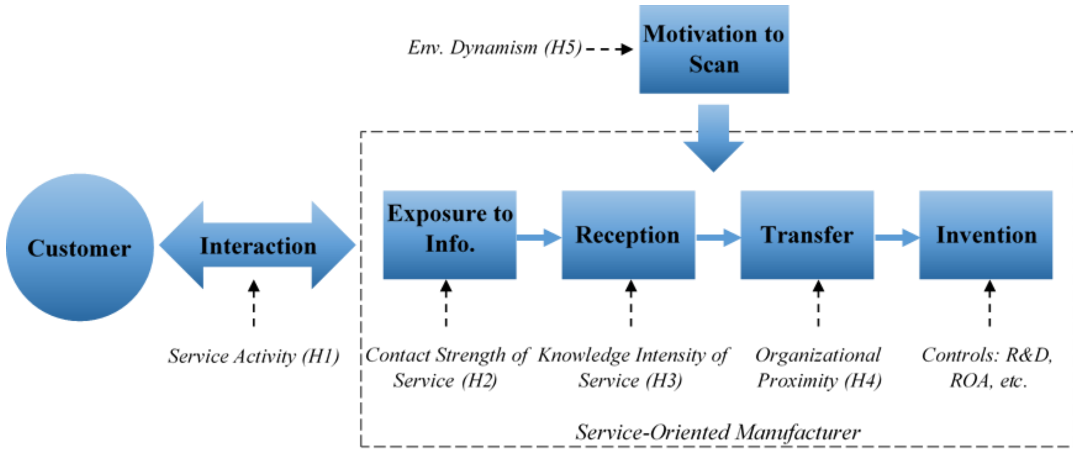

Figure 1.1. Process Model of Organizational Learning and Positioning of Hypotheses

High-Customer Contact Services

In analyzing the relationship between services and innovation, service content is an important factor, as different types of services may vary in their likelihood of generating new knowledge. Here, we focus on the customer contact dimension of services which has important implications for the richness of the service medium and organizational learning. We discussed that the increasing complexity of markets require that firms interact closely with their customers to obtain a rich understanding of their behavior, and that manufacturing services provide a context for such interaction. This characteristic is more pronounced for services with high customer contact. According to media richness theory media with higher personal contact are richer (Daft & Lengel, 1986; Huber & Daft, 1987). Personal contact allows parties to communicate a larger amount and variety of tacit and explicit information, obtain immediate feedback, and observe each other's personal circumstances. In a study of call center operations in insurance industry, Jerath et al. (2015) found that the informational value of a telephone conversation is three times larger than use of an online portal. They also found that customers prefer online contact for more structured inquiries and phone conversation when the inquiry is related to health incidents.

Ethnographic learning occurs within the frame of close human to human contact for an extended period of time (Arnould & Price, 2006; Mariampolski, 1999, 2006). High-contact services provide the opportunity for dialogue and information exchange to take place between customers and the organization, enabling it to identify unmet needs, spark novel insights, and develop new ideas. Such a dialogue allows the organization to understand customer cognition, emotion and behavior during the service experience. In essence, high-contact services enable absorption of tacit knowledge via observing the context to behavior and richer communication (Nonaka & Takeuchi, 1995). While, service with limited human-human contact, e.g. computerized services, will only be able to transfer explicit knowledge about customers.

Recognizing this issue, many leading brands have invested in expanding their physical contact with customers. Mercedes-Benz has, for instance, created “experience centers” throughout the world, in an attempt to better connect with its customers and understand how the company can create more value for them (Payne, Storbacka, & Frow, 2008).

Hypothesis 2. The positive relationship between services and manufacturer innovation is stronger for services with high customer contact compared to those with low customer contact.

Knowledge-Intensive Services

Another relevant dimension of manufacturing services is their knowledge intensity. Knowledge-intensive services are distinguished by the unique expertise and knowledge they rely on for providing customers with effective solutions. One of the key differentiators of such services is their knowledge-oriented employment structure. These services are largely delivered through engineers, scientists, and other highly educated persons (Eurostat, 2016). These individuals possess stronger cognitive abilities and deeper technical knowledge of the service being performed.

We also know that learning is more effective when new information is more closely tied to existing knowledge. An important driver of successful knowledge transfer is the recipient's existing stock of knowledge prior to the transfer (Galbraith, 1977; Ko, Kirsch, & King, 2005). In a study of process innovation in pharmaceutical industry, Pisano (1994) found employees learning from laboratory experiments is significantly stronger in environments where the underlying scientific knowledge is strong. Individuals working in a knowledge-intense environment will be better in learning and "connecting the dots" to arrive at innovative ideas and generate new solutions. Consequently, learning from external interactions should be stronger in knowledge-intensive service environments.

Knowledge-intensive services are also characterized by a higher level of interaction between the service provider and the customer compared to other services, which makes them a richer medium for understanding customer behavior (Daft & Lengel, 1986). Bettencourt et al. (2002) note that operation of knowledge-intensive services often require significant customization and customer involvement. Similarly, Roels (2014) demonstrates that as services become more customized, best outcomes are achieved when customers are highly involved in the service development process.

In a knowledge-intense service setting, exchange processes are complex, loosely structured and highly customized (Bettencourt et al., 2002). The desirable outcomes are less clearly defined and both parties need to engage in negotiation, discussion and knowledge exchange to shape the service (Mills & Morris, 1986; Skjølsvik, Løwendahl, Kvalshaugen, & Fosstenløkken, 2007). Xue and Field (2008) describe this exchange relationship as a coproduction process, where customer provides significant input and the service is produces through the joint effort of the customer and the provider. This tight interaction, in turn, can overcome the barriers to transfer of sticky knowledge and create a rich setting for learning (Szulanski, 2000; Von Hippel, 1994, 1998). Considering the above arguments, knowledge-intensive service settings provide more opportunities for learning and at the same time the employees have a higher learning capability. Therefore, we expect to see stronger innovation outcomes as the share of knowledge-intensive services increases for a manufacturer.

Hypothesis 3. The positive relationship between services and manufacturer innovation is stronger for knowledge-intensive services compared to non-knowledge-intensive services.

Product-Service Organizational Proximity

External knowledge acquisition effort needs to be complemented by efficient internal knowledge diffusion (Cohen & Levinthal, 1990; Foss et al., 2011). Presence of shared knowledge throughout an organization is a prerequisite of innovation and successful new product development (Dougherty, 2004; Özkan-Seely, Gaimon, & Kavadias, 2015). While offering services helps a firm to acquire knowledge about market demand, customer satisfaction and product performance, innovations can only emerge if this knowledge is sufficiently communicated within the firm. Communication among units and sub-units helps to refine the new knowledge and combine it with the existing knowledge in a meaningful way (Foss et al., 2011). Activities that are performed within the same unit or highly connected units will have a higher chance of providing constructive feedback to each other because of shared goals and language. Therefore, co-existence of products and services in the same unit should enhance their interaction and complementarity.

Mansfield (1969) argues that successful innovation involves tight connection between different innovating entities. Foss et al. (2011) highlight the importance of internal organization for successful use of external knowledge. They show that internal communication mediates the relationship between customer contact and innovation. Newly generated knowledge may be fragmented and dispersed among different organizational members. This, in turn, necessitates collaboration among these entities in order to aggregate pieces of knowledge into meaningful, cohesive and refined ideas. The newly created knowledge might also include a large tacit component, which further highlights the need for close collaboration (Foss et al., 2011). Communication between activities is facilitated when they belong to the same unit. Similarly, the services that are executed by manufacturing departments, rather than by standalone service departments, will be more likely to produce new knowledge that is usable for improving products, technologies and operations. The knowledge that is created through services in manufacturing departments is more likely to be well aligned with the firm's core manufacturing business and, therefore, has more relevance and higher fit to the firm's prior knowledge. When service and production personnel work closely with each other they will share a common language and their ideas tend to converge. This will increase the likelihood of cross-fertilization of ideas that yield subsequent innovation.

In general, knowledge transfer is easier within a single organizational business unit versus between multiple units, and the personnel and processes within the unit are likely to have richer and stronger communication with each other (Tortoriello, Reagans, & McEvily, 2011). Consequently, we expect the services offered by product units to have a richer knowledge transfer with manufacturing activities and, ultimately, a stronger impact on innovation output.

Hypothesis 4. The positive relationship between services and manufacturer innovation is positively moderated by the organizational proximity of manufacturing and service units.

Environmental Dynamism

Finally, we consider how the firm's environment may impact the linkage between service sales and innovation. We specifically focus on environmental dynamism which impacts organization's information processing requirements and hence the effectiveness of ethnographic learning. The impact of environmental dynamism on the efficacy of organizational learning and innovation has been widely acknowledged (e.g. Jansen, Van Den Bosch, & Volberda, 2006; Jansen, Vera, & Crossan, 2009; Wang & Li, 2008). Considering markets as complex systems, the level of dynamisms becomes an important differentiator that impacts both the motivation and the potential for learning.

Environmental dynamism refers to the rate of change and the degree of instability of the environment (Dess & Beard, 1984). Dynamic markets are more complex and uncertain. Market behavior and technology landscape change rapidly, rendering old knowledge obsolete and presenting new opportunities on an ongoing basis. Therefore, firms are encouraged to continually scan the environment, explore, learn, and adapt. Siemsen et al. (2008) note that high velocity of change makes traditional knowledge management approaches such as standardization ineffective. Rather, in a dynamic environment firms must constantly revise and adapt their practices by creating a free and fast flow of knowledge that continually converts employee knowledge into organizational learning. Exploration and obtaining novel information is shown to be especially effective in dynamic environments (Jansen, Volberda, & Van Den Bosch, 2005; Levinthal & March, 1993; Lewin, Long, & Carroll, 1999). The unstable business and perceived competitive threats highlight the need for constant adaptation of strategy and encourage firms to utilize their available resources for learning and exploration (Voss, Sirdeshmukh,

& Voss, 2008). Therefore, manufacturers in dynamism markets should have stronger motivated to utilize the service channel for tapping into customer behavior and generating new knowledge.

In addition, constant change in dynamic markets makes “learning at arms-length” more difficult. Media richness theory posits complexity and uncertainty of tasks as a major determinant of effectiveness of information media (Huber & Daft, 1987). The higher level of complexity and uncertainty in dynamic markets require use richer learning media. Efficient and automated methods of learning become less effective, while close observation, field presence and human-human contact become a key source of novel information. Encountered with a more complex reality, firms in dynamic markets cannot solely rely on traditional market research and need to complement it with ethnographic research. Ethnographic research allows a closer observation of customer behavior and appreciation of the context, processes, and causal and temporal relationships relevant to customer behavior. Only by obtaining this rich and close understanding of customers, firms can adapt to market dynamics effectively and in a timely manner. Consequently, we expect a higher level of learning from services in dynamic environments due to the higher potential and motivation for exploration.

Hypothesis 5. The positive relationship between services and manufacturer innovation is stronger in more dynamic environments.

METHODS

Data

To test our hypotheses, we combine financial and patent data for US publicly-traded manufacturers. Financial data are obtained from the Standard & Poor's (2015) Compustat. We use the North America Annual Fundamentals database as well as the Business Segments database from Compustat. The former contains fundamental data for U.S. and Canadian public firms, and, the latter provides historical data about business and geographic segments of over 24000 North American companies since 1976. Our analysis is limited to the manufacturing firms, i.e. the firms with the two-digit NAICS code of 31-33. We use the NAICS industry classification system because it contains a greater level of detail than the SIC system, especially for services. We combined the North America database with the Business Segments database by the GVKEY (Global Company Key) code, which is the unique company identifier in Compustat. Compustat database contains financial statement and segment data for 6292 distinct manufacturing firms in the period of 1990 to 2006.

We obtained patent data from the National Bureau of Economic Research (NBER). The Patent Data Project (PDP) conducted by the NBER provides a dataset of more than three million US Patents for 1976-2006 (National Bureau of Economic Research, 2015). It also offers information for matching patents data with major financial databases. The procedures used for constructing the PDP dataset are explained in detail in Hall et al. (2001). Matching patent assignees with firms in Compustat database is nontrivial since the original patent files provided by the U.S. Patent Office do not have unique firm identifiers; a firm's name can be stated in different ways or changed over time, e.g. due to merger and acquisition activities (Liu & Wong, 2011). For instance, the patents belonging to IBM are recorded under the assignee names "IBM", "International Business Machines Corporation", "International Business Machines Corp.", and many more spelling and misspelling variations.

We merged the Compustat financial dataset with the PDP dataset by the GVKEY code. Matching patent information was found for 4474 firms in the Compustat database. We applied the following data filtering steps to construct our final sample. First, all observations with negative values on total revenues, assets, service sales, and R&D expenditure were dropped. Second, observations with extreme values (i.e. below the 1st or above the 99th percentile) on total revenues, assets, service revenues, research and development expenditure, return on assets, return on sales, and the number of patents were deleted to mitigate the effect of outliers and mis-recorded data. The final sample includes 40,390 firm-year observations from 4467 manufacturing firms for the period of 1990 to 2006. Within this sample, 10,551 firm-year records from 1698 firms had positive service sales value.

Measures

Patents as innovation indicators. Many scholars have used patent data for analyzing innovation (Griliches, 1990; Hall, Jaffe, & Trajtenberg, 2005; Liu & Wong, 2011; Nagaoka et al., 2010; Schilling & Phelps, 2007). Patents provide an explicit, public trace of firm's knowledge creation. Patents have several advantages over the alternative measures of innovation. Large amounts of patent data are available on a global scale.

Patents are also very rich sources of data. Besides the description of the invented article, they include information about the inventor, the applicant/assignee, application and grant dates, references to other patent and non-patent documents (e.g. academic papers), and technology classes based on the International Patent Classification. Patents are the only source of innovation data that is systematically screened by governmental agencies over a long period of time. This unique combination of detail, objectivity, and coverage makes patents data well suited for econometric analysis.

The use of patents is particularly useful for our study since it indicates the initial stage of innovation. Given that our empirical exercise is directed at exploring the link between service offering and generation of innovative ideas, it is important to closely measure the rate of idea development, which is reflected in the number of patent applications. Other measures of innovation that reflect final outcomes, e.g. new product count, would be temporally more distant from knowledge creation and contaminated by factors such as marketing strategy, competition, etc.

A commonly noted issue with patent data is that the value of individual patents varies widely. Scholars have proposed that the number of citations that a patent receives reflects its importance, and therefore, the citation-weighted number of patents is a more suitable measure of innovation (Carpenter, Narin, & Woolf, 1981; Lanjouw, Pakes, & Putnam, 1998; Liu & Wong, 2011; Thompson & Fox-Kean, 2005; Trajtenberg, 1990). Following this literature, we weight patents by their citations. The use of citation data, however, introduces an additional methodological challenge due to the censoring of the unobserved future citations. This censoring is not homogenously distributed across time, as more recent patents are subject to more severe citation censoring. Hall et al. (2001)

propose a method for estimating the unobserved number of future citations. This method yields a correction multiplier to the citation count that adjusts for the citation truncation post-2006 and is available in the PDP dataset.

The dependent variable, $Patents_{it},$ is the censoring-corrected citation-weighted number of patents that are granted to firm *i* and applied in year *t*. To exclude the duration of the Patent Office application process, we measure patents at the application year. We only consider the successfully granted applications, not provisional applications that did not lead to a patent. The following equation shows the calculation of our dependent variables:

$$Patents_{it} = \sum_{j \in J_{it}} NCites_j . HJTwt_j$$

where: J_{it} is the set of all patents granted to firm i and applied for in year t; $NCites_j$ is the sum of all citations received by patent j up to the year 2006; and, $HJTwt_j$ is the citation truncation weight for patent j proposed by Hall et al. (2001).

Service revenues. Service revenues (in original or transformed forms) have been commonly used to measure the level of service-orientation of a manufacturing firm. A challenge in measuring service-orientation is that firms do not generally separate product and service revenues in their reports. Consequently, services sales data are not easily available. Some scholars have partnered with companies to acquire service sales data. For instance, Kastalli and Van Looy (2013) collect longitudinal data from 44 subsidiaries of a multinational equipment manufacturer. They use subsidiaries' service revenues (normalized to year 2000 using World Bank's GDP deflator) as a measure of service-orientation. Another approach is to focus on specific industries where companies report their revenues broken down into products and services. Suarez et al. (2013) focus on pre-packaged software products industry (SIC code 7372) in which around 400 firms were found to have stated service and product revenues separately in their 10-K reports. The authors normalize service revenues by the total revenues and study the effect of services on the operating margin. The above approaches, however, limit the analysis to a few firms or industries.

Fang et al. (2008) develop a novel approach for estimating service revenues for a wide range of industries. Their method is based on identifying service segments within a company. By examining the description and the SIC codes of the operating segments reported in the Compustat Business Segment database, the authors divide a firm's segments into service and non-service. By adding up the revenues coming from service segments, the authors compute the total service revenues for 477 publicly traded manufacturers. To our knowledge, Fang et al.'s (2008) procedure is the only method offered in the literature that is applicable to a wide variety of firms and industries. This method however only works for (a) a pure-service segment, in which case all its sales are considered service sales, or (b) a non-service segment, in which none of its sales are considered service sales. Therefore, this method alone cannot be used on mixed segments, i.e. segments with both manufacturing and service activities.

Our approach for measuring service revenue (*Service*) is inspired by Fang et al. (2008) with two modifications: (a) it is objective and does not involve researchers' judgment, (b) it accommodates two lines of activities for each segment, which helps better represent mixed service-product segments. The Compustat Business Segments database provides two NAICS codes (and their corresponding SIC codes) for each segment. We select a subset of NAICS codes as service codes. These codes, listed in

Table 1.1, correspond to the codes under the *service* category in the SIC system (i.e. the two-digit codes from 70 to 89).

Table 1.1. NAICS Service Codes

Two-digit NAICS Code	Description
51	Information
52	Finance and Insurance
53	Real Estate and Rental and Leasing
54	Professional, Scientific, and Technical Services
55	Management of Companies and Enterprises
56	Administrative and Support and Waste Mgt. and Remediation Services
61	Educational Services
62	Health Care and Social Assistance
71	Arts, Entertainment, and Recreation
72	Accommodation and Food Services
81	Other Services (except Public Administration)

The following rules are used to determine the annual service revenues for a given firm. If both segment codes are service codes, then all that segment's annual revenues will be considered service revenues. If only one of the two codes is a service code, then 50 percent of that segment's revenues are considered service revenues. Our post-hoc analyses (provided in the appendix) indicate that the results are robust to the reasonable variations in the percentage used in this rule. The firm's annual service revenues will be computed as the sum of the annual service revenues across the segments.

Customer contact. We followed Chase's (1978, 2010) customer contact theory to classify services into high-customer contact (*Hi-Contact*) and low-customer contact (*Lo-Contact*). Given the lack of a complete and up-to-date classification of services, we employed a systematic approach to develop such a scheme.

We base our approach on Lovelock's (1983) seminal article in which he reviews and aggregates the literature on service classification schemes. Three dimensions emerge from lovelock's work that are relevant to measuring customer contact: the nature of interacting parties in service delivery (whether people are interacting or things/systems), duration of relationship between service organization and customers (e.g. discrete vs. continuous), and level of customization and judgment involved in service delivery. Indeed in their work on measurement of customer contact, Kellog and Chase (1995) note that the intensity of customer contact is not only a functional physical proximity and length of contact but also of customization.

We define high-contact services as those that involve a high degree of human-human interaction and customization for an extended period of time. Human contact is the foundation of the definition. Customization ensures that the contact is rich and involves is significant information exchange between parties. Finally, the length of the relationship impacts the amount of the information exchanged over time.

Starting from the most granular level of NAICS system (6-digit level) we scored all service classes (366 codes) according to their level of human-human contact (1: very low to 5: very high), customization (1: very low to 5: very high), and relationship length (1: single transaction, 3: sporadic contact, 5: on-going relationship). Finally, the scores were added and a median split was applied to generate the two classes of low- and high-customer contact services.

Knowledge-intensive services. In order to identify knowledge-intensive services, we adopt the classification system offered by Eurostat, the statistical office of the European Union (Eurostat, 2016). The Eurostat classification distinguishes knowledge-intensive service activity from non-knowledge-intensive ones based on the share of tertiary educated persons at NACE 2-digit level. These NACE codes were converted into

NAICS codes using the concordance tables provided by the US Census Bureau (2016). For each firm-year combination we computed the share of services that are assigned knowledge-intensive NAICS codes.

Product-service organizational proximity. We classify services based on the type of segment they are located in. We identify three segment groups: (a) pure-service segments, which are segments that only have service activities, (b) mixed segments, which are segments that have both manufacturing and service activities, and (c) all other segments. The total amount of services sold by pure-service segments will be captured in the variable *Service_Pure*. The total amount of service sold by mixed segments will be captured in the variable *Service_Mixed*. The remainder of service sales will be captured in *Service_Other*. The following equation describes the relationship between service types:

$$Service_{it} = Service\_Pure_{it} + Service\_Mixed_{it} + Service\_Other_{it..}$$

Control variables. Previous studies in innovation have demonstrated several variables that influence innovation which we have controlled for in our analysis. First, we control for R&D intensity (*RDInt*) captures firm-level differences in innovation effort and is directly related to the amount of new knowledge and innovation generated by firms (Cohen & Levinthal, 1989; Griliches, 1981; Pakes & Griliches, 1984). We measured R&D intensity by dividing the dollar amount of R&D expenditure by total sales. Second, we controlled for firm size measured by the number of employees (*EMP*) and the total value of assets (*Assets*). Larger firms have more resources and slack to generate new knowledge. They may also have a higher propensity to patent because they can more easily afford the costs of patenting and enforcing patent rights. Thirds, we control for firm's return on investment (*ROA*) and return on sales (*ROS*) as measures of profitability. More profitable firms may be more willing to protect their intellectual properties. They may also be more successful in generating new knowledge due to their more effective management. Fourth, we control for employee qualities that may impact knowledge creation. The capabilities of employees, reflected in their productivity, could have influence on their ability to generate, absorb, or transfer new knowledge. Consistent with prior research (Datta, Guthrie, & Wright, 2005; Guthrie, 2001; Huselid, 1995; Koch & McGrath, 1996) we operationalize human resource productivity with sales per employee – the ratio of firm sales to number of employees (*SEMP*). This measure is not without limitations. It captures the average productivity of employees. Ideally, we would want to only capture the productivity of employees who are engaged in knowledge creation process. Unfortunately, we did not have more granular data to achieve this. Table 1.2 summarizes the descriptive statistics and correlations for our variables pooled across firms and time.

Table 1.2. Descriptive Statistics and Correlations

Variable	Patents	Service	Hi-Contact	Lo-Contact	KIS	NonKIS	Service_Pure
Patents							
Service	0.311						
Hi-Contact	0.232	0.808					
Lo-Contact	0.195	0.539	-0.060				
KIS	0.271	0.740	0.474	0.576			
NonKIS	0.152	0.639	0.658	0.142	-0.045		
Service_Pure	0.194	0.342	0.246	0.228	0.285	0.182	
Service_Mixed	0.254	0.802	0.679	0.387	0.579	0.528	-0.036
Dyn.	-0.010	0.086	0.079	0.034	0.069	0.050	0.039
RDInt	-0.050	-0.144	-0.122	-0.070	-0.107	-0.092	-0.044
Assets	0.299	0.453	0.353	0.262	0.362	0.259	0.309
EMP	0.301	0.430	0.282	0.325	0.365	0.220	0.345
ROA	0.092	0.223	0.189	0.108	0.161	0.148	0.064
ROS	0.062	0.159	0.136	0.076	0.117	0.103	0.046
SEMP	0.055	0.252	0.259	0.057	0.174	0.175	0.024

Table 1.2. Descriptive statistics and correlations *(continued)*

Variable	Service_Mixed	Dyn.	RDInt	Assets	EMP	ROA	ROS	Mean	Std. Dev.
Patents								65.331	235.636
Service								0.063	0.127
Hi-Contact								0.046	0.108
Lo-Contact								0.017	0.073
KIS								0.035	0.099
NonKIS								0.028	0.085
Service_Pure								7.797	51.740
Service_Mixed								44.007	104.163
Dyn.	0.062							0.009	0.009
RDInt	-0.122	-0.102						1.897	5.990
Assets	0.171	0.031	-0.074					0.599	2.151
EMP	0.143	0.031	-0.082	0.778				2.683	9.405
ROA	0.192	0.020	-0.228	0.131	0.134			-0.268	0.619
ROS	0.137	0.091	-0.890	0.082	0.088	0.359		-2.476	7.920
SEMP	0.246	0.100	-0.234	0.189	0.054	0.201	0.259	0.186	0.206

Analysis Methods

Our dependent variable, *Patents*, is created based upon a count variable (number of citations) and is highly skewed. The negative binomial model is commonly used for the analysis of over-dispersed count variables (Cameron & Trivedi, 1986; Hausman, Hall, Griliches, & others, 1984). It generalizes the Poisson model by including a dispersion parameter that allows the variance to be larger than the mean. We use the negative binomial panel regression models developed by Hausman et al. (1984) which explicitly consider the unobserved individual differences. Controlling for the unobserved heterogeneity is important in our analysis since patenting behavior differs across firms and periods of time. The Hausman specification test (Hausman, 1978) was not significant favoring the random effects model. We also include year dummies to control for idiosyncrasies in patenting activity over time.

We consider different lags between *Patents* and the regressors. The knowledge gained from service activities may take a certain period of time before it can be assimilated in the organization and be transformed into innovative ideas, actual inventions and ultimately patent applications. Additionally, this amount of time is likely to vary so we use 1-year, 2-year, and 3-year lags and compare their results as a robustness check. The general form of the base models is provided below:

$$Patents_{it+1(2,3)}$$
$$= f(Service_{i,t}, RDInt_{it}, Assets_{it}, EMP_{it}, ROA_{it}, ROS_{it}, SEMP_{it}, Firm\ Effects, Time\ Effects)$$

Firm Effects include the random effects and *Time Effects* refer to year dummies. Hypothesis 1 will be assessed by examining the main effects of *Service*. Hypotheses 2-4 will be assessed by comparing the effects of *Hi-Contact* vs. *Lo-Contact, KIS vs. nonKIS*, and *Service_Pure* vs. *Service_Mixed*. Finally, Hypothesis 5 will be assessed by examining the moderation effect of *Dynamism.* The models are estimated using Stata 13 (StataCorp, 2013).

RESULTS

Our main hypothesis, H1, states that the level of service activity is positively associated with innovation outcomes. Table 1.3 shows the results of the random effects negative binomial regression models for the main effect of *Service* using the positive sample. Models 1 and 2 report the regression results with a 1-year time lag between the dependent variable and the regressors. Models 3 and 4 report the regression results with a 2-year lag, and models 5 and 6 report the regression results with a 3-year lag. The estimation algorithm adjusts the multiple series for lagged data. The effect of *Service* is positive and highly significant under all lags (1–3 years; p=0.0000). We conclude that H1 is strongly supported. Based on the results from the first lag, for instance, we find that for every $10 million-dollar service sales activity innovation output of the firm increases by 2.31 percent.

Table 1.4 reports the results from the moderation analyses. We estimate the interaction effect of five variables under three lags. Hypothesis 2 states that customer contact positively moderates the relationship between service offering and innovation. Models 1, 2, and 3 in Table 1.4 indicate that high-contact services have a significantly stronger effect on innovation compared for all three lags to low-contact services (Wald tests: p=0.0057; p=0.0360; p=0.0047). Therefore, H2 is supported.

Table 1.3. Random Effects Negative Binomial Regression Results – Main Effect of Service

	Patentsit+1		Patentsit+2		Patentsit+3	
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	1.177***	1.305***	1.158***	1.195***	0.800***	0.847***
	(0.093)	(0.097)	(0.096)	(0.103)	(0.103)	(0.104)
RDInt	0.440**	0.119	0.459*	0.139	0.571*	0.577^
	(0.161)	(0.223)	(0.181)	(0.235)	(0.272)	(0.314)
Assets	0.013	0.004	0.009	0.005	0.080**	0.027
	(0.013)	(0.014)	(0.022)	(0.025)	(0.026)	(0.036)
EMP	0.031***	0.018***	0.041***	0.025***	0.032***	0.025***
	(0.002)	(0.003)	(0.004)	(0.005)	(0.006)	(0.008)
ROA	0.233***	0.174***	0.182**	0.118^	0.193**	0.136^
	(0.054)	(0.053)	(0.064)	(0.062)	(0.073)	(0.072)
ROS	0.006^	0.006^	0.003	0.003	0.004	0.004
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
SEMP	0.103	0.174	0.307	0.046	0.369	0.074
	(0.177)	(0.185)	(0.210)	(0.219)	(0.261)	(0.269)
Service		2.280***		2.392***		2.576***
		(0.204)		(0.233)		(0.271)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Log Likelihood	-1.94e+04	-1.94e+04	-1.55e+04	-1.54e+04	-1.22e+04	-1.21e+04
AIC	38884.056	38762.368	30960.669	30867.986	24354.883	24277.708
BIC	39048.003	38933.146	31113.363	31027.319	24496.660	24425.930
N	6844	6844	5647	5647	4649	4649

Standard errors in parentheses; ^ p<0.10; * p<0.05; ** p<0.01; *** p<0.001.

Hypothesis 3 predicts that service knowledge-intensity enhances its impact on innovation. Models 4, 5, and 6 in Table 1.4 demonstrate that knowledge-intensive services have a higher effect on innovation compared to non-knowledge-intensive services. The difference is significant in two of the lagged models; in one lag the difference is not significant but follows the same pattern (p=0.3129, p=0.0001, p=0.0007). We conclude that H3 is supported.

Hypothesis 4 requires that the effect of service sales on innovation be stronger in mixed-service segments than in pure-service segments. As shown in Table 1.4 the difference between regression coefficients of *Service_Pure* and *Service_Mixed* in models

7, 8, and 9 is significant under all three lags (p=0.0000, p=0.0029, p=0.0050). We conclude that H4 is supported.

Finally, Hypotheses 5 states that dynamism in the firm's environmental positively moderates the relationship between services and innovation. Model 10 and 11, and 12 in Table 1.4 indicate that the interaction effect between *Service* and *Dynamism* is positive and significant for the first two lags; the difference in third lag remains positive but is not significant (p=0.0040, p=0.0090, p=0.9090). We conclude that H5 is also supported, albeit not fully robust. Figure 1.2 below compares the magnitude differences in the relationship between service sales and patents caused by the moderators.

Table 1.4. Random Effects Negative Binomial Regression Results – Moderation Effects

	H2-Customer Contact			H3-Knowledge Intensity		
	Lag 1 (1)	Lag 2 (2)	Lag 3 (3)	Lag 1 (4)	Lag 2 (5)	Lag 3 (6)
Constant	-1.323***	-1.189***	-0.971***	-2.918***	-1.185***	-0.970***
	(0.093)	(0.096)	(0.095)	(0.100)	(0.095)	(0.095)
RDInt	0.060***	0.015	0.008	0.058***	0.015	0.008
	(0.013)	(0.012)	(0.011)	(0.013)	(0.012)	(0.011)
Assets	0.047***	0.065***	0.062**	0.015	0.061***	0.081***
	(0.014)	(0.017)	(0.020)	(0.016)	(0.017)	(0.021)
EMP	0.012***	0.006*	0.006*	0.017***	0.007*	0.006*
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
ROA	0.117*	0.137*	0.133^	0.147**	0.134*	0.132^
	(0.051)	(0.061)	(0.069)	(0.052)	(0.061)	(0.069)
ROS	0.038***	0.009	0.003	0.038***	0.009	0.004
	(0.011)	(0.010)	(0.010)	(0.011)	(0.010)	(0.010)
SEMP	-0.148	-0.251	-0.025	-0.585**	-0.288	-0.099
	(0.177)	(0.209)	(0.241)	(0.182)	(0.208)	(0.241)
Hi-Contact	2.811***	2.722***	3.293***			
	(0.261)	(0.294)	(0.371)			
Lo-Contact	2.025***	2.061***	2.233***			
	(0.216)	(0.250)	(0.274)			
KIS				2.236***	2.876***	2.954***
				(0.224)	(0.258)	(0.281)
NonKIS				1.958***	1.727***	1.845***
				(0.243)	(0.278)	(0.326)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Log Likelihood	-20644	-17301	-14377	-20874	-17296	-14375
AIC	41340	34652	28801	41798	34642	28797
BIC	41519	34821	28959	41970	34811	28956
N	7265	6286	5417	7265	6286	5417

Standard errors in parentheses; ^ p<0.10; * p<0.05; ** p<0.01; *** p<0.001.

Table 1.4. Random Effects Negative Binomial Regression Results – Moderation Effects *(continued)*

	H4-Org. Proximity			H5-Env. Dynamism		
	Lag 1 (7)	Lag 2 (8)	Lag 3 (9)	Lag 1 (10)	Lag 2 (11)	Lag 3 (12)
Constant	-1.209***	-1.145***	-0.814***	-1.145***	-1.021***	-0.897***
	(0.098)	(0.103)	-0.108	(0.083)	(0.090)	(0.095)
RDInt	0.071	0.222	-1.018**	0.061***	0.018	0.012
	(0.234)	(0.293)	-0.352	(0.013)	(0.013)	(0.012)
Assets	0.017	-0.016	0.072*	0.031^	0.057**	0.058*
	(0.015)	(0.029)	-0.033	(0.016)	(0.020)	(0.025)
EMP	0.028***	0.036***	0.031***	0.016***	0.007^	0.008^
	(0.003)	(0.007)	-0.007	(0.004)	(0.004)	(0.004)
ROA	0.173**	0.115^	0.119	0.118*	0.151*	0.149*
	(0.056)	(0.068)	-0.079	(0.053)	(0.064)	(0.072)
ROS	-0.005	-0.003	-0.003	0.038***	0.013	0.007
	(0.003)	(0.004)	-0.004	(0.011)	(0.011)	(0.010)
SEMP	-0.423*	0.058	-0.031	-0.146	-0.080	0.103
	(0.208)	(0.24)	-0.308	(0.181)	(0.216)	(0.249)
Service_ Pure	0.407	0.522	0.157			
	(0.419)	(0.601)	-0.796			
Service_ Mixed	2.183***	1.875***	2.108***			
	(0.218)	(0.257)	-0.293			
Service				1.891***	1.786***	2.666***
				(0.262)	(0.318)	(0.371)
Dynamism				-7.841*	-14.776***	-10.552*
				(3.629)	(4.327)	(5.049)
Service* Dynamism				34.781**	38.515**	1.863
				(12.321)	(14.664)	(16.354)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Log Likelihood	-12900	-10000	-7686.8	-18410	-15080	-12212
AIC	25924.8	20069.1	15417.5	36870	30209	24470
BIC	26081	20213.5	15550.9	37040	30368	24619
N	4937	3931	3166	6636	5675	4838

Standard errors in parentheses; ^ p<0.10; * p<0.05; ** p<0.01; *** p<0.001.

Figure 1.2. The Effect of Moderators on the Relationship Between Service Sales and Patents.
Vertical axis in all graphs is the log of citation wgt. patent count.
High (low) levels of the variables correspond to one standard deviation above (below) the mean, or the maximum (minimum) observed value.

ROBUSTNESS OF RESULTS

We checked robustness of the results in several ways.

Lags. First, we assessed the robustness of our results across different lag structures. As reported in Tables 1.4 and 1.5, results are robustness and consistent across different lags structures.

Sample selection bias. As we discussed earlier, our original data includes both service offering and non-service offering manufacturers. If the two groups have innovation-related differences, exclusion of the non-service offering firms may introduce sample selection bias. To address this issue, we re-estimated all models with including non-service firms (we identified three distinct types of zeros and added them to the sample sequentially, yielding 4 samples overall). The service-patent link was also supported in these tests (Table A1 in the appendix). In the next section, we will also use instrumental variable estimation on the expanded samples to further mitigate concerns regarding sample-induced endogeneity (Certo, Busenbark, Woo, & Semadeni, 2016).

Robustness to higher-order effects. Cortina (1993) shows that a moderator can also be correlated with the unmeasured nonlinear terms for the main effect, and become spuriously significant only because of this overlap. Following the author's recommendation, we included the second- and third-order terms for *Service* in our models, but, our results remained qualitatively unchanged. Within each set all three lags and all of four samples are tried (yielding 24 robustness models in total).

Model choice. While we believe the negative binomial model is the most appropriate, we also made comparisons with other alternatives for modeling count data including Poisson and negative binomial with fixed effects, random effects and hybrid estimators proposed by Allison and Waterman (2002). Table A2 in the Appendix provides further details, indicating that our results are not driven by the choice of model. For brevity, only the first lag is reported.

Prior patenting behavior. Following Blundell et al. (1995) and Schilling and Phelps (2007), we also control for the heterogeneity of firms' patenting behavior due to differential knowledge stocks prior to entering the sample. Blundell et al. (1995) show that in patent data models controlling for the patent stock with which firms enter the sample adequately adjusts for the unobserved heterogeneity in firms' knowledge stocks and eliminates persistent serial correlation. We used the citation-weighted cumulative number of patents from 1976 to 1990 to compute the *Pre-sample Patent Stock* as a measure of firm's pre-sample accumulated knowledge. Following the literature (Liu & Wong, 2011) we assume an annual depreciation rate of 20 percent for the value of older patents. The following equation shows the computation of *Pre-sample Patent Stock* for each firm:

$$Presample\ Patent\ Stock_i = \sum_{t=1976}^{1990} (0.2)^{1990-t} \sum_{j \in J_{it}} NCites_j$$

Where, i is the firm index, t is time index, and J_{it} is the set of firm i's patents in year t. While *Pre-sample Patent Stock* explained a significant portion of the dependent variable, the effect Service remained positive and highly significant.

Slack resources. Although our measures of firm profitability (ROA, ROS) and size (sales, number of employees) capture firm's access to financial resources, we also controlled specifically for slack in the service-patents relationship and the results still held. In operationalizing slack resources, we followed Fang et al. (2008) and Lee and

Grewal (2004) and computed the common principal component of two financial ratios (1) retained earnings to total assets and (2) working capital to total assets. We used Stata's *PCA* command to run a principal component analysis on these two variables and extract a single component. Retained earnings is the portion of net earnings that a company chooses not to pay out as dividends, but to retain for unforeseen eventualities and implementation of corporate strategies (Bourgeois, 1981). Working capital is the difference between current assets and current liabilities. Current assets are the liquid assets (cash, inventories, receivables, etc.) and current liabilities are the payments due in one year.

Industry heterogeneity. We checked whether the results are driven by heterogeneity among industries. We included dummy variables for 2-digit and 3-digit NAICS codes, separately, and the effect of service on innovation remained positive and significant.

A concern in our analysis is whether learning about customers necessarily lead to patents. As discussed, patents are not perfect measures of organizational learning. While patents highly correlate with learning and innovation, depending on the industry, more or less emphasis is placed on patenting. To make sure that our results are not driven by the differences in patenting propensity, we focus on the hi-tech sector where there is a greater motivation for patenting and inventions are actively patented. The high rate of innovation and fierce competition in the hi-tech sector, lead firms to patent even those inventions with unclear immediate usage in anticipation of long-term benefits. The results remained unchanged in the hi-tech sample.

Citation weighting and censoring correction. Another methodological question is whether the citation weighting and the correction for censoring affected the results. We repeated our analysis once using the simple count of patents and once using the uncorrected citation count. The main effect of *Service* remained significant under all models and lags. Using sales as a control variable instead of assets also yielded similar results.

Service measurement rule. We examined the robustness of results relative to our chosen method for measuring service revenues. In the models reported above, we have assumed that when revenue is reported in a business segment with both service and non-service activities, service revenues were equal to half (0.5) of the total revenues, i.e. equal to product revenue. We changed this weight parameter from 0.5 to 0.1, 0.25, 0.75, and 0.9, and re-ran the main-effects models. The results remained qualitatively unchanged.

Customer contact measurement. We also checked the sensitivity of results to the method we used for constructing the contact measure. We used multiplication instead of summation for aggregating the three underlying dimensions, and mean splitting instead of median splitting. Doing so did not change the results qualitatively.

Triangulation of findings using text analysis. Finally, to triangulate our results and further ensure validity of findings, we measured service-offering in a different way. As a proxy for manufacturer's attention to services, we used the number of times the word "service" is mentioned in the 10-K reports filed by a random sample of firms in our analysis. This analysis, reported in Appendix 4, also confirmed our theory.

Causality and Endogeneity

An important threat to our results is the potential endogeneity of regressors. Endogeneity occurs when the error term in the regression model correlates with an independent variable and leads to biased estimation of the effects (Baum, 2006; Semadeni, Withers, & Trevis Certo, 2014). Our strategy for addressing causality is both theoretical and empirical. We first investigate the potential causes of endogeneity and how they might have impacted our estimation. Then we empirically address causality via instrumental variable estimation and Granger causality test.

We have observed a positive link between service sales and patent activity in the next three years. Heterogeneity among firms or industries, if untreated, could cause endogeneity and bias. For example, firm's infrastructure, access to resources, and supplier relationships may simultaneously allow it to rapidly innovate and efficiently develop services. Location advantages, e.g. being an industrial cluster, may have a similar effect. Also, some industries may happen to be both very innovative and very service-oriented. The consistency among the results from the fixed effects (FE) and random effects (RE) models mitigates this concern since the former eliminates the endogeneity due to firm- and industry-level effects and the latter eliminates concerns due to incidental parameter bias. Another concern is that over time US economy has shifted towards services, and innovation has become increasingly important. Even if these two trends are independent, their simultaneity may lead to a spurious correlation. However, our use of time fixed effects prevents economy-wide shifts from impacting the results. In addition, our control variables help prevent other sources of endogeneity. For instance, as a firm becomes larger its service and patent activity can both become larger. Diversifying into services as well as pursuing innovation would both be impacted by firm's prior performance and availability of funds.

Another concern with our results is endogeneity due to time-variant shocks in business opportunities. For instance, new product development activity generates novel and patentable ideas. At the same time, these new products may require additional services to succeed in the market. In this case, it is the innovation that is pulling services with it rather than services causing innovation. First, we note that inclusion of R&D activity in our model can mitigate the effect of such an omitted variable. Second, the endogeneity due to new product development requires that innovation and patent application precede service sales, given that patent application can immediately follow R&D but development and successful introduction of a new service would take additional time. Our results hold even when service precedes is lagged by three years.

Instrumental variable estimation. We use instrumental variable (IV) estimation method to empirically address endogeneity (Antonakis, Bendahan, Jacquart, & Lalive, 2010). The IV method involves finding a variable that is correlated strongly with the endogenous variable (instrument strength) but is uncorrelated with the residual variance in the dependent variable (instrument validity). Therefore, IV can only be linked to the dependent variable through the measured variables in the model (Wooldridge, 2012). Finding suitable instruments is often the most difficult aspect of IV estimation.

We take two approaches to identifying instruments. First, we use lagged values of *service* as instruments, since lagged realizations are less likely to be influenced by current shocks. These IVs (hereafter referred to as IV set I) are service sales of firm i lagged by three and four years, $ServiceIV1_{it}$ and $ServiceIV2_{it}$, correspondingly.

We only use the third and fourth lags to create sufficient separation of IVs from the current shocks. This choice, together with the existing 1 to 3 lags create a separation of 4 to 7 years between the IVs and the DV, which further enhances the validity of IVs. While past service activity is linked to future service activity (instrument strength), the knowledge generated from services is unlikely to impact patenting activity several years later (instrument validity). Unlike R&D, service interactions are not planned activities for knowledge generation. Rather, many ideas may emerge from interactions with customers, which only be absorbed if they are deemed clearly relevant to the business. Otherwise, they will be dismissed and not further pursued. In addition, knowledge is inherently and practically perishable (Schilling & Phelps, 2007), and, firms have incentive to use it as fast as possible. Therefore, service activity is unlikely to predict patent applications in four to seven years later. Even if an organization keeps some service-generated knowledge for an unknown reason, it will likely still need further research and development to be applicable to dynamic business needs. Therefore, such an effect will ultimately be controlled for via inclusion of R&D intensity. This approach to finding instrumental variables in not without limitations; although not very likely, it is still possible that some confounding factors retain their effect after 4-7 years. We note, however, that from an empirical standpoint the larger the time-lag between two variables the smaller the correlation would be. Hence we expect such lingering effects to be small if present at all. Yet to safeguard against their possible impact we use a different identification approach as follows.

Second, we follow the IV identification strategy adopted by some studies in the economics literature (Berry, Levinsohn, & Pakes, 1995; Bresnahan, Stern, & Trajtenberg, 1997; Nevo, 2001) and also used recently in study of manufacturing services (Suarez et al., 2013). This approach relies on the richness of panel data and utilizes information from other units (such as competitors of a focal firm) for identifying valid IVs. Berry et al. (1995) suggested that suitable instruments for price of a product can be obtained using data from all other products except the focal one. They argue that, in an oligopoly, pricing decision for a product is influenced by availability of competing substitutes. So, price differences reflect observed and unobserved product heterogeneity in the market. Consequently, once prices are measured and controlled for, demand for a product will be determined only by the features of that product itself. Similarly, in a study of cereal margins across brands, Nevo (2001), used product prices in other cities as instruments. Following these studies, we construct two additional instruments based on the service sales of all other firms in the 4-digit NAICS industry. The patent activity of a service-oriented manufacturing firm is impacted, in part, by its prior performance, size, R&D, and service activity. However, it will not be directly impacted by the service sales of other firms in the industry. Rather a manufacturer is likely to respond to service activity of a competitor by adjusting its own service offering, sales composition, or R&D activity to gain competitive advantage. For example, Dell's acquisition of the IT service company EMC in 2016 was made in competition with Hewlett-Packard's introduction of cloud computing services. Consequently, any future innovation benefits that Dell obtains from these acquisitions will directly come from its new service business, rather than HP. We add the following IVs (hereafter referred to as IV set II) to our analysis: $Competitor\_ServiceIV1_{it}$ and $Competitor\_ServiceIV2_{it}$ defined, correspondingly, as the total and average service sales of all firms except firm i in the four-digit NAICS industry of firm i. Table 1.5 shows the correlation between the two sets of instrumental variables and Service.

Table 1.5. Correlation Between Service and the Instrumental Variables

Set Name	IV Name	Correlation with Service
IV I	ServiceIV1	0.8275
	ServiceIV2	0.7807
IV II	Competitor_ServiceIV1	-0.1209
	Competitor_ServiceIV2	0.1998

Given that our models are non-linear in parameters, control function (CF) approach is a preferred alternative to 2SLS (Imbens & Wooldridge, 2009; Wooldridge, 2012). Table 1.6 provides our control function IV estimation results. The estimate of Service remains positive and highly significant (p=0.0000) under all three lags, with and without zeros, and using either sets of IVs.

Table 1.6. Instrumental Variable Estimation of Random Effects Negative Binomial Model Using Samples I and IV

	IV I-Sample I			IV I-Sample IV		
	Lag 1 (1)	Lag 2 (2)	Lag 3 (3)	Lag 1 (4)	Lag 2 (5)	Lag 3 (6)
Constant	-1.364***	-1.261***	-1.160***	-1.469***	-1.266***	-0.914***
	-0.042	-0.042	-0.043	-0.095	-0.101	-0.105
RDInt	0.047***	0.013	0.003	0.060***	0.035*	0.037*
	-0.01	-0.009	-0.009	-0.015	-0.015	-0.015
Assets	0.003	0.010^	0.005	-0.042**	-0.048*	-0.007
	-0.005	-0.006	-0.007	-0.015	-0.021	-0.034
EMP	0.023***	0.022***	0.023***	0.022***	0.023***	0.013^
	-0.001	-0.001	-0.001	-0.003	-0.005	-0.007
ROA	0.310***	0.348***	0.396***	0.06	0.027	0.036
	-0.039	-0.045	-0.05	-0.053	-0.063	-0.073
ROS	0.025***	0.001	-0.007	0.037**	0.022^	0.025^
	-0.007	-0.007	-0.007	-0.012	-0.012	-0.013
SEMP	0.076	0.098	0.341**	-0.076	-0.028	-0.24
	-0.087	-0.094	-0.118	-0.182	-0.219	-0.272
Residual	-2.693***	-2.801***	-3.035***	-3.125***	-3.200***	-4.173***
	-0.235	-0.251	-0.276	-0.356	-0.409	-0.469
Service	2.560***	2.467***	2.618***	3.537***	3.723***	4.334***
	-0.197	-0.216	-0.24	-0.243	-0.288	-0.346
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Log Likelihood	-72650	-62578	-53428	-18957	-15132	-11923
AIC	145353	125205	106903	37966	30314	23895
BIC	145563	125404	107091	38143	30480	24049
N	24358	21258	18523	6726	5560	4586

Standard errors in parentheses; ^ p<0.10; * p<0.05; ** p<0.01; *** p<0.001.
Sample I: with all zero observations on service sales; Sample IV: with no zeros.

Table 1.6. Instrumental Variable Estimation of Random Effects Negative Binomial Model Using Samples I and IV *(continued)*

	IV II-Sample I			IV II-Sample I		
	Lag 1	Lag 2	Lag 3	Lag 1	Lag 2	Lag 3
	(7)	(8)	(9)	(10)	(11)	(12)
Constant	-0.905***	-0.925***	-0.732***	-0.609***	-0.740***	-0.447**
	-0.046	-0.05	-0.053	-0.122	-0.137	-0.155
RDInt	0.067***	0.023	0.007	0.074**	0.009	-0.011
	-0.016	-0.016	-0.014	-0.027	-0.029	-0.035
Assets	-0.021**	-0.006	-0.001	-0.071	0.014	0.014
	-0.008	-0.009	-0.011	-0.044	-0.063	-0.085
EMP	0.031***	0.029***	0.029***	0.028^	0.006	0.002
	-0.002	-0.002	-0.002	-0.014	-0.018	-0.021
ROA	0.387***	0.424***	0.571***	0.128	0.009	0.177
	-0.06	-0.074	-0.091	-0.091	-0.111	-0.145
ROS	0.040**	0.008	-0.008	0.048*	-0.001	-0.028
	-0.013	-0.013	-0.013	-0.023	-0.027	-0.033
SEMP	0.392**	0.521***	0.744***	-0.313	0.125	0.16
	-0.125	-0.145	-0.165	-0.343	-0.418	-0.504
Residual	-1.877***	-1.961***	-2.074***	-5.458***	-4.420***	-3.548***
	-0.343	-0.375	-0.409	-0.656	-0.748	-0.864
Service	2.288***	2.511***	2.775***	4.425***	4.261***	4.598***
	-0.243	-0.276	-0.317	-0.408	-0.494	-0.655
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Log Likelihood	-38202	-30693	-24448	-7039	-5192	-3728
AIC	76448	61428	48936	14122	10426	7497
BIC	76614	61583	49080	14254	10548	7608
N	14106	11901	10012	3042	2423	1920

Standard errors in parentheses; ^ p<0.10; * p<0.05; ** p<0.01; *** p<0.001.
Sample I: with all zero observations on service sales; Sample IV: with no zeros.

Recently, Suarez et al. (2015) followed a similar strategy for instrumenting service sales of manufacturing firms. They used the aggregate and mean values of competitor employees and sales as instruments for estimating the effect of services on operating margin (four instruments in total). To gain further assurance regarding our treatment of endogeneity, we also used the same IVs employed by Suarez et al. (2015) in our main effect model and found similarly strong support for our hypothesis.

Granger causality. To test another aspect of causality (the necessary conditions) we ran a Granger causality test which tests whether the predictor (Service) contains unique information about the dependent variable (*Patents)* over and above the current and past realizations of the DV and all other control variables. This test, reported in Appendix 3, also supported our hypothesis.

DISCUSSION AND CONCLUSIONS

Many manufacturers have realized that competition in the global market is not limited to products. This has ignited a race among manufacturers to offer services and integrated product-service solutions (Neely et al., 2011). Services can create new channels of communication with the market and customers. We argue that service offering can enhance innovation by providing manufacturers with new, and potentially richer, sources of knowledge and market intelligence. Proper use of such sources can generate knowledge of how the existing products and services are performing against market needs, which attributes are most critical to improve, and what new offerings can be developed to satisfy unmet and often unarticulated customer needs. The current paper is the first to use a large-scale study to empirically examine innovation in service-oriented manufacturing organizations.

We analyzed 17 years of data (1990-2006) from publicly-traded manufacturers in the US using random effects negative binomial regression. The results indicate a strong and robust association between services and innovation. For service-offering manufacturers, change in the level of service sales is positively associated with change in the citation-weighted number of patents in all three subsequent years. This finding portrays services as a channel for accessing knowledge and boosting innovation in manufacturing firms. Services extend manufacturers' contact with the market and enable a richer communication with customers. Manufacturers who wish to enhance their innovation outcomes can leverage the potential of services to absorb external knowledge and uncover new aspects of complex customer behavior.

This result also provides a potential explanation for the bridge decay phenomenon in service outsourcing (Li & Choi, 2009). Li and Choi (2009) argued that service outsourcing can lead to degradation of a firm's position as a bridge between the supplier and customers and eventually loss of control over the service interactions between the two parties. Our study empirically shows that service interactions can generate valuable insights for manufacturers, over and above what is achieved via R&D. Outsourcing services limits a manufacturer's direct contact with the customers and leaves strategic information in the hands of suppliers. Consequently, power dynamics may change to increase supplier's influence in the triad. Manufacturers should take into account the cost of lost intelligence and the risk of supplier opportunism in their service outsourcing decisions. Proper use of coordination mechanisms can mitigate this loss for the manufacturer. For instance, if Apple were to outsource its repair operations it would lose the early and first-hand knowledge of design flaws at the time of new product launch. Alternatively, Apple can work with the service supplier to develop processes in which supplier collects and shares information about product failures and repair requests. Notably, such a sharing mechanism works better for explicit knowledge, which can be easily codified and transferred, compared tacit knowledge, which may better capture the contextual complexity of the opportunity space.

As noted by Kamarkar (2015), customer's involvement in the service co-production means that their behavior is not only a marketing object but an operational object, therefore thinking of customers solely as purchasers is not adequate. Expanding this view, our results suggest that the co-production of service also allows the firm to learn about the customer and adjust its operations to better match customer needs. Therefore, services are not only channels of delivering value but also channels for information reception.

Studies (e.g., Tucker, 2007) have found the frontline service staff can contribute innovative solutions to process improvement efforts due to their closeness to the actual operations and failure points. Our study implies that service staff can also contribute significantly to inventive efforts. In addition, the analysis results suggest that the innovation value of service offering depends on features of the services, organization of services in relation to manufacturing activity, and the firm's environment. High-customer contact and knowledge-intensive services are especially more valuable in generating ethnographic knowledge. Our study also highlights a positive side of customer contact for operations management. Many studies in operations management consider higher service contact as being detrimental to performance; while, more recent findings suggest a more complex effect for contact intensity and customization on operational performance (Bitran, Ferrer, & Rocha e Oliveira, 2008; Kumar & Telang, 2011). We show that longer customer contact has positive outcomes for organizational learning, which can lead to improved operational performance in the longer term. Future research can build on this findings and disentangle the short- and long-term implications of service contact for operations performance and customer outcomes. Notably predicting the effects of automation on performance in service delivery may not be as clear as it is in manufacturing. Reduction of customer contact during automation may lead to loss of key customer information and opportunities for future business.

We also found that proximity of service and manufacturing activities, both organizational and geographic, improves the innovation outcomes of service offering. Organizational proximity can indicate relatedness of the content of activities and smoother interaction between them. Communication of tacit knowledge or new ideas, for instance, can be significantly harder when in-person interaction is limited or business routines are different. This finding suggests that rich communication between service and manufacturing activities is more important for innovation performance of a service-oriented manufacturer than for a traditional manufacturer. Also, relatedness of service and production activities means that the knowledge absorbed from the market during service activities will be more relevant to product development and manufacturing activities. The higher relevance of information coupled with the added benefit of richer and more frequent interaction between employees make organizational proximity especially important for spillover between service and manufacturing activities.

We also demonstrate the knowledge value of services are significantly larger in dynamic markets. In such environments, constant obsolescence of knowledge makes learning especially important and the larger number of unknowns offers more opportunities for learning. Meanwhile, due to higher complexity the most useful information is one that is context-aware and rich in detail. Hence, ethnographic learning offered by service activities become more valuable and effective.

We acknowledge that our study suffers from several limitations. First, we do not directly observe the learning and knowledge absorption that occurs because of service offering. While our theory suggests knowledge transfer is the mediating mechanism, there may also be other mechanisms by which services are linked to innovation. For instance, a differentiation strategy may induce higher emphasis on innovation as well as on superior service. Our adjustments for firm-specific effects, time effects, firm's past patenting behavior as well as instrumental variable estimation aimed at mitigating such influences. In addition, the harmony between the empirical results is helpful in strengthening confidence in the proposed mechanism. All of the five hypotheses depend on the ethnographic knowledge transfer mechanism. Therefore, if another mechanism were responsible for the findings it would have likely manifested in weak results for some of the hypotheses. In essence, each of the seven findings add a separate layer of support for the common underlying mechanism.

Second, in absence of a direct measure of service sales, we needed to estimate the fraction of total revenue due to services. Our assumption that product and service revenues are equal is unbiased with respect to our hypotheses, and the use of multiple observations of the same firms further mitigates any potential bias. Moreover, lower reliability in a regressor will attenuate the regression coefficient of that regressor, all else equal, and make the results more conservative (Liu, 1988). Our robustness check indicated that results were consistent under different weightings between product and service revenue. Finally, triangulation of findings using the textual measure of service-orientation provides further support for the results.

ESSAY II

DIVERSIFICATION OF MANUFACTURING FIRMS INTO SERVICES: ANALYSIS OF ANTECEDENTS

ABSTRACT

Manufacturers are increasingly complementing their products with new services in order to satisfy a broader array of customer needs and increase the value of their offerings. A manufacturer's diversification into services (i.e. "servitization") requires a significant organizational transformation and has been shown to be a very challenging process. However, our understanding of the factors that motivate a manufacturer to diversify into the service arena is limited. This paper empirically investigates the drivers of servitization by manufacturing firms. We suggest that servitization represents a new type of diversification which cannot be fully explained by the extant diversification theory unless critical customer-related elements are considered in the theory. We construct a sample of 2450 public manufacturing firms for the period of 1976 to 2006 by combining financial statement data and patent data and analyze it using multilevel regression models. We find that firms in industries characterized with high technology or firms in their earlier life cycle stage offer a higher level of service. We also demonstrate that a larger market share and larger stock of proprietary knowledge encourage manufacturers to introduce more services. Our results are robust and consistent under multiple lag structures and extend theoretical precision in explaining servitization.

INTRODUCTION

Manufacturers have increasingly introduced services to accompany their existing products in order to satisfy a broader array of customer needs and differentiate themselves from the competition (Lusch et al., 2007; Sawhney, Balasubramanian, & Krishnan, 2003). These services include repair and maintenance, warranties, installation, financial services, consulting, training, product analytics, performance monitoring, etc. This phenomenon is frequently referred to as "*servitization*" (Vandermerwe & Rada, 1988). In this study, we define servitization as the provision of services by an organization whose primary business activity is manufacturing products. A manufacturing firm (or unit) that has added services to its existing offerings is referred to as a *servitized* firm (or unit).

Servitization can be a means to achieve sustainable competitive advantage and counteract commoditization. Value-added services transform commodities to differentiated goods (Bowen, Siehl, & Schneider, 1989); they create synergies with the existing products which cannot be achieved by pure service or pure product firms. Portfolios of products and services are harder to imitate (Baines, Lightfoot, Benedettini, & Kay, 2009; Kastalli & Van Looy, 2013). Porter (1980) views service as an important element of product strategy. He argues that superior customer service, financing facilities, and logistics services can enhance value offering and increase the cost of switching for customers. Therefore services can also be used to lock-in customers and lock-out competitors (Vandermerwe & Rada, 1988).

Servitization has been a popular strategy in the manufacturing sector. In almost every manufacturing industry a growing portion of firms are complementing their products with value-added services (Baines, Lightfoot, Benedettini, et al., 2009; Fang et al., 2008; Vandermerwe & Rada, 1988; Wise & Baumgartner, 1999). Yet, despite wide industry adoption and the claimed benefits, many manufacturers have refrained from stepping into the uncharted territory of services (Cohen et al., 2006; Oliva and Kallenberg, 2003). In order to successfully develop and deliver services, a manufacturer must go through an organizational transformation, develop a service-centric culture, acquire new resources, and train employees. Such a bold transition has often proved to be a tough challenge and would requires strong motivation (Oliva and Kallenberg, 2003). It is not clearly understood why some manufacturers choose to, or are able to, make the transition from products to services while others do not. While diversification theory offered insights into why manufacturers enter services, we argue that there exists certain customer-side elements that are critical to servitization decision but ignored in the extant theory.

The main goal of this study is to develop a theory of servitization. This study is concerned with the following research question: *What factors motivate a manufacturing firm to develop and offer services?* In order to address this question, we use S&P Capital IQ's Compustat North America database as well as patent data construct a panel of 2450 publicly held manufacturers for the time period of 1976 to 2006. We analyze this data using multi-level regression analysis.

LITERATURE REVIEW

There exists limited empirical evidence in servitization literature with regards to the drivers of the phenomenon. Diversification literature also seems to ignore important aspects of servitization. Below we will discuss the insights that could be gained from each stream of literature.

Servitization

Since the introduction of servitization to the literature (Vandermerwe & Rada, 1988) research has been steadily growing in this area (Baines, Lightfoot, Benedettini, et al., 2009). Academic research emphasized servitization’s marketing-related benefits (DeBruicker & Summe, 1985; Hull & Cox, 1994; Lele & Karmarkar, 1983) as well as operations issues (Armistead & Clark, 1991; Goffin & New, 2001; Loomba, 1996). Scholars have suggested that there is great potential for manufacturers in integrating services into their core products (Baines, Lightfoot, Peppard, et al., 2009; Baines, Lightfoot, Benedettini, et al., 2009; Oliva & Kallenberg, 2003; Wise & Baumgartner, 1999). Following prior empirical work (Fang et al., 2008; Kastalli & Van Looy, 2013; Suarez et al., 2013) we study servitization at the organization level and focus on all services sold by manufacturers.

Drivers of Servitization. Examination of previous research reveals a number of factors that potentially motivate manufacturers to adopt service strategies. Suarez et al. (2013) argue that decline of product revenues encourages manufacturers to diversify into services. The desire for differentiation is another factor that is emphasized as a reason for servitization (Lusch et al., 2007; Sawhney, 2004; Wise & Baumgartner, 1999). Kastalli and Van Looy (2013) state that manufacturers develop services in order to escape the commoditization trap. The competition in the manufacturing sector has led to commoditization of many product categories. Consequently, some manufacturers have shifted focus to services as a new basis for differentiation. Servitization may also be explained by complementarity between manufacturing and service activities. The availability of excess capacity in immobile production resources, such as knowledge and facilities, can motivate development of new services that can leverage the unused capacity and create synergies with manufacturing activities (Fang et al., 2008). Scholars have noted that services and products can play a complementary role and influence each other. Fang et al. (2008) state that the main benefit of servitization is due to the synergy realized between products and services. In many cases, firms offer services, such as repair and maintenance, to support their product business. Kastalli & Van Looy (2013) show that offering services increases the demand for products. The role of industry-level factors have also been examined by scholars. Cusumano et al. (2015) offer a conceptual framework that links different life cycle stages of a manufacturing industry to the different levels and types of services offered by the firms.

Given the significant attention to servitization in industry and academia, it is surprising how sparse our knowledge is regarding the circumstances that favor or discourage servitization. To the best of our knowledge, Cusumano et al. (2015) is the only study directed at explaining the factors that influence manufacturers' decision to offer services (industry lifecycle stage in this case) and we are not aware of any empirical evidence regarding their propositions or other possible drivers. Furthermore, there exist theoretical tensions that demand an empirical resolution. For instance, as we discussed earlier it has been argued that manufacturing firms resort to services when product revenues are declining. However servitization is a challenging strategic move (Baines, Lightfoot, Peppard, et al., 2009; Baines, Lightfoot, Benedettini, et al., 2009; Brax, 2005) and requires a significant upfront investment, which is less likely of a firm with declining revenues. A successful manufacturer with profitable business may have the necessary resources for developing new services. On the other hand, path-dependence due to the current success (Sydow, Schreyögg, & Koch, 2009) may limit the motivation for entering services as a radically new line of activity. It is not clear then whether servitization is motivated by financial success or loss. These effect may also realize at different levels of analysis.

Diversification

Diversification is one of the most investigated topics in strategic management. For the purpose of this study we define diversification as the degree to which a firm classified in one industry produces goods from other industries (Berry, 2015). The drivers of diversification have been extensively studied. As broad as it is, the literature on diversification also seems to lack sufficient attention to servitization.

Drivers of diversification. Various proactive and defensive reasons have been suggested for diversification (Reed & Luffman, 1986). Chatterjee and Wernerfelt (1988) notes that if transaction costs are higher in the market than in the organization diversification becomes an attractive strategy. Economies of scope and utilizing the unused capacity in immobile resources is one of the major rationales put forth by scholars to explain firms' move towards diversification. Excess capacity in physical assets (e.g.

plant, equipment) is usually non-tradable in the market and is therefore a basis for diversification (Porter, 1985). Additionally, knowledge assets and production know-how can also be bases for diversification due to their minimal cost of transfer to other activities and difficulty to trade in the market (Porter, 1985, 1987).

Public policy has also been a major factor in firm's decision to diversify. Scholars have documented the role of anti-trust policies in incentivizing diversification (Auerbach & Reishus, 1988). Tax consideration have also been major factors in diversification decisions. If the taxation on dividends are high such that the shareholders prefer that their income be reinvested, company will be motivated to buy or develop other businesses in order to profitably use the free cash flow (Hoskisson & Hitt, 1990; Turk & Baysinger, 1989). Acquisitions typically lead to lowering of taxable income for corporations through increasing depreciable asset allowances (Auerbach & Reishus, 1988; Kaplan, 1989).

Low performance, uncertainty of future cash flow, and desire for risk reduction have also discussed as motives for diversification internal to the firm. Rumelt (1974) argues that high performance erodes the motivation for diversification. Research suggests that low performance motivate firms to diversify, however, continued low performance post-diversification leads to divestiture (Baysinger & Hoskisson, 1990; Hoskisson & Turk, 1990).

Firms may also diversify in order to hedge against uncertainties in the market and the business environment (Rumelt, 1974). Uncertainty in expected future performance, or maturity of an industry motivate diversification as a defensive strategy (Leontiades, 1982). Portfolio theory suggests that having multiple businesses reduces the risk as long the cash flows from those businesses are not perfectly correlated (Markham, 1973).

Diversification has also been suggested to help firm through decreasing the cost of capital since businesses can borrow from each other and decrease the threat of bankruptcy (Lewellen, 1971). This perspective assumes imperfect capital markets and information asymmetry between managers and investors, which means that internal funding will be more efficient than market funding (Chatterjee & Wernerfelt, 1988).

Furthermore, research has suggested managerial motives for diversification. Taking the perspective of agency theory (Jensen & Meckling, 1976) scholars have argued that managers' may pursue diversification for their own benefit. For example Amihud and Lev (1981) suggest that diversification may reduce the risk of job loss or income reduction for top management. Additionally, diversification increases firm size and consequently management compensation (Dyl, 1988). If managerial motives are involved, the threat, of course, is that diversification may be pursued even if it is detrimental to the firm.

However, there does not exist a specific theory to explain why a firm would diversify into services not in other products. We argue that this gap is due to lack of attention to customer-side complementarity, as explained below. This paper aims to extend the diversification literature and provide a theory of the drivers of servitization. By introducing the concept of customer-side complementarity we will attempt to broaden the applicability of diversification theories to the servitization phenomenon.

Customer-side Complementarity. The current theory of diversification does not completely address the interaction between the products and services in a servitized organization. What makes servitization different from the previously studied types of diversification is not only the fundamental differences in managing a service organization and a product organization (Bowen & Ford, 2002), but also, that products and services have interrelationship and will end up with the same customer. In most cases, there is complementarity between the two, i.e. customer-side complementarity. Two goods, as we define, have customer-side complementarity when the value of one increases for the customer once they also obtain the other one. For example, an engine and a maintenance package have customer side-complementarity because it is more beneficial for the customer to have both goods rather than either one. Ceteris paribus, buying the maintenance package from the same company saves time and search costs for the customer and ensures a better service due to higher compatibility with the product (compared to purchasing from a third-party).

Customer Value Chain. There is typically a process that a customer has to go through for buying an item, of which the purchase transaction is only one activity (Figure 2.1). We refer to this process as customer value chain. The customer first needs to identify the item and supplier that meet his needs best. Once the product is selected and the suitable supplier is identified, the customer needs to secure funds for making the purchase. The actual transaction then takes place which involves the costs of visiting the supplier, negotiation, contracting, transfer of funds, and receiving the purchased item. The next phases are transportation of the items to the customer's site (e.g. plant, office, home), installation, putting the product in use and maintaining it. Once the usage life of the product come to the end (i.e. when customer no longer needs the product), end-of-use activities, such as disposal or reselling, are carried out.

Each of these steps may involve costs and risks for the customer, and correspondingly, opportunities for the supplier to create additional value. The selection step may involve considerable costs (money, time, etc.) of search and information acquisition. As a result, customers may prefer long term relationships with fewer suppliers in order to economize on these costs (Bowen & Jones, 1986). There is a large risk element in this step due to the possibility of selecting the wrong item. Suppliers can offer consultation services in order to help customers select among a number of alternatives. Financing costs can also be a barrier for customers. It is fairly common for suppliers of expensive items to offer financing services, e.g. loan, to smooth the purchase process. The actual purchase transaction can also be made easier through the use of information technology, e.g. online ordering.

There is also a sunk cost of initiating the connection with the supplier which can be a basis for servitization. That is when a customer has already invested in information acquisition, visiting the supplier, or deciding on purchase of a product (sunk costs), they can economize on these costs if they make other purchases (e.g. accompanying services) from the same supplier rather than other suppliers. Such customer-side complementarities can be bases for the supplier to develop more and more services around the core product. This is especially true for the cases where purchase of product automatically creates the need for purchasing a service. For example, the buyer of an automobile will typically need maintenance service, which will be less costly to buy from the same seller. There are also risks for customers due to supplier's failure of fulfilling the promise. For example, the product may be defective or may not be delivered according to the agreements. These risks, then, creates the opportunity for sellers to offer return and warranty services.

For some products, e.g. production machinery, proper installation and use of the product needs extensive knowledge and training, and may not be hassle-free for the customer. As a result, some manufactures provide installation and training services to help customers gain the most value from their purchased product. Finally, the customers may face risks and costs due to not being able to resell or dispose of the product at the end of its useful life. As a result, manufacturers may offer buyback, disposal, or swapping services. Leasing services are also aimed at decreasing not only the initial investment but also the hassle (i.e. costs and risks) of reselling or disposing of the products that are not needed anymore.

Based on the above framework, we will offer hypotheses in the next section to shed light on the drivers of servitization. In our theory development we will place a stronger emphasis on the effects that are specific to the relationship between products and services.

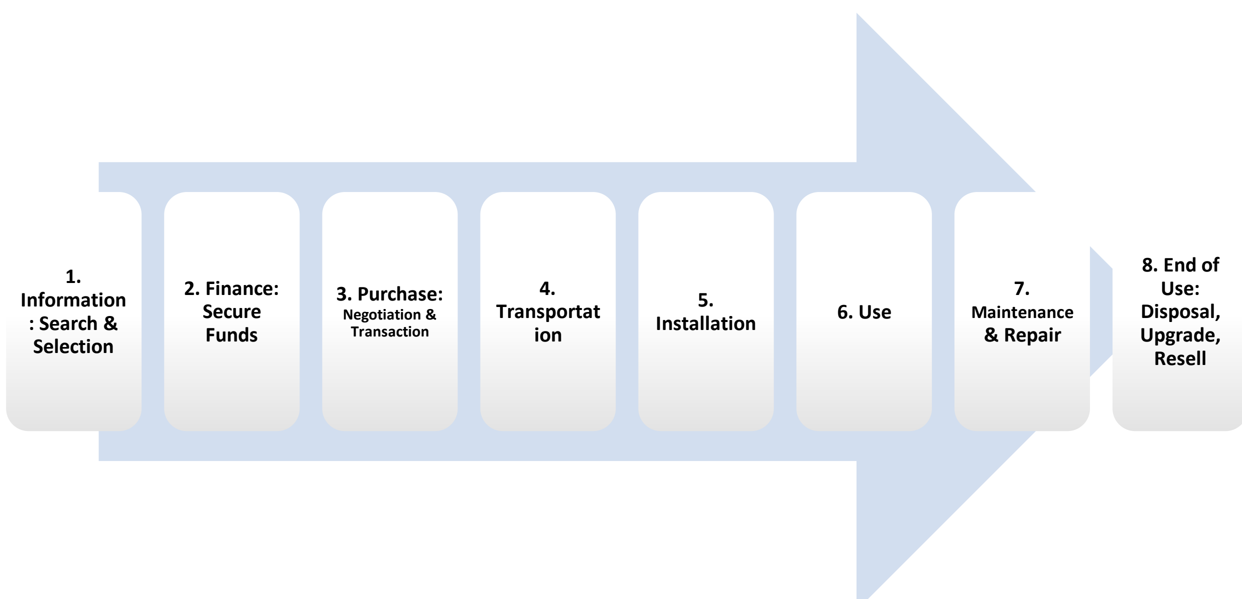

Figure 2.1. The Customer Value Chain

HYPOTHESES

Hi-Tech Industries

In this section we examine the effect of hi-tech industries. Companies in hi-tech industry produce more complex products and need a higher level of service to support customers. As we discussed earlier, one of the reasons a customer may need services along with the product is to reduce the risks and uncertainties associated with the purchase process and post-purchase experience. Examples of the risks involved in the customer value chain in Figure 2.1 include buying the wrong product type – one that does not meet customer needs well, buying a defective product, product failure under use, not being able to find suitable parts or a repair service provider, system downtime and lost business during the repair time.

These risks emanate from customers' lack of expertise and knowledge about the product. If a customer is sufficiently knowledgeable about a product they can better assess the suitability and quality of the product before purchase and use the product post-purchase. For instance, often times finding the right maintenance and repair service (M&R) provider is easier when the customer knows the product better. Knowing the technical characteristics of the product helps the owner to find a supplier with matching technical capabilities. Additionally, the relationship between M&R provider and the firm involves agency and knowledge asymmetry since the owner hires the M&R provider to perform a service on the product on his behalf (Bowen & Jones, 1986). Assessing the quality and performance of products is more difficult in hi-tech markets both pre- and post-purchase. Higher decision making difficulty, consequently, increases customer's need for services, e.g. recommendation service (Swaminathan 2003).

Hi-tech sectors use the most advanced technology available and continuously create new knowledge through heavy investment in research and development (Chandler and Hikino 1990). Continuous creation and accumulation of product-related knowledge gives manufacturers an edge over external service providers. We conclude that in industries characterized by higher technology both customer's need for receiving services and manufacturer's advantage for offering them increase; therefore, we should observe a higher level of servitization in these industries.

To the extent that product owner is knowledgeable about product, they can better observe the quality of the service delivered by the provider. In essence higher knowledge about the product decreases the knowledge asymmetry between the owner and service provider. As firms continue to operate in the market, their customers become more and more familiar with their products and the knowledge asymmetry between firms and customers shrinks. External service providers also become more mature and offer better service at lower cost. As a result, we expect servitization level to decrease with company's age.

Earlier in a firm's life cycle, there are at least two sources of ambiguity for the customer. First, the reliability and quality of the product may be uncertain due to supply chain and operations uncertainty. The production and distribution processes are not optimized and as a result many defects and incompatibilities may exist. Additionally, the design of the product itself is not optimized and may undergo multiple changed before a robust model is introduced. Second, customers may not be familiar with the product.

There may be ambiguity in whether the new product actually matches their needs, how to install and use it. Simply put, the pros and cons of the product and its value relative to competitor products are not fully understood (Cusumano et al., 2015; Utterback & Abernathy, 1975). The mainframe computers introduced by IBM during the 1950s and 1960s were expensive machines based on a new and largely unknown technology. Customers perceived a high level of risk and were reluctant to purchase the products. However, IBM developed various services such as maintenance or leasing packages to attract buyers to the new product. Xerox had to offer similar services at the time of introducing the plain-paper copier in the 1960s since the market was not familiar to the new technology and was reluctant to adopt it (Cusumano et al., 2015). Due to these ambiguities, purchase risk is significantly higher earlier in the products' life cycle. Therefore, we expect manufacturing firms to offer a higher level of services in their earlier life cycle stages.

Hypothesis 1. Manufacturers in hi-tech industries have a higher level of servitization.

Hypothesis 2. Manufacturers with higher age have a lower level of servitization.

Industry Competitiveness and Market Share

Competitive dynamics also have important implications for servitization. Scholars have emphasized that servitization can be a means to differentiate a firm's offering from those of the competitors (Sawhney et al., 2003; Vargo & Lusch, 2004; Wise & Baumgartner, 1999). When competition increases in an industry due to entry of lower-cost competitors, margins shrink and differences among products fade due to imitation. The incumbents, in turn, attempt to diversifying into services which have higher margins. The motive and capabilities for such a maneuver is stronger for industry leaders and firms with higher market share. Suarez et al. (2013) argue that decline of product margins encourages manufacturers to diversify into services. Kastalli and Van Looy (2013) also state that manufacturers develop services in order to escape the commoditization trap. The competitive pressures from low-cost competitors in the manufacturing sector has led to commoditization of many product categories. Consequently, some manufacturers, especially the ones with stronger technology and knowledge base, will shift focus to services as a new basis for differentiation. Value-added services transform commodities to differentiated goods (Bowen et al., 1989). Therefore, beyond the traditional product diversification attempts to grow their business, manufacturers also have incentive to develop services around their products to increase the margin that they receive from the current product classes. Portfolios of products and services are distinctive, complex, and harder to imitate (Baines & Lightfoot, 2013; Kastalli & Van Looy, 2013); therefore, they provide strong bases for competition against low cost competitors.

This phenomenon is observed, for instance, when products from low-cost countries find their way to the market of a country with higher technology and product quality. The incumbents will not be able to lower their cost, especially since they have exploited cost reduction opportunities in response to existing competition among themselves. However, they have a technology advantage over the new entrants and the more promising route to competition is through differentiation. As we discussed, servitization is a means to differentiation specially to save product margins. One of the factors that helped Caterpillar keep its competitive advantage over Komatsu was its strong global service network, something that Komatsu lacked. IBM's redesigning of its strategy in 1990s also aligns with our argument. In the early 1990s IBM faced strong competition from Dell and Gateway who sold lower-priced computers directly to consumers. The consequence was a record loss of $5 billion. However, IBM started to rethink its business. By acquisition of Lotus the company began selling solutions instead of products. These solutions were combinations of products and services, designed to meet a broad array of customer needs. These examples, portray firms with stronger foothold in the market that were challenged by smaller entrants and ventured into services. The above arguments lead us to expect a higher level of servitization for firms that are in more competitive industries and firms that already possess a higher market share.

Hypothesis 3. Level of servitization is positively associated with industry competitiveness.

Hypothesis 4. Manufacturers with higher market share have a higher level of servitization.

Knowledge Stock

Knowledge is a special resource. It is path-dependent and accumulates over time. It is also indivisible but can be applied to new activities with minimal cost. As a result, accumulated knowledge should provide strong motivation for diversification. Especially, successful development of services such as maintenance or product analytics requires leveraging proprietary knowledge about the products and generating economies of scope.

Teece (1980) points out that a key factor in analyzing diversification based on economies of scope is the transaction cost. He argues that only the shared resources that are difficult to trade through market mechanisms provide the conditions for diversification. According to Teece (1980) transfer of proprietary knowledge through the market mechanism entails three difficulties: 1- recognition of trading partners: it is not readily clear who would be willing to purchase or buy firm's knowledge, 2- disclosure: firms are not willing to share proprietary knowledge due to risks of opportunism by the trading party, and 3- even if the first two issues are solved, the buyer of proprietary knowledge faces challenges in forming the teams or sub-organizations that are capable of utilizing the acquired knowledge. Due to these features Teece argues that existence of proprietary knowledge provides sufficient condition for diversification. We expect that a manufacturer is more likely to develop services around its products if it possesses a large stock of proprietary knowledge.

Hypothesis 5. A manufacturer's stock of proprietary knowledge is positively associated with its level of servitization.

METHODS AND ANALYSIS

Data

To test our hypotheses, we use financial data and patent for US publicly-traded manufacturers. We will use the North America Annual Fundamentals database as well as the Business Segments database from Standard & Poor's (2015) Compustat. The former contains fundamental data for U.S. and Canadian public firms, and, the latter provides historical data about business and geographic segments of over 24000 North American companies since 1976. Our analysis is limited to the manufacturing firms, i.e. the firms with the one-digit NAICS code 3. We use NAICS industry classification system because it contains a greater level of detail than the SIC system, especially for services. We will combine the North America database with the Business Segments database by the GVKEY (Global Company Key) code, which is the unique company identifier in Compustat. Finally, we will capture each firms patent data from patent data provided by National Bureau of Economic Research (2015).

Following the literature, we will apply the following data filtering steps in order to construct the final sample. First, all of the observations with negative values on total revenues, assets, and R&D expenditure will be dropped. Second, firms with negative service revenues will be deleted. Third, observations with extreme values (i.e. the 1st and the 99th percentiles) on total revenues, assets, annual income, and research and development expenditure will be deleted in order to mitigate the effect of outliers or miss-recorded data. Finally, we will delete missing data list-wise. This leaves a sample of

2450 manufacturing firms and 16115 firm-year observations for the period of 1976 to 2015.

Dependent Variable - Servitization

Service revenues (or its transformed versions) have been commonly used as a measure of servitization by the econometric analyses in the literature. A challenge in measuring servitization is that firms do not generally separate product and service revenues in their reports; consequently, services sales data are not easily available. Some scholars have partnered with companies in order to acquire service sales data. For instance, Kastalli and Van Looy (2013) collect longitudinal data from 44 subsidiaries of a multinational equipment manufacturer. They use subsidiaries' service revenues (normalized to year 2000 using World Bank's GDP deflator) as a measure of servitization. Another approach is to focus on specific industries where companies report their revenues broken down into products and services. Suarez et al. (2013) focus on pre-packaged software products industry (SIC code 7372) in which around 400 firms were found to have stated service and product revenues separately in their 10-K reports. The authors normalize service revenues by the total revenues and study the effect of services on the operating margin. The above approaches, however, limit the analysis to a few firms or industries.

Fang et al. (2008) develop a novel approach for estimating service revenues for a wide range of industries. Their method is based on identifying service segments within a company. By examining the description and the SIC codes of the operating segments reported in the Compustat Business Segment database, the authors divide a firm's segments into service and non-service. By adding up the revenues coming from service segments, the authors compute the total service revenues for 477 publicly traded manufacturers. To our knowledge, Fang et al.'s (2008) procedure is the only method offered in the literature that is applicable to a wide variety of firms and industries. Our approach for measuring service revenue (*Service*) is inspired by Fang et al. (2008).

Independent Variables

We will determine hi-tech industries *(Hi-Tech)* based on the list provided by Hall and Vopel (1996). Firm age *(Age)* will be measured from the year of initial public offering to date. We measure *market share* by dividing firm sales by total sales of the industry in a specific year. Industry is defined as all firms with the same 4 digit NAICS codes. Industry competitiveness will be measured using *Herfindahl index* (Kwoka, 1985). Herfindahl index is the sum of squared market shares of all firms in an industry. Herfindahl index varies between zero and one, and a higher number indicates higher concentration of market share and lack of competition. In order to measure *knowledge stock*, we use patent information. We used the cumulative number of patents from 1976 to date as a measure of firm's accumulated knowledge. Following the literature (e.g. Liu and Wong, 2011) we assume an annual depreciation rate of 20 percent for the value of older patents.

Control Variables

R&D intensity captures firm-level differences in innovation effort and can be linked to the amount of new services developed by the firm. Therefore, we will control for it in the analysis. Firm size is another important factor to consider. Larger firms have more resources to develop new services. In order to control for firm size, we include total sales *(Sales)* in our analysis. We control for firm's *return on assets* and *net margin* as measures of profitability. More profitable firms may be more willing to develop new services. They may also be more successful in marketing new services. We also control for *slack* resources. Following Fang et al. (2008) and Lee and Grewal (2004), we operationalize slack as the common principal component between from two financial ratios (1) retained earnings to total assets and (2) working capital to total assets. Retained earnings is the portion of net earnings that a company chooses not to pay out as dividends, but to retain for unforeseen eventualities and implementation of corporate strategies (Bourgeois, 1981). Working capital is the difference between current assets and current liabilities. Current assets are the liquid assets (cash, inventories, receivables, etc.) and current liabilities are the payments due in one year. We also control for human resource productivity as an indicator of human resource qualifications. Firms with higher qualified workers are at an advantage for offering services. Consistent with prior research (Datta et al., 2005; Guthrie, 2001; Huselid, 1995; Koch & McGrath, 1996) we operationalize human resource productivity with *sales per employee* – the ratio of firm sales to number of employees. Furthermore, we control for B2B vs B2C industries *(B2B)* as the need for service offering may be different in these two environments. We also control for industry growth *(Ind_Growth)* as firms in high-growth industry may have higher incentive to further focus on manufacturing compared to services. Finally, we account for competitive pressures and imitation effects by controlling for *service ratio of the leader* in the focal industry as well as total *service ratio of rivals* to a focal firm. In each case, the focal firm is excluded and the total services sales (of the firm with the largest market share or of all firms in the industry) is divided by the total sales. Additionally, we included year dummy variables to control for year to year variations in the industry.

Analysis Results

We analyze the data using multilevel regression model (Snijders & Bosker, 2011), particularly because our data has a multilevel structure. Firms will constitute the first level and industries the second level. Time, firm and industry were considered as levels of analysis. Since the distribution of sales and service sales are highly skewed we used their logged version in our analysis. Tables 2.1 and 2.2 below, show descriptive statistics and correlation among the variables, correspondingly. Table 2.3 presents results of the multi-level regression analysis.

Table 2.1. Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
ln(Service)	101137	1.038	1.902	0	8.5
Hi-Tech	101137	0.343	0.475	0	1
Age	97805	9.058	7.085	1	31
Herfindahl Index	101137	0.279	0.19	0	1
Market Share	100596	0.072	0.154	0	1
Knowledge Stock	27703	205.285	815.422	1	28588
ln(Sale)	100597	4.31	2.277	0	10.46
Return on Assets	100567	-0.092	0.476	-6.91	0.33
Net Margin	90429	-0.008	0.169	-1	0.37
Leader Service Ratio	100663	0.098	0.177	-0.02	1.35
Rivals Service Ratio	97355	0.144	0.098	0	1.24
Industry Growth	101136	1.007	0.013	0.92	1.14
B2B	84766	0.574	0.495	0	1
Sales Per Employee	93654	161.33	557.474	0	91135
Slack	96313	0.031	0.015	-1.07	0.1
R&D Intensity	67490	0.336	1.587	0	48.2

Table 2.2. Correlation Table

	ln(Service)	Hi-Tech	Age	Herfindahl Index	Market Share	Knowledge Stock	ln(Sale)
Hi-Tech	0.01						
Age	0.10	-0.02					
Herfindahl Index	0.00	-0.09	0.07				
Market Share	0.17	-0.19	0.17	0.35			
Knowledge Stock	0.12	0.02	0.25	0.05	0.26		
ln(Sale)	0.33	-0.21	0.33	0.00	0.46	0.34	
Return on Assets	0.11	-0.12	0.09	0.04	0.13	0.06	0.41
Net Margin	0.05	-0.10	0.07	0.02	0.13	0.07	0.34
Leader Service Ratio	0.07	0.09	0.00	0.04	-0.01	0.00	-0.03
Rivals Service Ratio	0.14	0.31	-0.07	-0.04	-0.11	0.00	-0.17
Industry Growth	0.02	0.01	-0.04	-0.05	-0.08	0.00	0.04
B2B	-0.06	-0.22	0.05	-0.08	0.06	0.03	0.13
Sales Per Employee	0.06	-0.01	0.09	-0.02	0.00	0.03	0.13
Slack	0.04	-0.05	0.01	0.03	0.04	0.01	0.18
R&D Intensity	-0.06	0.13	-0.10	-0.06	-0.09	-0.05	-0.28

Table 2.2. Correlation Table *(continued)*

	Return on Assets	Net Margin	Service Ratio of Leader	Service Ratio of Rivals	Industry Growth	B2B	Sales Per Employee	Slack
Net Margin	0.79							
Leader Service Ratio	-0.04	-0.03						
Rivals Service Ratio	-0.12	-0.11	0.35					
Industry Growth	-0.01	0.02	0.03	0.00				
B2B	0.08	0.05	-0.13	-0.36	0.00			
Sales Per Employee	0.04	0.02	0.02	0.03	0.02	0.02		
Slack	0.35	0.32	-0.02	-0.07	-0.01	0.04	0.02	
R&D Intensity	-0.31	-0.46	0.06	0.21	0.01	-0.13	-0.10	-0.35

Table 2.3. Multi-level Regression Results

	(1) ln(Service $_{t-1}$)	(2) ln(Service $_{t-2}$)	(3) ln(Service $_{t-3}$)
Hi-Tech	0.565***	0.525***	0.510***
Age	-0.017***	-0.020***	-0.016**
Herfindahl Index	-0.111	-0.193	-0.232^{+}
Market Share	0.542**	0.467**	0.433*
Knowledge Stock	0.001***	0.001***	0.001***
ln(Sale)	0.313***	0.294***	0.280***
Return on Assets	-0.038	0.181	0.193
Net Margin	-0.037	-0.124	-0.080
Leader Service Ratio	0.200*	0.168^{+}	0.227*
Rivals Service Ratio	0.547*	0.458*	0.307
Industry Growth	-1.997^{+}	-1.652	-0.818
B2B	-0.315**	-0.358**	-0.356**
Sales Per Employee	-0.001	-0.001	-0.001
Slack	-13.648	-7.126	-7.342
R&D Intensity	0.043	-0.010	0.132
Constant	1.821	1.598	0.874
Year Dummies	Y	Y	Y
ln(sd(Industry Effect)	-0.810***	-0.729***	-0.665***
ln(sd(Firm Effect)	0.446***	0.465***	0.484***
ln(sd(Residual)	0.248***	0.258***	0.269***
LL	-2.94e+04	-2.78e+04	-2.64e+04
AIC	58852.228	55693.940	52827.388
BIC	59228.915	56067.605	53198.118
N	16115	15151	14270

$^{+}$ $p<0.10$
* $p<0.05$
** $p<0.01$
*** $p<0.001$

As a robustness check we use three lag values between dependent and independent variables. Models 1 to 3 use lag values of 1 to 3 years, correspondingly. The results indicate that firms in hi-tech industries have a higher level of servitization. Additionally, servitization is negatively associated with firm age. Therefore, we conclude that H1 and H2 are supported. Contrary to our expectation industry competition was not significantly related to servitization. However, market share had a significant and positive influence on servitization. Therefore, H3 is not supported, while, H4 is supported. Finally, the coefficient of knowledge stock is positive and significant in all three models indicating support for H5.

DISCUSSION AND CONCLUSION

Servitization is a major shift in the manufacturing sector. Many manufacturers have decided to add services to their offerings in an effort to differentiation themselves from the competition and secure higher margins. This work analyzes the factors that motivate manufacturers to offer services. We combined financial statement data and patent data in order to empirically analyze these motivating factors. We obtained a sample of 2450 firms and 16115 firm-year observations and analyzed it using multi-level regression. The results indicate that firms in hi-tech sector have a higher degree of servitization. This is in line with our argument that because hi-tech products are more complex and technology intensive, customers' need a higher level of services from the firm. All aspects of the economic transaction from search, selection, purchase, installation, use and maintenance are more complex in the case of hi-tech products and therefore there is demand for manufacturers support of the product in the form of add-on services. We also find that manufacturing firm offer less and less service as they age. We argue that this is due to increased familiarity of customers with products, higher diffusion of product-related information, shift towards commoditization and maturity of service suppliers.

Surprisingly, we found that industry competitiveness was not significantly related to servitization. This result could be due to mixed indications of competitiveness for high and low ends of the market. Higher competition may drive high-end manufacturers to differentiate themselves through services, while, it may drive lower-end manufacturers to further focus on process improvement and cost reduction in their product business. This possibility is further strengthened by our finding that market share is positively associated with level of servitization. On average, firms with higher market share tend to offer a higher level of service due to their superior resources and technology. Manufacturers with larger market share also find a larger business opportunity for developing services, and therefore, they can better justify the costs of servitization. Finally, we show that firms with larger knowledge stock tend to offer more services. This is in line with our argument that diversifying into services requires a high level of knowledge and technology that can be widely different from knowledge required for manufacturing. Once a firm has invested in innovation and accumulated knowledge, its ability to venture into new areas of business increases and the marginal cost of applying knowledge is small. Therefore, a firm with a large stock of knowledge has higher ability and economic motive to diversify into services. Our findings are robust under different lag structures and shed light on the enabler and drivers of servitization across all manufacturing industries. Using the new framework of customer value chain, we were able to point to some aspects of servitization that are ignored in diversification theories. Some of the concepts proposed in this study such as knowledge asymmetry between firm and customer in hi-tech sector, firm age and maturity of service suppliers are particularly important in analysis of servitization and have not been explored sufficiently in the diversification literature. Our study advances this literature by showing that servitization has different characteristics compared to the traditional forms of diversification and offers new explanations as to why manufacturers become servitized.

ESSAY III

THE CONTRIBUTION OF DEALER NETWORKS TO THE SUCCESS OF AUTOMAKERS

ABSTRACT

Democratization of information has eroded much of the informational advantage of automobile dealerships over their customers. Savvy consumers research extensively online before even visiting a dealer and do not depend on salesmen to guide them for their purchase. This trend has commoditized several aspects of dealership activities and called into question the importance of their role played in the automobile supply chain. This paper investigates how important dealer services are for the market success of a car brand. By scraping web we obtain sales and consumer rating information for all dealerships in the US and all new cars offered for sale in five car classes. Our findings demonstrate that the aggregate quality ratings of dealerships influences consumers' choice between brands, which confirms the importance of services that go along with the product in the automobile market. Results further demonstrate that this effect is stronger in markets where the brand's dealer network is sparse (increasing internal switching cost), and the competing dealer networks are dense (decreasing external switching cost).

Keywords:

Automobile industry, dealerships, automakers, service quality

THE ROLE OF DEALERSHIP NETWORK IN THE SUCCESS OF AUTOMAKERS

INTRODUCTION

Distribution and services play a major role in many capital goods industries. Capital goods are bought to deliver value throughout their lifetime, and manufacturers that can help their customers get the most out of their products will be able sustain their competitiveness. Capital goods manufacturers typically distribute their product through dealership network. Dealers not only sell the products but also offer a wide array of other services during and after sales. The quality of service provided these dealers can make the difference between success and failure of the manufacturer.

> "The biggest reason for Caterpillar's success has been our system of distribution and product support. Don't get me wrong. We think we are better engineers and manufacturers than our competitors. But we are convinced that our single greatest advantage over our competition was and still is our system of distribution and product support" – Chief Executive Officer of Caterpillar (Fites, 1996: 85)

Caterpillar is a prominent example of how dealership networks can save a manufacturer in times of fierce competition. In the 1980's, when Japanese manufacturers were overcoming their American counterparts and capturing US market, Caterpillar did not fall to Komatsu despite Komatsu's significant cost advantage and remarkable product quality. Many observers attribute this success primarily to Caterpillars strong dealership network that offered unparalleled service quality to customers over the product lifetime (Fites, 1996; Hitt, Tyler, Hardee, & Park, 1995; International Council on Sustainable Development, 2017).

Similarly, dealerships in the automotive industry play a key role. Almost all new car sales in the US are made by dealers. Auto dealers provide a number of critical services to consumers. Besides executing sales, they build long-term relationship with their local community, provide information and financing services to customers, trade in their old cars, provide spare parts, and handle maintenance, repair and recalls. In other words, almost all of the services that need to accompany automobiles are offered by the dealerships.

That being said, there has been significant controversy about the actual value that automobile dealers provide in the supply chain. The dealership business model has stood the test of time and many attempts at disintermediating dealers and direct selling have failed. Some argue that underneath this resilience is the significant and unique value that dealers offer to customers and manufacturers which cannot be bypassed (Keller & Elias, 2014).

Yet others argue that technology is eroding the role of dealers, and dealership business model is doomed to fail (Economist, 2015). Savvy consumers increasing obtain car information and obtain loans and insurance online and only visit dealerships for the purchase transaction. Additionally, manufacturers continue to experiment with alternative distribution models such as direct selling and showrooming. This perspective implies that dealers no longer provide significant value in the supply network to justify a separate middleman entity connecting manufacturers with customers.

Evaluating these opposing views on the value of dealerships is an empirical task, and should be based on objective analysis of real data. Existing studies of automobile industry offer little evidence on this issue. Therefore, we propose an empirical study to disentangle the economic value of dealers for automakers.

Our research questions is how important the service performance of the dealership network is for the success of automakers. In other words, how much of the variation in sales of a car in a market is explained by the quality of services offered by the dealerships, as reflected in consumer ratings and reviews. All of the activities done by dealerships are considered as services in our study. These include sales, financing, repair and maintenance, spare parts provision, managing recalls, and trade-ins.

We leverage sales and performance data of various car models in the US market as well as quality ratings, characteristics and practices of dealerships. We model automobile sales at the dealership- and the manufacturer-level in each market and use multi-level regression analysis to quantify the effect of dealership consumer ratings and characteristics of dealer network on car sales. This analysis will allow us to understand the factors that matter most for the success of the individual dealership and for the overall market share of the manufacturer.

If consumers' decision to buy from a brand is influenced by their satisfaction with its dealerships, then the variation in market share of that brand should be, in part, explained by variation of consumer ratings of dealerships across different markets. This would mean that reduction of performance of dealerships of a brand would encourage customers to switch to another brand and that loyalty to product brand does not prevent the damage due to bad service (between-brand switching behavior). Conversely, if brand loyalty trumps satisfaction with dealership service, we should see customers switching to better dealerships of the same brand (within-brand switching behavior). It is our goal to quantify the extent of between-brand switching behavior and understand how manufacturers can minimize it.

Besides the main effect of dealership performance on sales, we also explore the moderating role of dealership network structure. In particular, we explore the role of internal and external network densities. Dealer network density is defined as the number of dealerships. For a car brand and in a specific market, internal density of the dealership network is defined as the density of its own dealerships network while external density is defined as the aggregate density of other brands' dealership networks. Density measures are critical because they determine the ease of switching within and between brands. If the internal density is high for a brand, consumers may have an easier job switching internally and staying with that brand. Similarly, if the external network density if high there will be plenty of opportunities for consumers to switch to a different brand. Therefore, the two network density metrics are important factors in evaluating the impact of dealership performance on market success of the automaker.

LITERATURE REVIEW

In analyzing the contribution of dealerships to brands, the studies on brand loyalty offer useful insights. Several issues of customer equity and the (service) quality have investigated the antecedents of brand loyalty and market success of brands (Bolton, 1998; Bolton, Kannan, & Bramlett, 2000; Bolton & Lemon, 1999; Mittal & Kamakura, 2001; Zeithaml, 1988; Zeithaml, Berry, & Parasuraman, 1996)

However, this body of work is largely focused on the dyadic relationships with consumers. The interplay between manufacturer success and dealer performance remains an understudied area. And, studies that do consider this interplay tend to focus on loyalty and re-purchase behavior issues as only one of several factors that contribute to market success of manufacturers. For instance, in lower-end segments of the market, consumers are driven by utilitarian aspects of the product, e.g., features and packages. As these characteristics are becoming increasingly similar, brand loyalty may be weak and not a major determinant of success.

Bloemer and Lemmink (1992) conduct a mail survey of car buyers investigate the association between customer satisfaction, dealer loyalty and brand loyalty. The authors find that brand loyalty is impacted by customer satisfaction with the car as well as loyalty to dealer. They also demonstrate that satisfaction with the sales service and with the after-sales service both drive loyalty to dealer. It is important to note that a survey of car buyers after a successful purchase from a dealer is likely to find that customer are receptive to conducting their future business with that dealer. However, consumers' actual behavior in future may be different as several other factors will play a role when it is time for a new purchase.

Mittal, Kumar, and Tsiros (1999) sheds light on this issue. They conduct a longitudinal survey of car purchasers and focus on temporal aspect of the relationship between satisfaction and purchase intentions. The authors find that satisfaction with dealers and cars influences short term repurchase intention. But a second survey administered 21 months later, showed that there is no relationship between initial satisfaction and longer-term purchase intention.

Punj and Brookes (2002) present a different perspective. They focus on the actual re-purchase behavior, rather than stated intentions. In a survey of new automobile buyers, they find that about 67% percent of new car buyers had a clear pre-purchase intention about the make or model they want to purchase before visiting a dealer. Contrary to the findings of Bloemer and Lemmink (1992), the study shows that only a very small portion of customers considered the dealer important in their purchase decision.

These mixed findings might partly be due different measurement methods, e.g., loyalty intention (Mittal et al., 1999) versus actual switching behavior (Punj & Brookes, 2002) to investigate the dealer's contribution to brand loyalty. Studies that use intention instead of actual behavior can over-estimate results by ignoring all intervening factors at the time of purchase decision.

Verhoef et al. (2007) attempt to reconcile prior findings by arguing that contribution of dealers to brand loyalty depends on the type of brand. They propose that high prestige cars are bought for status and superior product characteristics. Also, economy models are bought for their price. In both cases customer has strong pre-purchase constraints and dealers cannot make a significant difference. While, for volume models dealers can make a significant difference in customer decision making and ultimately loyalty to the brand.

Repeat purchase may also be a function of customer characteristics. Lambert-Pandraud et al. (2005) demonstrate that older customers tend to search fewer brands and dealerships, and are more likely to repurchase the same car. Consumer characteristics and demographics offer important avenues for exploring contingencies.

It is important to note that consumer's loyalty towards a single dealer could have different effects on purchase intention than consumer's perception of the dealer network as a whole. A customers' affinity with a single dealer may not play a role in repurchase intention since it may fade over time and alternative dealers are available. However, a customer's perception of the overall level of service offered by the dealership network can be more salient in consumer's mind. Our study is different from prior literature in that it measure quality of service at the level of dealer network, rather than a single dealer.

In addition, the studies on contribution of dealers to brand manufacturers has been concentrated on loyalty and re-purchase decision issues. Many studies have used survey and interview methods which can suffer from memory recall limitations and the gap between original intentions and future behavior.

As indicated by Mittal et al. (1999), the salience of determinants of customer intentions shift over time. When asking recent new car buyers about their purchase, customers may place emphasis on dealer's role in their decision. However, after the purchase customers spend a lot more time with the product than the dealer and salience of dealer's actions may diminish for customers. By the time the customer wants to purchase a new product the original impact of the dealer may have been forgotten. This finding shows that customers' expressed loyalty is not the best measure for investigating dealers' impact. To overcome this issue, we use market share as the outcome variable, which reflects customers' actual purchase behavior in an objective manner.

Furthermore, dealers' performance does not impact existing customers only. It impacts first time buyers as well, directly, via interaction at the time of shopping and, indirectly, via word of mouth. Purchasers from a brand constitute a mixture of repeat and first-time buyers with unknown proportions. Our measure of market share captures the combined purchases of these customers with their current composition, which is the ultimate figure impacting manufacturers' bottom line.

Several factors also have changed since the above-mentioned studies were conducted. The automobile distribution channels are changing rapidly by proliferation of information via online and offline sources that diminish the role traditionally played by dealerships. Automobiles are increasingly similar as manufacturers quickly imitate each other and replicate the features of competing cars. In many cases, a new technology appears in competing brand in the same year. For instance most mid-size automobiles in the US market added adaptive cruise control capabilities to their models in 2018. These harmonic maneuvers suggests that manufacturers access similar information and technologies long before any competing model hits the market. Growing similarly of cars can have important implications for the role played by dealerships that need to be investigated.

Our study also uses a much larger dataset compared to previous studies. Our dataset incudes demographic and economic characteristics of regions as well as availability of competing alternative within customers' reach that have been ignored in previous studies. Note that a customer may re-purchase a brand merely due to lack of other options, e.g., long distance to dealerships of other brands. Finally, we consider the dealership network of a manufacture as a whole rather than individual dealerships. This may also increase the accuracy of our results as customers can switch between dealerships.

HYPOTHESES

Consumers' satisfaction with a brand's dealerships may have mixed implication for their attitude towards the brand. With the exception of Tesla, almost all new car sales in the US are made by dealerships. Consumers' purchase from a dealer may be reflective of their satisfaction with the sales practices of that dealer. At the individual level, a consumer would view the product and the service as an integrated bundle. Automobiles need a significant amount of service both at the time of purchase (e.g., consultation, trade-in, and financing) and after purchase (e.g., maintenance and repair). Mittal et al. (1999) demonstrate that loyalty to dealers and brands have cross over effects and impact each other. For most consumers, dealerships are either the sole or the most convenient way to access automobile services. Therefore, they are likely to view dealerships' services and automaker's products as parts of the same package, and their perception of these parts would be tied together. If the only way to purchase and maintain a high-quality car brand is through a poor performing dealer network, consumers' satisfaction with the product is likely to suffer. Similarly in heavy machinery industry, scholars have argued that dealer services are significant considerations in customers' purchase decisions (International Council on Sustainable Development, 2017). Therefore, a higher product price can be well worth the outstanding service from dealerships.

In addition, the Appraisal-Tendency Framework suggests, emotions carry over from past situations to color future judgments and choices (Han, Lerner, & Keltner, 2007; Lerner & Keltner, 2000; Lerner & Tiedens, 2006). Therefore, consumer's experience with the service offered by dealerships is likely to also impact their view of the automobile, the brand, and ultimately future purchase intentions.

On the flip side, recent evolutions in the economy and consumer habits may have diminished the role played by dealerships. Expansion of internet and democratization of information have eroded much of the informational advantage previously enjoyed by auto dealers. Consumers increasingly use internet to learn about automobiles and make their selection. Autotrader (2016) reports that automobile buyers spend 59% of their time researching online. This trend has downplayed the dealer’s role in providing consultation and pricing, making the sales process a commodity.

In addition, many consumers do not find their experience with dealerships particularly enjoyable. In the 2016 Consumer Automotive Index survey (Beepi Inc., 2016) 52% of car shoppers reported they feel anxious or uncomfortable at dealerships, 62% reported feeling pressured to buy, and 54% said they would “love” to be able to purchase a car online. These findings are by no means good news for auto dealers. If anything, they show that car buyers are inclined to embrace other forms purchasing cars. However, dealerships remain the dominant channel for distribution of automobiles. In addition, the high startup cost of opening a dealership keep entry barriers high and limits competition. As a result, consumers do not have many choices when it comes to purchasing a car, and satisfaction with dealership services, or lack thereof, may not play a large role in their purchase decisions. The improvement in quality of cars over time has decreased the risk to the buyers and therefore the transaction costs. It has also reduced the need for servicing the automobile. This means consumers need less help and support from dealers (Autopolis, 2000).

Ratchford et al. (2003) also note that car buyers meet dealers only intermittently while they use the car on an ongoing basis. In this process, dealers can have an impact when customer visits them, however, this impact will fade away gradually. By the time the customer is ready to make a new purchase previous dealer experience may not be relevant any more.

In addition, the growing similarity of models in their features and technology makes the purchase decision a matter of taste rather than a rational comparison of utility, leading to two opposite effects. First, it makes the purchase easier in terms of comparison and information acquisition. Second, it may make psychological and soft factors such as the experience at the dealership more of a determinant in customer's decision.

Taken together these arguments suggest that consumers' response to the quality of service received at dealerships is mixed. It remains an empirical question whether and how much purchase decisions and ultimately automakers' market performance is impacted by dealership performance.

H1a(b). *Quality of services offered by dealerships of a car brand in a market positively impacts (does not impact) market share of that brand.*

The arguments above suggest that limited options, commoditization and access to information may have dampened consumers' response to dealership quality. In what follows, we explore each of these factors as a boundary condition.

Competition and Option Availability. As a brand gains more presence in a market and the rival brands lose presence the benefits of higher quality dwindle since the focal brand already captures a high level of market share and moves towards monopolizing the market. Therefore, there are decreasing returns to service quality. Consumer's react to low quality by moving their business between dealerships or brands. The extent to which customers can exercise this option depends on availability of other dealerships within reach. In response to undesirable quality of a dealership, consumers would be motivated to take their business to another dealership of that brand. And if those dealerships are densely located in the market, consumer would have an easy job switching. Cachon et al. (2005) demonstrate that this search is beneficial for consumers due to the overlapping assortment at various dealers particularly when there are limited options available within each product class. From the manufacturer's perspective this is a desirable outcome since lower performance of one dealer is compensated by better performance of another keeping consumers within the brand's network. By the same logic, if dealerships of competing brands are abundant in vicinity of a poor performing dealership, consumers would have an easier job switching to another brand. However, higher service quality keeps customers loyal to the brand and therefore the external switching behavior will be forestalled. Internal switching will also no longer be as beneficial since the service quality is generally high and there is not much room for finding an even better option. Therefore, we expect service quality to moderate the effect of density of dealership network for the focal brand (internal network density) and the rival brands (external network density). Figure 3.1 below summarizes our theoretical model.

H2. *Dealer network service quality negatively moderates the effect of internal network density on market share.*

H3. *Dealer network service quality positively moderates the effect of external network density on market share.*

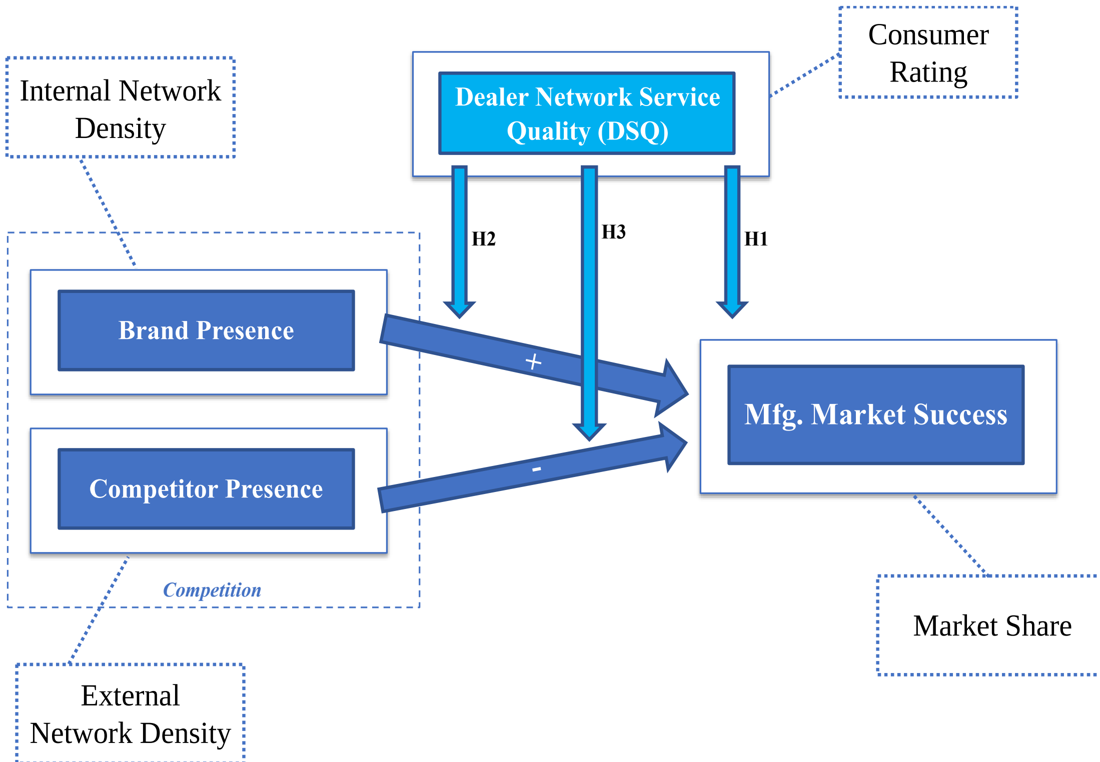

Figure 3.1. Theoretical Model

METHODS AND FINDINGS

Data Collection

We scraped a consumer-facing website to access new car inventory of all dealerships in the United States during an 11-day period (Jan 18th-30th, 2018 – except 20th and 21st due to technical issue leading to incomplete download of data). To cover a wide range of cars, we included five classes of automobiles – Subcompact Sedan, Compact Sedan, Mid-Size Sedan, Mid-Size SUV, and Full-Size Luxury. Within each class we included all major makes-models according to their US market share as reported in Table 3.1 (refer to “US Car Sales,” 2018 for market share analysis of various make-models within each class). There are 25 makes (in this paper also referred to as brands) in our sample for which Figure 3.1 reports the average daily sales.

We observed about 800,000 unique cars in the inventory in any given day. By comparing the VINs across consecutive days we were able to identify cars that are sold in each day by each dealership. The scraping procedure provided make, model and price of each car as well as consumer rating and review count for dealerships.

Table 3.1. List of Makes-Models by Class

SubCompact	Compact	Mid-Size	Mid-Size SUV	Full-Size Luxury
Chevrolet Sonic	Chevrolet Bolt EV	Chevrolet Malibu	Buick Enclave	Audi A8/S8
Ford Fiesta	Chevrolet Cruze	Chrysler 200	Buick Envision	Bentley Flying Spur
Honda Fit	Chevrolet Volt	Ford Fusion	Chevrolet Captiva Sport	Bentley Mulsanne
Hyunda Accent	Ford C-Max	Honda Accord	Chevrolet Traverse	BMW 7-series
Kia Rio	Ford Focus	Hyundai Sonata	Dodge Durango	Cadillac CT6
Kia Soul	Honda Civic	Kia Optima	Ford Edge	Genesis G90
Nissan Versa	Hyundai Elantra	Mazda Mazda6	Ford Explorer	Hyundai Equus
Toyota iA	Hyundai Ioniq	Nissan Altima	Ford Flex	Jaguar XJ
Toyota Pius C	Kia Forte	Subaru Legacy	GMC Acadia	Kia K900
Toyota Yaris	Mazda Mazda3	Subaru Outback	Honda Pilot	Lexus LS
	Mitsubishi Lancer	Toyota Camry	Hyundai Santa Fe	Maserati Quattroporte
	Nissan Leaf	Volkswagen Passat	Jeep Grand Cherokee	Mercedes-Benz S-class
	Nissan Sentra		Kia Sorento	Porsche Panamera
	Subaru Impreza		Mazda CX-9	
	Toyota Corolla		Nissan Murano	
	Toyota Prius		Nissan Pathfinder	
	Toyota Prius Prime		Toyota 4Runner	
	Toyota Prius V		Toyota Highlander	
	Volkswagen Golf		VW Atlas	
	Volkswagen Jetta		VW Touareg	

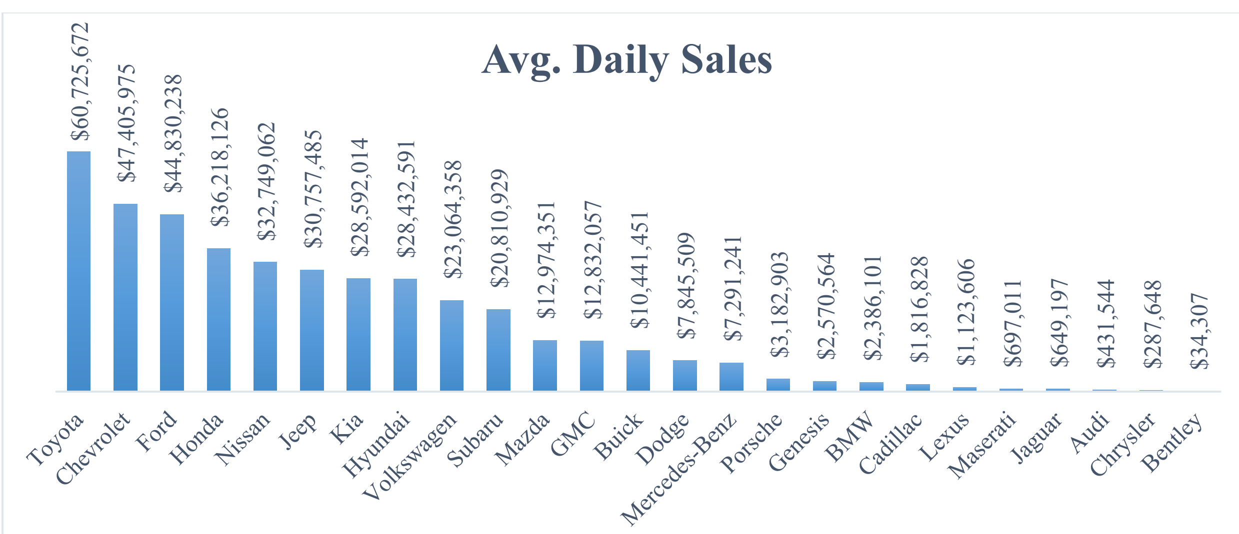

Figure 3.1. Average Daily US Sales of the Makes Included in the Sample

Next we used census data for identifying markets, their geographic boundaries, and demographic characteristics. We used an established classification of cities into core-based statistical areas (CBSAs) which identifies a metropolitan or micropolitan core as well as all surrounding cities that are integrated with it – based on commuting patterns of the residents. We considered each CBSA as a separate market. This classification is well suited for our study as we would like to consider all adjacent cities whose residents have significant commuting among them as one market. Using census concordance tables we assigned every dealerships to one of 791 CBSAs in the US by their zip code. Our final sample had 36394 observations including 10619 unique CBSA-make-class combinations.

In order to measure rating of a brand's dealer network in the market, we took the weighted average of consumer ratings across all dealerships in a market, with weights being the dealers' review count. Brand's success in the market was measured as its market share. Internal (external) network densities were also measured via the number of dealerships of the same (competing) brands in the same market per square mile of land within the CBSA(i.e., market). Finally, we control for the effect of weighted average rating of competitors in the same class, education (percent high school graduated or higher), median income, median age, population, average commute time to work, average vehicles owned and percent households with access to a broadband internet. We use the following random effects econometric model to test our hypotheses. Descriptive statistics of the variables in the analysis are presented in Table 3.2 below.

Table 3.2. Descriptive Statistics

		Mean	S.D.	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1)	Market Share	37.3	34	0.2	100												
(2)	Rating	4.6	0.5	1	5	-0.03											
(3)	IND	15.2	14	0.8	138.3	-0.1	0.03										
(4)	END	127.1	118.1	0	757	-0.34	0.06	0.65									
(5)	Land Area	3.6	3.7	0.1	27.3	-0.27	-0.01	-0.22	-0.06								
(6)	Education	87.9	4.3	63.3	96.8	-0.08	0.09	0.1	0.13	-0.14							
(7)	Family Income	69.2	13.1	35.9	112.5	-0.3	0.07	0.28	0.51	0.1	0.44						
(8)	Age	38.1	4	24.7	67.3	0.07	0.05	0.19	0.15	-0.25	0.16	-0.08					
(9)	Pop.	2	3.1	0.1	20.2	-0.34	0.03	0.29	0.6	0.43	-0.15	0.33	-0.09				
(10)	Commute Time	14.1	3.1	5.2	30.4	-0.14	-0.02	-0.02	0.09	0.25	-0.19	0	0.05	0.27			
(11)	Vehicles Owned	1.2	0.7	0	7.8	0.03	0	-0.02	-0.03	-0.01	-0.01	-0.1	0.12	-0	0.45		
(12)	Internet Pen.	81.7	5.1	49.4	90.8	-0.3	0.06	0.09	0.26	0.22	0.43	0.69	-0.12	0.27	0.04	-0.1	
(13)	Comp. Rating	4.5	0.4	0.5	5	-0.08	0.14	0.05	0.11	0.03	0.13	0.09	0.07	0.08	0.01	0.03	0.11

The Econometric Model

We introduce the following notation, in formulating our econometric model.

Indexes

- m: car make, e.g., Toyota
- c: car class, e.g., Mid-Size Sedan
- k: market, e.g., Phoenix metropolitan area
- d: dealership
- t: time

Variables

- $MaketShare_{mckt}$: Market share of make m, in class c, in market k, at time t.
- $Rating_{mk}$: Aggregate (i.e., wgt. average) rating of dealers of make m, in market k at time t.
- IND_{mk}: Internal dealer network density of make m, in market k.
- END_{mk}: External dealer network density of make m, in market k.
- C: Vector of control variables
- D_m, D_s, D_c, D_t : Dummy variables for make, state, class and time
- $\beta_.$: individual regression coefficients (with number index) or vectors thereof (with letter index).
- u_{mck}: random effect for each market-class-make unit
- ε_{mckt}: random error term

The model used for analysis of the data is presented below.

$$MaketShare_{mckt} = \beta_0 + \beta_1{*}Rating_{mk} + \beta_2{*}IND_{mk} + \beta_3{*}Rating_{mk}{*}IND_{mk} + \beta_4{*}END_{mk} + \beta_5{*}\,Rating_{mk}{*}END_{mk} + \beta_c{*}C + \beta_m{*}D_m + \beta_s{*}D_s + \beta_c{*}D_c + \beta_t{*}D_t + u_{mck} + \varepsilon_{mckt}$$

Estimation Results

The estimation results are reported in Table 3.1 below. We find that the same car brand gains higher market share in markets where the brand has highly rated dealerships. As model 1 in Table 3.3 suggests, one unit increase in rating is equivalent to 0.93% increase in market share on average. Therefore, hypothesis 1a is confirmed.

Next we look at the moderating effect of service quality on the relationship between competition and market share. As suggested in model 4 in Table 3.1, higher service quality rating attenuates both the positive effect of internal network density and the negative effect of external network density. Models 2 and 3, present separate tests of these moderations effects. While, the moderation effect for END hold without inclusion of IND, the reverse is not true. We conclude, hypothesis 2 is weakly supported and hypothesis 3 is supported.

We also test the robustness of results to several modeling choices. The results of robustness checks are reported in Table 3.4. We first include the second- and third-order terms for Rating to ensure that the interaction effects found for IND and END are not due to unmodeled non-linearity in Rating. As shown in models 1 and 2 the interaction effects are robust albeit the IND interaction becomes marginally significant ($p=0.051$ and $p=0.099$, respectively). Next we estimate the original models using maximum likelihood. Models 3 shows that the main effect of Rating is significant. Model 4 shows that interaction of Rating is significant with END but not with IND. Next we check how lack of competition in some markets affect results. Market share analysis has meaning only if there are alternative available to consumers. Therefore, we limit our sample to markets with at least two dealers of the focal brand and two dealers of competing brands. The results, as reported in models 5 and 6, remain significant. Finally, we test the assumption of normality on distribution of market share. We test the hypotheses using a logistic regression which satisfied the desirable property of limiting the distribution between 0 and 1. As indicated in models 7 and 8 the main effect of Rating and the interaction effect of END are significant, while the interaction of IND is not.

Table 3.3. Random Effects Estimation Results

Market Share	Main Model (1)	IND Moderation (2)	END Moderation (3)	Full Model (4)
Rating	0.934**	1.043*	0.211	0.423
	(0.343)	(0.449)	(0.549)	(0.550)
IND	0.418***	0.450***	0.419***	0.595***
	(0.029)	(0.071)	(0.029)	(0.083)
END	-0.117***	-0.117***	-0.146***	-0.161***
	(0.005)	(0.005)	(0.015)	(0.017)
Rating*IND		-0.007		-0.040*
		(0.016)		(0.019)
Rating*END			0.006*	0.010**
			(0.003)	(0.003)
Land Area	-3.030***	-3.030***	-3.033***	-3.034***
	(0.163)	(0.163)	(0.163)	(0.163)
Education	-0.227*	-0.227*	-0.225*	-0.228*
	(0.100)	(0.100)	(0.100)	(0.100)
Family Income	-0.424***	-0.424***	-0.423***	-0.421***
	(0.038)	(0.038)	(0.038)	(0.038)
Age	0.340***	0.340***	0.342***	0.343***
	(0.079)	(0.079)	(0.079)	(0.079)
Pop.	-0.036	-0.036	-0.039	-0.040
	(0.216)	(0.216)	(0.215)	(0.215)
Commute Time	0.012	0.012	0.011	0.013
	(0.112)	(0.112)	(0.112)	(0.112)
Vehicles Owned	0.804*	0.801*	0.801*	0.786*
	(0.386)	(0.386)	(0.386)	(0.386)
Internet Pen.	-0.599***	-0.599***	-0.598***	-0.601***
	(0.081)	(0.081)	(0.081)	(0.081)
Comp. Rating	-1.392*	-1.390*	-1.343*	-1.307*
	(0.579)	(0.579)	(0.579)	(0.581)
Constant	255.750***	255.288***	258.834***	257.954***
	(13.485)	(13.523)	(13.589)	(13.585)
Make Dummies	Y	Y	Y	Y
Class Dummies	Y	Y	Y	Y
State Dummies	Y	Y	Y	Y
Date Dummies	Y	Y	Y	Y
N	31884	31884	31884	31884

Standard errors in parentheses; ^ $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$"

Table 3.4. Robustness Checks

	Rating2 (1)	Rating3 (2)	MLE (3)	MLE (4)	Oligopoly (5)	Oligopoly (6)	GLM (7)	GLM (8)
Rating	-3.824^	-35.216***	0.890**	0.300	0.998**	0.539	0.047*	-0.033
	(2.102)	(7.757)	(0.339)	(0.526)	(0.344)	(0.553)	(0.019)	(0.032)
Rating2	0.563*	10.736***						
	(0.267)	(2.435)						
Rating3		-1.006***						
		(0.240)						
IND	0.581***	0.562***	0.415***	0.577***	0.396***	0.574***	0.020***	0.022**
	(0.085)	(0.088)	(0.026)	(0.112)	(0.029)	(0.082)	(0.002)	(0.007)
END	-0.158***	-0.158***	-0.117***	-0.163***	-0.118***	-0.161***	-0.006***	-0.011***
	(0.017)	(0.017)	(0.004)	(0.019)	(0.005)	(0.017)	(0.000)	(0.002)
Rating*IND	-0.037^	-0.033^		-0.036		-0.040*		-0.000
	(0.019)	(0.020)		(0.025)		(0.018)		(0.001)
Rating*END	0.009**	0.009*		0.010*		0.009**		0.001**
	(0.003)	(0.004)		(0.004)		(0.003)		(0.000)
Land Area	-3.023***	-3.046***	-3.010***	-3.014***	-3.464***	-3.468***	-0.177***	-0.177***
	(0.162)	(0.163)	(0.100)	(0.100)	(0.203)	(0.203)	(0.016)	(0.016)
Education	-0.229*	-0.219*	-0.230**	-0.231**	-0.253*	-0.254*	-0.012**	-0.012**
	(0.100)	(0.100)	(0.089)	(0.089)	(0.099)	(0.099)	(0.004)	(0.004)
Family Income	-0.419***	-0.424***	-0.422***	-0.420***	-0.430***	-0.428***	-0.018***	-0.018***
	(0.038)	(0.038)	(0.036)	(0.036)	(0.038)	(0.038)	(0.002)	(0.002)
Age	0.341***	0.344***	0.349***	0.352***	0.395***	0.398***	0.020***	0.020***
	(0.079)	(0.079)	(0.068)	(0.068)	(0.077)	(0.077)	(0.004)	(0.004)
Pop.	-0.039	-0.036	-0.008	-0.012	0.310	0.306	-0.025	-0.025
	(0.215)	(0.216)	(0.156)	(0.156)	(0.222)	(0.221)	(0.019)	(0.019)
Commute Time	0.012	0.016	0.004	0.005	0.050	0.051	-0.006	-0.006
	(0.112)	(0.112)	(0.100)	(0.100)	(0.111)	(0.111)	(0.005)	(0.005)
Vehicles Owned	0.789*	0.801*	0.806*	0.789*	0.764*	0.746^	0.043*	0.043*
	(0.386)	(0.387)	(0.353)	(0.353)	(0.384)	(0.384)	(0.017)	(0.017)
Internet Pen.	-0.601***	-0.607***	-0.603***	-0.604***	-0.554***	-0.556***	-0.025***	-0.024***
	(0.081)	(0.081)	(0.073)	(0.073)	(0.080)	(0.080)	(0.004)	(0.004)
Comp. Rating	-1.310*	-1.349*	-1.340**	-1.257*	-1.405*	-1.325*	-0.030	-0.026
	(0.580)	(0.580)	(0.493)	(0.494)	(0.573)	(0.575)	(0.026)	(0.026)
Constant	265.194***	293.495***	255.891***	258.448***	221.785***	223.784***	10.297***	10.644***
	(14.000)	(15.639)	(14.688)	(14.784)	(14.891)	(14.986)	(0.736)	(0.745)
Make Dummies	Y	Y	Y	Y	Y	Y	Y	Y
Class Dummies	Y	Y	Y	Y	Y	Y	Y	Y
State Dummies	Y	Y	Y	Y	Y	Y	Y	Y
Date Dummies	Y	Y	Y	Y	Y	Y	Y	Y
N	31884	31884	31884	31884	31702	31703	31884	31884

Standard errors in parentheses; ^ p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Post-Hoc Analyses

In this section we will test additional hypotheses about moderating role of variation of dealer ratings, internet penetration and car class. Table 3.5 summarizes the results from post-hoc analyses. In models 1 we report results for moderation analysis of internet penetration when treated as a binary variable. We made a median split on internet penetration and interacted with Rating. The results show marginally significant results indicating that the effect of Rating is stronger in markets with higher internet penetration. In model 2, we perform a similar analysis except that we use the continuous form of internet penetration. This analysis does not confirm existence of a linear moderation. Model 3 reports the estimation results for the effect of variation of dealer ratings. We measure variation as the standard deviation of dealer ratings for a brand within a market and within a class. The results indicate that when variation is higher the effect of rating on market share is also stronger. Finally, in model 4 we look at the effect of product class. The result indicate that class as a whole is a significant moderator for Rating. Particularly, we see that the effect of Rating is stronger for lower-end cars while it becomes non-significant for luxury cars.

Table 3.5. Post-Hoc Analyses

	Internet (binary) (1)	Internet (2)	Rating Variation (3)	Car Class (4)
Rating	0.032	-4.025	0.309	1.703
	(0.609)	(5.114)	(0.547)	(1.452)
IND	0.592***	0.590***	0.542***	0.657***
	(0.082)	(0.083)	(0.084)	(0.085)
Rating*IND	-0.039*	-0.039*	-0.038*	-0.053**
	(0.018)	(0.019)	(0.019)	(0.019)
END	-0.152***	-0.154***	-0.149***	-0.171***
	(0.018)	(0.019)	(0.017)	(0.016)
Rating*END	0.008*	0.008*	0.008*	0.012***
	(0.004)	(0.004)	(0.004)	(0.003)
Internet Pen. (binary)	-9.069**			
	(3.435)			
Rating*Internet Pen.(binary)	1.310^			
	(0.730)			
Internet Pen.		-0.857**	-0.596***	-0.599***
		(0.304)	(0.082)	(0.081)
broadband		0.000		
		(.)		
Rating*Internet Pen.		0.057		
		(0.065)		
Rating Variation			-7.465**	
			(2.735)	
Rating*Rating Variation			3.627***	
			(0.625)	
Subcompact Sedan				base
Compact Sedan				-1.220
				(1.527)
Mid-Size Sedan				-0.530
				(1.560)
Mid-Size SUV				-1.895
				(1.454)
Full-Size Luxury				-6.886**
				(2.481)
Control Variables	Y	Y	Y	Y
N	31884	31884	31884	31884

Standard errors in parentheses; ^ p<0.10, * p<0.05, ** p<0.01, *** p<0.001
+ Controls variables are not reported to conserve space; these variables are: Land Area, Education, Family Income, Age, Population, Commute Time, Vehicles Owned, Competitor Rating, Constant, and dummy variables for make, class, state and date.

CONCLUSIONS AND LIMITATIONS

We set out to resolve a debate about the importance of dealership service performance for brand manufacturers' market success. Our results demonstrate that consumers react positively to better service received from dealerships. This sends a message to brand manufacturers that it is not only the product itself that matters for their bottom line but also the quality of service offered by their dealership network.

In addition, we find evidence confirming that service quality moderates the competitive effect of brand or rival market presence. These findings suggest that external competition .– manifested in a dense network of competing brand dealerships – matters more when quality of dealer network is low. This suggests that car manufacturers need to pay specific attention to their dealerships in markets where competitors are densely located. In this situation switching is easier for customers and lower performance of their dealer network will lead to loss of more market share.

The results of the analysis also show that high dealer quality, neutralizes the benefit of brand presence – manifested in high network density for brands dealership. Abundance of dealerships of the same brand in proximity of each other makes internal switching easier for customers. However, this switching is only beneficial when the average quality of dealers is not high. In this situation, the negative effect of one dealer's low performance will be absorbed by other dealerships in vicinity and this prevents the customer from switching to a different brand. This finding also has implications for managing dealership networks. Low performance is particularly detrimental to manufacturer's market share when there are no compensating dealerships. Therefore, in markets where the brand's dealers are sparsely located, the quality performance of those dealers become more critical for the competitive fate of the brand.

This study helps manufacturers gain understanding of the role played by their dealership network in their market performance. The study highlights the importance of services for manufacturing firms and carefully managing and developing dealership networks that support products. We extend servitization and product-service bundling literatures by studying an underserved area – franchised dealership model – in which manufacturing and service activities are performed by different but tightly connected entities. The franchised dealership model represents a tighter relationship compared to that of buyer-supplier arrangement.

Our post-hoc analyses indicate that variation in dealer ratings is also an important factor. When variation is higher, the effect of low or high average rating is amplified. This finding can imply that dealers with extreme quality ratings either very high or very low might have stronger impact on market share that mediocre dealerships. In addition, we find strong evidence that importance of dealer network depends on the type of car. Particularly, for utility cars dealer rating is a significant predictor of market share while for luxury cars dealer rating does not matter. One explanation for this finding is that brand loyalty and variation in car features is stronger for higher-end products. Whereas, in lower-end car classes functionality of cars are increasingly similar and consumers also place lower weight on hedonic aspects of the car or brand identity which leads them to be more willing to switch brands for better service experience.

The findings of this study should be viewed in light of its limitations. While the main effect of consumer rating of dealer network and the moderating effect of external network density are robust to several modeling choices, we find that moderating effect of internal network density was not robust. Furthermore, we only observe the overall consumer ratings of dealerships. While we significant effect for ratings we are not able to disentangle the several factors that drive satisfaction and identify which one is more critical for market success of brands. Of particular interest is the distinction between sales and service activities. Dealerships perform very different roles during sales and after-sales service. Consumer rating of those as well as their ultimate effect on brand market share is not clear. We are planning to categorize reviews based on the subject of rating, e.g., sales process, maintenance quality, speed, attitude, etc. This categorization will allow us identify and distinguish various dealer practices that influence automaker success at a more granular level. Another closely related limitation of this work is that we do not observe the specific practices and features of dealerships. Issues related to human resource, design, amenities, inventory and assortment planning can be other sources of gaining consumer satisfaction which we were not able to observe. Finally, we only scratch the surface in study of dealership network designs. We analyze the aggregate quality rating, internal network density and external network density. Understanding how intermediate choices of manufacturers in managing their dealership network, such as contract types, training, spare parts support, and recall management, can influence brand's market success is also of significant importance which is not address by this study.

REFERENCES

Allison, P. D., & Waterman, R. P. 2002. Fixed–Effects Negative Binomial Regression Models. ***Sociological Methodology***, 32(1): 247–265.

Amihud, Y., & Lev, B. 1981. Risk reduction as a managerial motive for conglomerate mergers. ***The Bell Journal of Economics***, 605–617.

Anderson, K. 2009, March 1. Ethnographic Research: A Key to Strategy. ***Harvard Business Review***.

Antonakis, J., Bendahan, S., Jacquart, P., & Lalive, R. 2010. On making causal claims: A review and recommendations. ***The Leadership Quarterly***, 21(6): 1086–1120.

Apple.com. 2015. iSight Camera Replacement Program for iPhone 6 Plus. ***Apple.com***. https://www.apple.com/support/iphone6plus-isightcamera/.

Armistead, C., & Clark, G. 1991. Improving service delivery. ***Managing Service Quality***, 1(5).

Arnould, E. J., & Price, L. L. 2006. Market-oriented ethnography revisited. ***Journal of Advertising Research***, 46(3): 251–262.

Auerbach, A. J., & Reishus, D. 1988. ***Taxes and merger decisions. Knights, raiders, and targets: The impact of the hostile takeover: 300-313***. New York: Oxford University Press.

Autopolis. 2000. ***The Natural Link between Sales and Service: An Investigation for the Competition Directorate General of the European Commission***. http://ec.europa.eu/competition/sectors/motor_vehicles/documents/sales_and_service.pdf.

Autotrader. 2016. ***2016 Car Buyer Journey***. Autotrader Publications. https://agameautotrader.com/agame/pdf/2016-car-buyer-journey.pdf.

Baines, T. S., & Lightfoot, H. W. 2013. ***Made to Serve: How manufacturers can compete through servitization and product service systems*** (1 edition). Chichester, West Sussex, United Kingdom: Wiley.

Baines, T. S., Lightfoot, H. W., Benedettini, O., & Kay, J. M. 2009. The servitization of manufacturing: A review of literature and reflection on future challenges. ***Journal of Manufacturing Technology Management***, 20(5): 547–567.

Baines, T. S., Lightfoot, H. W., Peppard, J., Johnson, M., Tiwari, A., et al. 2009. Towards an operations strategy for product-centric servitization. ***International Journal of Operations & Production Management***, 29(5): 494–519.

Barnard, J. 1991. The information environments of new managers. ***The Journal of Business Communication (1973)***, 28(4): 312–324.

Bar-Yam, Y. 1997. ***Dynamics of complex systems***, vol. 213. Addison-Wesley Reading, MA. http://www.me.sc.edu/grad/russellj/Critiques%5Cskinner3.doc.

Baum, C. F. 2006. ***An introduction to modern econometrics using Stata***. Stata press.

Baysinger, B., & Hoskisson, R. E. 1990. The composition of boards of directors and strategic control: Effects on corporate strategy. ***Academy of Management Review***, 15(1): 72–87.

Beepi Inc. 2016. ***Americans Feel Taken Advantage of at the Car Dealership***. https://www.prnewswire.com/news-releases/study-americans-feel-taken-advantage-of-at-the-car-dealership-300301866.html.

Berry, C. H. 2015. ***Corporate growth and diversification***. Princeton University Press.

Berry, S., Levinsohn, J., & Pakes, A. 1995. Automobile prices in market equilibrium. ***Econometrica: Journal of the Econometric Society***, 841–890.

Bettencourt, L. A., Ostrom, A. L., Brown, S. W., & Roundtree, R. I. 2002. Client co-production in knowledge-intensive business services. ***California Management Review***, 44(4): 100–128.

Bitran, G. R., Ferrer, J.-C., & Rocha e Oliveira, P. 2008. OM forum—managing customer experiences: Perspectives on the temporal aspects of service encounters. ***Manufacturing & Service Operations Management***, 10(1): 61–83.

Bloemer, J. M., & Lemmink, J. G. 1992. The importance of customer satisfaction in explaining brand and dealer loyalty. ***Journal of Marketing Management***, 8(4): 351–363.

Blundell, R., Griffith, R., & Van Reenen, J. 1995. Dynamic count data models of technological innovation. ***The Economic Journal***, 333–344.

Bolton, R. N. 1998. A dynamic model of the duration of the customer's relationship with a continuous service provider: The role of satisfaction. ***Marketing Science***, 17(1): 45–65.

Bolton, R. N., Grewal, D., & Levy, M. 2007. Six strategies for competing through service: an agenda for future research. ***Journal of Retailing***, 83(1): 1–4.

Bolton, R. N., Kannan, P. K., & Bramlett, M. D. 2000. Implications of loyalty program membership and service experiences for customer retention and value. ***Journal of the Academy of Marketing Science***, 28(1): 95–108.

Bolton, R. N., & Lemon, K. N. 1999. A dynamic model of customers' usage of services: Usage as an antecedent and consequence of satisfaction. ***Journal of Marketing Research***, 171–186.

Bourgeois, L. J. 1981. On the measurement of organizational slack. ***Academy of Management Review***, 6(1): 29–39.

Bowen, D. E., & Jones, G. R. 1986. Transaction Cost Analysis of Service Organization-Customer Exchange. ***The Academy of Management Review***, 11(2): 428–441.

Bowen, D. E., Siehl, C., & Schneider, B. 1989. A Framework for Analyzing Customer Service Orientations in Manufacturing. ***The Academy of Management Review***, 14(1): 75.

Bowen, J., & Ford, R. C. 2002. Managing Service Organizations: Does Having a "Thing" Make a Difference? ***Journal of Management***, 28(3): 447–469.

Brax, S. 2005. A manufacturer becoming service provider – challenges and a paradox. ***Managing Service Quality***, 15(2): 142–155.

Bresnahan, T. F., Stern, S., & Trajtenberg, M. 1997. Market Segmentation and the Sources of Rents from Innovation: Personal Computers in the Late 1980s. ***RAND Journal of Economics***, S17–S44.

Brumback, B. A., Dailey, A. B., Brumback, L. C., Livingston, M. D., & He, Z. 2010. Adjusting for confounding by cluster using generalized linear mixed models. ***Statistics & Probability Letters***, 80(21): 1650–1654.

Bruner, J. 1991. The narrative construction of reality. ***Critical Inquiry***, 18(1): 1–21.

Bruner, J. S. 2009. ***Actual minds, possible worlds***. Harvard University Press.

Burrows, D. 2014, May 9. How to use ethnography for in-depth consumer insight. ***Marketing Week***. https://www.marketingweek.com/2014/05/09/how-to-use-ethnography-for-in-depth-consumer-insight/.

Cachon, G. P., Terwiesch, C., & Xu, Y. 2005. Retail assortment planning in the presence of consumer search. ***Manufacturing & Service Operations Management***, 7(4): 330–346.

Cameron, A. C., & Trivedi, P. K. 1986. Econometric models based on count data. Comparisons and applications of some estimators and tests. ***Journal of Applied Econometrics***, 1(1): 29–53.

Carpenter, M. P., Narin, F., & Woolf, P. 1981. Citation rates to technologically important patents. ***World Patent Information***, 3(4): 160–163.

Cassiman, B., & Veugelers, R. 2006. In search of complementarity in innovation strategy: Internal R&D and external knowledge acquisition. ***Management Science***, 52(1): 68–82.

Cayla, J., & Arnould, E. 2013. Ethnographic Stories for Market Learning. ***Journal of Marketing***, 77(4): 1–16.

Certo, S. T., Busenbark, J. R., Woo, H., & Semadeni, M. 2016. Sample selection bias and Heckman models in strategic management research. ***Strategic Management Journal***. http://onlinelibrary.wiley.com/doi/10.1002/smj.2475/pdf.

Chase, R. B. 1978. Where does the customer fit in a service operation? ***Harvard Business Review***, 56(6): 137–142.

Chase, R. B. 2010. Revisiting "Where Does the Customer Fit in a Service Operation?" In P. P. Maglio, C. A. Kieliszewski, & J. C. Spohrer (Eds.), ***Handbook of Service Science***: 11–17. Springer US.

Chatterjee, S., & Wernerfelt, B. 1988. Related or Unrelated Diversification: A Resource Based Approach. ***Academy of Management Proceedings***, 1988: 7–11. Academy of Management.

Chatterji, A. K., & Fabrizio, K. R. 2014. Using users: When does external knowledge enhance corporate product innovation? ***Strategic Management Journal***, 35(10): 1427–1445.

Chesbrough, H. W. 2003. ***Open innovation: The new imperative for creating and profiting from technology***. Harvard Business Press.

Christensen, C. M., Anthony, S. D., & Roth, E. A. 2004. ***Seeing what's next: Using the theories of innovation to predict industry change***. Harvard Business Press.

Cohen, M. A., Agrawal, N., & Agrawal, V. 2006. Winning in the aftermarket. ***Harvard Business Review***, 84: 129.

Cohen, W. M., & Levinthal, D. A. 1989. Innovation and learning: the two faces of R & D. ***The Economic Journal***, 569–596.

Cohen, W. M., & Levinthal, D. A. 1990. Absorptive capacity: a new perspective on learning and innovation. ***Administrative Science Quarterly***, 128–152.

Cohen, W. M., Nelson, R. R., & Walsh, J. P. 2002. Links and impacts: the influence of public research on industrial R&D. ***Management Science***, 48(1): 1–23.

Colvin, G. 2011. Caterpillar is absolutely crushing it. ***Fortune***. http://fortune.com/2011/05/12/caterpillar-is-absolutely-crushing-it/.

Cortina, J. M. 1993. Interaction, nonlinearity, and multicollinearity: Implications for multiple regression. ***Journal of Management***, 19(4): 915–922.

Cusumano, M. A., Kahl, S. J., & Suarez, F. F. 2015. Services, industry evolution, and the competitive strategies of product firms. ***Strategic Management Journal***, 36(4): 559–575.

Daft, R. L., & Lengel, R. H. 1986. Organizational information requirements, media richness and structural design. ***Management Science***, 32(5): 554–571.

Damanpour, F. 1991. Organizational Innovation: A Meta-Analysis of Effects of Determinants and Moderators. ***The Academy of Management Journal***, 34(3): 555–590.

Damanpour, F., & Evan, W. M. 1984. Organizational Innovation and Performance: The Problem of "Organizational Lag." ***Administrative Science Quarterly***, 29(3): 392–409.

Datta, D. K., Guthrie, J. P., & Wright, P. M. 2005. Human Resource Management and Labor Productivity: Does Industry Matter? ***The Academy of Management Journal***, 48(1): 135–145.

Day, G. S., & Schoemaker, P. J. 2006. ***Peripheral Vision: Detecting the Weak Signals That Will Make or Break Your Company***. Harvard Business Press.

DeBruicker, F. S., & Summe, G. L. 1985. Make sure your customers keep coming back. ***Harvard Business Review***, 63(1): 92–98.

Dess, G. G., & Beard, D. W. 1984. Dimensions of organizational task environments. ***Administrative Science Quarterly***, 52–73.

Diebold, F. X. 2001. Elements of Forecasting. ***Cincinnati, Ohio***.

Dooley, K. 2002. Organizational complexity. ***International Encyclopedia of Business and Management***, 6: 5013–5022.

Dooley, K. J., & Van de Ven, A. H. 1999. Explaining complex organizational dynamics. ***Organization Science***, 10(3): 358–372.

Dougherty, D. 2004. Organizing practices in services: capturing practice-based knowledge for innovation. ***Strategic Organization***, 2(1): 35–64.

Dyl, E. A. 1988. Corporate control and management compensation: Evidence on the agency problem. ***Managerial and Decision Economics***, 9(1): 21–25.

Economist. 2015, August 20. Death of a car salesman. ***Economist.Com***.

Elliott, R., & Jankel-Elliott, N. 2003. Using ethnography in strategic consumer research. ***Qualitative Market Research: An International Journal***, 6(4): 215–223.

Engle, R. F., & Granger, C. W. J. 1987. Co-Integration and Error Correction: Representation, Estimation, and Testing. ***Econometrica***, 55(2): 251–276.

Eurostat. 2016, October 6. Glossary:Knowledge Intensive Activity (KIA) - Statistics Explained. ***Eurostat***. http://ec.europa.eu/eurostat/statistics-explained/index.php/Glossary:Knowledge_Intensive_Activity_(KIA).

Fang, E. (Er), Palmatier, R. W., & Steenkamp, J.-B. E. M. 2008. Effect of Service Transition Strategies on Firm Value. ***Journal of Marketing***, 72(5): 1–14.

Field, J. M., Victorino, L., Buell, R. W., Dixon, M. J., Goldstein, S. M., et al. n.d. Service Operations: What’s Next? ***Journal of Service Management***, (forthcoming).

Fites, D. V. 1996. Make your dealers your partners. ***Harvard Business Review***, 74(2): 84–95.

Foss, N. J., Laursen, K., & Pedersen, T. 2011. Linking customer interaction and innovation: the mediating role of new organizational practices. ***Organization Science***, 22(4): 980–999.

Freeman, J. R. 1983. Granger causality and the times series analysis of political relationships. ***American Journal of Political Science***, 327–358.

Fuller, S. 2001. ***Thomas Kuhn: A Philosophical History for Our Times***. University of Chicago Press.

Galbraith, J. R. 1977. Organization design: An information processing view. ***Organizational Effectiveness Center and School***, 21.

Gattiker, T. F., Huang, X., & Schwarz, J. L. 2007. Negotiation, email, and Internet reverse auctions: How sourcing mechanisms deployed by buyers affect suppliers' trust. ***Journal of Operations Management***, 25(1): 184–202.

Gebauer, H. 2007. An Investigation of Antecedents for the Development of Customer Support Services in Manufacturing Companies. ***Journal of Business-to-Business Marketing***, 14(3): 59–96.

Goetgeluk, S., & Vansteelandt, S. 2008. Conditional generalized estimating equations for the analysis of clustered and longitudinal data. ***Biometrics***, 64(3): 772–780.

Goffin, K., & New, C. 2001. Customer support and new product development-An exploratory study. ***International Journal of Operations & Production Management***, 21(3): 275–301.

GoreMedical.com. 2010. ***The Stretch Advantage for Peripheral Reconstruction***. http://www.goremedical.com/AD0411-EN4.pdf.

Granger, C. W. 1969. Investigating causal relations by econometric models and cross-spectral methods. ***Econometrica: Journal of the Econometric Society***, 424–438.

Granger, C. W. 1988. Some recent development in a concept of causality. ***Journal of Econometrics***, 39(1): 199–211.

Gries, B., Gericke, K., Blessing, L., & others. 2005. ***How Companies Learn from Design Flaws: Results from an Emprical Study of the German Manufacturing Industry***.

Griliches, Z. 1981. Market value, R&D, and patents. ***Economics Letters***, 7(2): 183–187.

Griliches, Z. 1990. ***Patent statistics as economic indicators: a survey***. National Bureau of Economic Research. http://www.nber.org/papers/w3301.

Guthrie, J. P. 2001. High-involvement work practices, turnover, and productivity: Evidence from New Zealand. ***Academy of Management Journal***, 44(1): 180–190.

Hald, K. S., Kinra, A., & Das, A. 2016. Understanding the factors that enable and inhibit value creation in buyer-supplier relationship within the outsourcing of IT services. ***5th World Conference onProduction and Operations Management. P&OM 2016***.

Hall, B. H., Jaffe, A. B., & Trajtenberg, M. 2001. ***The NBER patent citation data file: Lessons, insights and methodological tools***. National Bureau of Economic Research. http://www.nber.org/papers/w8498.

Hall, B. H., Jaffe, A., & Trajtenberg, M. 2005. Market value and patent citations. ***RAND Journal of Economics***, 16–38.

Hall, B. H., & Vopel, K. 1996. Innovation, market share and market value. ***Strasbourg, France: Prepared for the International Conference on the Economics and Econometrics of Innovation, The European Parliament***. Citeseer.

Han, J. K., Kim, N., & Srivastava, R. K. 1998. Market Orientation and Organizational Performance: Is Innovation a Missing Link? ***Journal of Marketing***, 62(4): 30–45.

Han, S., Lerner, J. S., & Keltner, D. 2007. Feelings and Consumer Decision Making: The Appraisal-Tendency Framework. ***Journal of Consumer Psychology***, 17(3): 158–168.

Hausman, J. A. 1978. Specification tests in econometrics. ***Econometrica: Journal of the Econometric Society***, 1251–1271.

Hausman, J. A., Hall, B. H., Griliches, Z., & others. 1984. Econometric Models for Count Data with an Application to the Patents-R&D Relationship. ***Econometrica***, 52(4): 909–38.

Hill, T. P. 1977. On goods and services. ***Review of Income and Wealth***, 23(4): 315–338.

Hoberg, G., & Phillips, G. 2010. Product market synergies and competition in mergers and acquisitions: A text-based analysis. ***Review of Financial Studies***, 23(10): 3773–3811.

Hoskisson, R. E., & Hitt, M. A. 1990. Antecedents and performance outcomes of diversification: A review and critique of theoretical perspectives. ***Journal of Management***, 16(2): 461–509.

Hoskisson, R. E., & Turk, T. A. 1990. Corporate restructuring: Governance and control limits of the internal capital market. ***Academy of Management Review***, 15(3): 459–477.

Huber, G. P. 1991. Organizational learning: The contributing processes and the literatures. ***Organization Science***, 2(1): 88–115.

Huber, G. P., & Daft, R. L. 1987. ***The information environments of organizations.*** http://psycnet.apa.org/psycinfo/1987-98580-005.

Hull, D. L., & Cox, J. F. 1994. The field service function in the electronics industry: providing a link between customers and production/marketing. ***International Journal of Production Economics***, 37(1): 115–126.

Hurley, R. F., & Hult, G. T. M. 1998. Innovation, Market Orientation, and Organizational Learning: An Integration and Empirical Examination. ***Journal of Marketing***, 62(3): 42–54.

Huselid, M. A. 1995. The impact of human resource management practices on turnover, productivity, and corporate financial performance. ***Academy of Management Journal***, 38(3): 635–672.

Imbens, G. W., & Wooldridge, J. M. 2009. Recent developments in the econometrics of program evaluation. ***Journal of Economic Literature***, 47(1): 5–86.

International Council on Sustainable Development. 2017. Caterpillar vs. Komatsu: Four Decades of Global Competition. ***International Council on Sustainable Development***. https://theinternationalcouncil.blogspot.com/2005/08/caterpillar-vs-komatsu-four-decades-of.html.

Jacobs, F. R., Chase, R. B., & Lummus, R. R. 2014. ***Operations and supply chain management***. McGraw-Hill Education.

Jansen, J. J., Van Den Bosch, F. A., & Volberda, H. W. 2006. Exploratory innovation, exploitative innovation, and performance: Effects of organizational antecedents and environmental moderators. ***Management Science***, 52(11): 1661–1674.

Jansen, J. J., Vera, D., & Crossan, M. 2009. Strategic leadership for exploration and exploitation: The moderating role of environmental dynamism. ***The Leadership Quarterly***, 20(1): 5–18.

Jansen, J. J., Volberda, H. W., & Van Den Bosch, F. A. 2005. Exploratory innovation, exploitative innovation, and ambidexterity: The impact of environmental and organizational antecedents. ***Schmalenbach Business Review***, 57: 351–363.

Jensen, M. C., & Meckling, W. H. 1976. Theory of the firm: Managerial behavior, agency costs and ownership structure. ***Journal of Financial Economics***, 3(4): 305–360.

Jerath, K., Kumar, A., & Netessine, S. 2015. An information stock model of customer behavior in multichannel customer support services. ***Manufacturing & Service Operations Management***, 17(3): 368–383.

Kaplan, S. 1989. Management buyouts: Evidence on taxes as a source of value. ***The Journal of Finance***, 44(3): 611–632.

Karmarkar, U. 2015. OM Forum—The Service and Information Economy: Research Opportunities. ***Manufacturing & Service Operations Management***, 17(2): 136–141.

Kastalli, I. V., & Van Looy, B. 2013. Servitization: Disentangling the impact of service business model innovation on manufacturing firm performance. ***Journal of Operations Management***, 31(4): 169–180.

Keller, M., & Elias, K. 2014. ***Consumer Benefits of the Dealer Franchise System***. White Paper, Maryann Keller & Associates. https://maryannkeller.com/consumer-benefits-of-the-franchised-dealer-report/.

Kellogg, D. L., & Chase, R. B. 1995. Constructing an Empirically Derived Measure for Customer Contact. ***Management Science***, 41(11): 1734–1749.

Ko, D.-G., Kirsch, L. J., & King, W. R. 2005. Antecedents of knowledge transfer from consultants to clients in enterprise system implementations. ***MIS Quarterly***, 59–85.

Koch, M. J., & McGrath, R. G. 1996. Improving labor productivity: Human resource management policies do matter. ***Strategic Management Journal***, 17(5): 335–354.

Kumar, A., & Telang, R. 2011. Product customization and customer service costs: An empirical analysis. ***Manufacturing & Service Operations Management***, 13(3): 347–360.

Kwoka, J. E. J. 1985. Herfindahl Index in Theory and Practice, The. ***Antitrust Bull.***, 30: 915.

Lambert-Pandraud, R., Laurent, G., & Lapersonne, E. 2005. Repeat purchasing of new automobiles by older consumers: empirical evidence and interpretations. ***Journal of Marketing***, 69(2): 97–113.

Lanjouw, J. O., Pakes, A., & Putnam, J. 1998. How to Count Patents and Value Intellectual Property:The Uses of Patent Renewal and Application Data. ***The Journal of Industrial Economics***, 46(4): 405–432.

Laursen, K., & Salter, A. 2006. Open for innovation: the role of openness in explaining innovation performance among UK manufacturing firms. ***Strategic Management Journal***, 27(2): 131–150.

Lee, R. P., & Grewal, R. 2004. Strategic Responses to New Technologies and Their Impact on Firm Performance. ***Journal of Marketing***, 68(4): 157–171.

Lele, M. M., & Karmarkar, U. S. 1983. Good product support is smart marketing. ***Harvard Business Review***, 61(6): 124–132.

Leonard, D., & Rayport, J. F. 1997. Spark innovation through empathic design. ***Harvard Business Review***, 75: 102–115.

Leontiades, M. 1982. Choosing the right manager to fit the strategy. ***Journal of Business Strategy***, 3(2): 58–69.

Lerner, J. S., & Keltner, D. 2000. Beyond valence: Toward a model of emotion-specific influences on judgement and choice. ***Cognition and Emotion***, 14(4): 473–493.

Lerner, J. S., & Tiedens, L. Z. 2006. Portrait of the angry decision maker: How appraisal tendencies shape anger's influence on cognition. ***Journal of Behavioral Decision Making***, 19(2): 115–137.

Levinthal, D. A., & March, J. G. 1993. The myopia of learning. ***Strategic Management Journal***, 14(S2): 95–112.

Levitt, B., & March, J. G. 1988. Organizational learning. ***Annual Review of Sociology***, 319–340.

Lewellen, W. G. 1971. A pure financial rationale for the conglomerate merger. ***The Journal of Finance***, 26(2): 521–537.

Lewin, A. Y., Long, C. P., & Carroll, T. N. 1999. The coevolution of new organizational forms. ***Organization Science***, 10(5): 535–550.

Li, F., Lundholm, R., & Minnis, M. 2013. A Measure of Competition Based on 10-K Filings. ***Journal of Accounting Research***, 51(2): 399–436.

Li, M., & Choi, T. Y. 2009. Triads in Services Outsourcing: Bridge, Bridge Decay and Bridge Transfer*. ***Journal of Supply Chain Management***, 45(3): 27–39.

Lilien, G. L., Morrison, P. D., Searls, K., Sonnack, M., & Hippel, E. von. 2002. Performance assessment of the lead user idea-generation process for new product development. ***Management Science***, 48(8): 1042–1059.

Liu, K. 1988. Measurement error and its impact on partial correlation and multiple linear regression analyses. ***American Journal of Epidemiology***, 127(4): 864–874.

Liu, Q., & Wong, K. P. 2011. Intellectual capital and financing decisions: Evidence from the US patent data. ***Management Science***, 57(10): 1861–1878.

Loomba, A. P. 1996. Linkages between product distribution and service support functions. ***International Journal of Physical Distribution & Logistics Management***, 26(4): 4–22.

Loughran, T., & McDonald, B. 2011. When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. ***The Journal of Finance***, 66(1): 35–65.

Lovelock, C. H. 1983. Classifying Services to Gain Strategic Marketing Insights. ***Journal of Marketing***, 47(3): 9–20.

Lusch, R. F., Vargo, S. L., & O'Brien, M. 2007. Competing through service: insights from service-dominant logic. ***Journal of Retailing***, 83(1): 5–18.

Mansfield, E. 1969. ***The economics of technological change***, vol. 120. Longmans London.

March, J. G. 1991. Exploration and exploitation in organizational learning. ***Organization Science***, 2(1): 71–87.

Mariampolski, H. 1999. The power of ethnography. ***International Journal of Market Research***, 41(1): 75.

Mariampolski, H. 2006. ***Ethnography for marketers: A guide to consumer immersion***. Sage. https://books.google.com/books?hl=en&lr=&id=O88vfGNiH_8C&oi=fnd&pg=PR9&dq=Ethnography+for+Marketers:+A+Guide+to+Consumer+Immersion&ots=CYqhi4Sc6w&sig=fiXxYIYufBQ9Doa55iMyzpmwURw.

Markham, J. W. 1973. ***Conglomerate enterprise and public policy***. Boston, MA: Harvard Business School.

Metters, R., & Verma, R. 2008. Service outsourcing: historical perspectives and future research directions. ***Journal of Operations Management***, 26(2): 141–7.

Mills, P. K., & Morris, J. H. 1986. Clients as “partial” employees of service organizations: Role development in client participation. ***Academy of Management Review***, 11(4): 726–735.

Mittal, V., & Kamakura, W. A. 2001. Satisfaction, repurchase intent, and repurchase behavior: Investigating the moderating effect of customer characteristics. ***Journal of Marketing Research***, 38(1): 131–142.

Mittal, V., Kumar, P., & Tsiros, M. 1999. Attribute-level performance, satisfaction, and behavioral intentions over time: a consumption-system approach. ***The Journal of Marketing***, 88–101.

Nagaoka, S., Motohashi, K., & Goto, A. 2010. Patent statistics as an innovation indicator. ***Handbook of the Economics of Innovation***, 2: 1083–1127.

Nash, K. S. 2014, January 1. State of the CIO 2014: The Great Schism. ***CIO***. http://www.cio.com/article/2380234/cio-role/state-of-the-cio-2014-the-great-schism.html.

National Bureau of Economic Research. 2015. ***Patent Data Project***. https://sites.google.com/site/patentdataproject/Home.

Neely, A. 2008. Exploring the financial consequences of the servitization of manufacturing. ***Operations Management Research***, 1(2): 103–118.

Neely, A., Benedettini, O., & Visnjic, I. 2011. The servitization of manufacturing: Further evidence. ***18th European Operations Management Association Conference***, 1.

Nevo, A. 2001. Measuring market power in the ready-to-eat cereal industry. ***Econometrica***, 69(2): 307–342.

Nonaka, I., & Takeuchi, H. 1995. ***The knowledge-creating company: How Japanese companies create the dynamics of innovation***. Oxford university press. https://books.google.com/books?hl=en&lr=&id=tmziBwAAQBAJ&oi=fnd&pg=PA3&dq=nonaka+takeuchi&ots=pS3fJK-GFw&sig=e9utg5VZvCbRHY1w4_si9EwpbP8.

Oliva, R., & Kallenberg, R. 2003. Managing the transition from products to services. ***International Journal of Service Industry Management***, 14(2): 160–172.

Ostrom, A. L., Bitner, M. J., Brown, S. W., Burkhard, K. A., Goul, M., et al. 2010. Moving forward and making a difference: research priorities for the science of service. ***Journal of Service Research***, 13(1): 4–36.

Ostrom, A. L., Parasuraman, A., Bowen, D. E., Patrício, L., & Voss, C. A. 2015. Service Research Priorities in a Rapidly Changing Context. ***Journal of Service Research***, 18(2): 127–159.

Özkan-Seely, G. F., Gaimon, C., & Kavadias, S. 2015. Dynamic Knowledge Transfer and Knowledge Development for Product and Process Design Teams. ***Manufacturing & Service Operations Management***, 17(2): 177–190.

Pakes, A., & Griliches, Z. 1984. Patents and R&D at the firm level: a first look. ***R&D, patents, and productivity***: 55–72. University of Chicago Press.

Payne, A. F., Storbacka, K., & Frow, P. 2008. Managing the co-creation of value. ***Journal of the Academy of Marketing Science***, 36(1): 83–96.

Phene, A., Fladmoe-Lindquist, K., & Marsh, L. 2006. Breakthrough innovations in the US biotechnology industry: the effects of technological space and geographic origin. ***Strategic Management Journal***, 27(4): 369–388.

Pisano, G. P. 1994. Knowledge, integration, and the locus of learning: An empirical analysis of process development. ***Strategic Management Journal***, 15(S1): 85–100.

Porter, M. E. 1980. Competitive strategy: Techniques foranalyzing industries and competitors. ***FreePress, New York***.

Porter, M. E. 1985. ***Competitive Advantage***. New York: Free Press.

Porter, M. E. 1987. From Competitive Advantage to Corporate Strategy. ***Harvard Business Review***, 65(3): 43–59.

Punj, G., & Brookes, R. 2002. The influence of pre-decisional constraints on information search and consideration set formation in new automobile purchases. ***International Journal of Research in Marketing***, 19(4): 383–400.

Randall, D., & Rouncefield, M. 2012. Ethnography. ***The Encyclopedia of Human-Computer Interaction***. The Interaction Design Foundation. https://www.interaction-design.org/literature/book/the-encyclopedia-of-human-computer-interaction-2nd-ed/ethnography.

Ratchford, B. T., Lee, M.-S., & Talukdar, D. 2003. The Impact of the Internet on Information Search for Automobiles. ***Journal of Marketing Research***, 40(2): 193–209.

Reed, R., & Luffman, G. A. 1986. Diversification: The growing confusion. ***Strategic Management Journal***, 7(1): 29–35.

Roels, G. 2014. Optimal Design of Coproductive Services: Interaction and Work Allocation. ***Manufacturing & Service Operations Management***, 16(4): 578–594.

Rorty, R. 1982. ***Consequences of Pragmatism: Essays, 1972-1980***. U of Minnesota Press.

Rosenkopf, L., & Almeida, P. 2003. Overcoming local search through alliances and mobility. ***Management Science***, 49(6): 751–766.

Rothwell, R., Freeman, C., Horlsey, A., Jervis, V. T. P., Robertson, A. B., et al. 1974. SAPPHO updated-project SAPPHO phase II. ***Research Policy***, 3(3): 258–291.

Roy, R., & Cohen, S. K. 2016. Stock of downstream complementary assets as a catalyst for product innovation during technological change in the US machine tool industry. ***Strategic Management Journal***. http://onlinelibrary.wiley.com/doi/10.1002/smj.2557/full.

Rumelt, R. P. 1974. ***Strategy, structure, and economic performance***. Cambridge MA: Harvard University Press.

Sawhney, A. 2004. ***The new face of environmental management in India***. Aldershot, UK: Ashgate.

Sawhney, M. 2006. Going beyond the product. ***The Service-Dominant Logic of Marketing***, 365–80.

Sawhney, M., Balasubramanian, S., & Krishnan, V. V. 2003. Creating growth with services. ***Mit Sloan Management Review***, 45: 34–44.

Schilling, M. A., & Phelps, C. C. 2007. Interfirm collaboration networks: The impact of large-scale network structure on firm innovation. ***Management Science***, 53(7): 1113–1126.

Semadeni, M., Withers, M. C., & Trevis Certo, S. 2014. The perils of endogeneity and instrumental variables in strategy research: Understanding through simulations. ***Strategic Management Journal***, 35(7): 1070–1079.

Siemsen, E., Roth, A. V., & Balasubramanian, S. 2008. How motivation, opportunity, and ability drive knowledge sharing: The constraining-factor model. ***Journal of Operations Management***, 26(3): 426–445.

Skjølsvik, T., Løwendahl, B. R., Kvalshaugen, R., & Fosstenløkken, S. M. 2007. Choosing to learn and learning to choose: Strategies for client co-production and knowledge development. ***California Management Review***, 49(3): 110–128.

Snijders, T. A. B., & Bosker, R. 2011. ***Multilevel Analysis: An Introduction to Basic and Advanced Multilevel Modeling*** (Second Edition edition). Los Angeles, Calif.: SAGE Publications Ltd.

Standard & Poor's. 2015. ***Capital IQ Compustat***. https://www.capitaliq.com/home/what-we-offer/information-you-need/financials-valuation/compustat-financials.aspx.

StataCorp. 2013. ***Stata Statistical Software: Release 13***. College Station, TX: StataCorp LP.

Stock, J. H., & Watson, M. W. 2003. ***Introduction to econometrics***, vol. 104. Addison Wesley Boston.

Suarez, F. F., Cusumano, M. A., & Kahl, S. J. 2013. Services and the business models of product firms: An empirical analysis of the software industry. ***Management Science***, 59(2): 420–435.

Sundin, E., Lindahl, M., & Ijomah, W. 2009. Product design for product/service systems: Design experiences from Swedish industry. ***Journal of Manufacturing Technology Management***, 20(5): 723–753.

Swan, J. E., & Bowers, M. R. 1998. Services quality and satisfaction. ***Journal of Services Marketing***, 12(1): 59–72.

Sydow, J., Schreyögg, G., & Koch, J. 2009. Organizational path dependence: Opening the black box. ***Academy of Management Review***, 34(4): 689–709.

Szulanski, G. 2000. The process of knowledge transfer: A diachronic analysis of stickiness. ***Organizational Behavior and Human Decision Processes***, 82(1): 9–27.

Teece, D. J. 1980. Economies of scope and the scope of the enterprise. ***Journal of Economic Behavior & Organization***, 1(3): 223–247.

Thompson, P., & Fox-Kean, M. 2005. Patent citations and the geography of knowledge spillovers: A reassessment. ***American Economic Review***, 450–460.

Tortoriello, M., Reagans, R., & McEvily, B. 2011. Bridging the Knowledge Gap: The Influence of Strong Ties, Network Cohesion, and Network Range on the Transfer of Knowledge Between Organizational Units. ***Organization Science***, 23(4): 1024–1039.

Trajtenberg, M. 1990. A penny for your quotes: patent citations and the value of innovations. ***The Rand Journal of Economics***, 172–187.

Tucker, A. L. 2007. An Empirical Study of System Improvement by Frontline Employees in Hospital Units. ***Manufacturing & Service Operations Management***, 9(4): 492–505.

Tuli, K. R., Kohli, A. K., & Bharadwaj, S. G. 2007. Rethinking customer solutions: from product bundles to relational processes. ***Journal of Marketing***, 71(3): 1–17.

Turk, T. A., & Baysinger, B. 1989. ***The impact of public policy on corporate strategy: Taxes, antitrust policy, and diversification clienteles***. Working paper, Texas A&M University, Department of Management, College Station, TX.

US Car Sales. 2018. ***carsalesbase.com***. http://carsalesbase.com/car-sales-us/.

US Census Bureau. 2016, November 4. ***North American Industry Classification System (NAICS), Concordances - US Census Bureau***. https://www.census.gov/eos/www/naics/concordances/concordances.html.

Utterback, J. M., & Abernathy, W. J. 1975. A dynamic model of process and product innovation. ***Omega***, 3(6): 639–656.

Vandermerwe, S., & Rada, J. 1988. Servitization of business: Adding value by adding services. ***European Management Journal***, 6(4): 314–324.

Vargo, S. L., & Lusch, R. F. 2004. Evolving to a new dominant logic for marketing. ***Journal of Marketing***, 68(1): 1–17.

Verhoef, P. C., Langerak, F., & Donkers, B. 2007. Understanding brand and dealer retention in the new car market: The moderating role of brand tier. ***Journal of Retailing***, 83(1): 97–113.

Von Hippel, E. 1994. “Sticky information” and the locus of problem solving: implications for innovation. ***Management Science***, 40(4): 429–439.

Von Hippel, E. 1998. Economics of product development by users: The impact of “sticky” local information. ***Management Science***, 44(5): 629–644.

Voss, G. B., Sirdeshmukh, D., & Voss, Z. G. 2008. The Effects of Slack Resources and Environmental Threat on Product Exploration and Exploitation. ***Academy of Management Journal***, 51(1): 147–164.

Wang, H., & Li, J. 2008. Untangling the effects of overexploration and overexploitation on organizational performance: The moderating role of environmental dynamism. ***Journal of Management***, 34(5): 925–951.

Wise, R., & Baumgartner, P. 1999. Go downstream: the new profit imperative in manufacturing. ***Harvard Business Review***, 77: 133–141.

Wooldridge, J. M. 2012. ***Introductory econometrics: A modern approach***. Cengage Learning.

Wuyts, S., Rindfleisch, A., & Citrin, A. 2015. Outsourcing customer support: The role of provider customer focus. ***Journal of Operations Management***, 35: 40–55.

Xue, M., & Field, J. M. 2008. Service coproduction with information stickiness and incomplete contracts: Implications for consulting services design. ***Production and Operations Management***, 17(3): 357–372.

Zahra, S. A., & George, G. 2002. Absorptive Capacity: A Review, Reconceptualization, and Extension. ***The Academy of Management Review***, 27(2): 185–203.

Zeithaml, V. A. 1988. Consumer perceptions of price, quality, and value: a means-end model and synthesis of evidence. ***The Journal of Marketing***, 2–22.

Zeithaml, V. A., Berry, L. L., & Parasuraman, A. 1996. The behavioral consequences of service quality. ***The Journal of Marketing***, 31–46.

APPENDIX A

NON-SERVITIZED MANUFACTURERS AND SAMPLE SELECTION BIAS

The population includes both service offering and non-service offering manufacturers. Service offering firms may also report zero service sales in some years. Therefore, there exist multiple types of zero observations on service sales (hereafter referred to as zeros) and careful treatment of these zeros is necessary. Zeros for non-service offering manufacturers (type I) might represent a different population, since these manufacturers can be systematically different from their service offering counterparts. Within service offering firms, too, there exists different types of zeros. There are zeros that represent an inactive stage of services (type II): zeros before the firm starts service activity (the first year with positive service sales), and zeros after the firm completely stops service activity (the last year with positive service sales). Finally, a manufacturer that is actively selling services may experience a temporary halt of service activity (type III). These events are characterized by a period with zero observation between two periods with positive observation. In sum, these conditions create three types of zeros. Type I are zero observations for traditional pure manufacturers, Type II are zero observations representing inactive stage of service activity, i.e. before services are developed or after complete shutdown of services, and Type III are zero observations representing temporary halt of service activity.

These types represent different positions along a continuum of service activity, from temporary halt to non-existence. By sequentially excluding these different cases from our sample, we can observe if the results of our hypotheses change. This approach leads to four different samples that we use in our analysis:

- Sample I: all data (all positive and zero observations on service sales),
- Sample II: all positive observations plus type II and type III zeros,
- Sample III: all positive observations plus type III zeros,
- Sample IV or the *positive sample*: only positive observations.

Inclusion of different types of zeros may have consequences for the analysis as they may represent firms with distinctive characteristics or special conditions. For instance, firms with type I zeros only make things and never offer services; they pursue a purely product-focused strategy and have no service infrastructure or assets. By contrast, firms with type III zeros have a service arm that reports zero sales in a few years but sells services in most years. Mixing these two very different manufacturers may lead to inaccurate conclusions. It will also inflate the frequency of zero observations beyond what the negative binomial distribution would natural yield. Therefore, we initially remove the zero values to eliminate confounding effects due to various types of firms. This filtering gives the positive sample (sample IV) the highest level of data quality. Table A1, demonstrates that results still hold if any group of zeros are included in the sample.

Table A1. Robustness of the Main Effect to Inclusion of Zeros

	Sample I			Sample II			Sample III		
	Lag 1	Lag 2	Lag 3	Lag 1	Lag 2	Lag 3	Lag 1	Lag 2	Lag 3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	-1.343***	-1.237***	-1.143***	-1.428***	-1.344***	-1.198***	-1.315***	-1.194***	-0.983***
	(0.042)	(0.043)	(0.044)	(0.068)	(0.068)	(0.068)	(0.094)	(0.095)	(0.095)
RDInt	0.047***	0.013	0.002	0.054***	0.008	0.002	0.060***	0.01	0.007
	(0.01)	(0.009)	(0.009)	(0.011)	(0.01)	(0.01)	(0.013)	(0.012)	(0.011)
Assets	0.010*	0.018**	0.011^	0.050***	0.056***	0.050***	0.032**	0.065***	0.077***
	(0.005)	(0.006)	(0.007)	(0.007)	(0.008)	(0.009)	(0.012)	(0.015)	(0.018)
EMP	0.023***	0.021***	0.023***	0.019***	0.017***	0.019***	0.013***	0.005*	0.005^
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
ROA	0.329***	0.368***	0.419***	0.212***	0.270***	0.264***	0.158**	0.184**	0.181**
	(0.039)	(0.045)	(0.051)	(0.045)	(0.052)	(0.057)	(0.05)	(0.059)	(0.066)
ROS	0.025***	0.001	-0.006	0.033***	0	-0.005	0.039***	0.004	0.001
	(0.007)	(0.007)	(0.007)	(0.009)	(0.008)	(0.008)	(0.011)	(0.009)	(0.009)
SEMP	0.121	0.147	0.435***	-0.267^	-0.151	0.219	-0.223	-0.249	-0.046
	(0.086)	(0.094)	(0.118)	(0.142)	(0.154)	(0.18)	(0.175)	(0.201)	(0.232)
Service	0.846***	0.682***	0.654***	0.971***	0.867***	0.817***	2.199***	2.240***	2.314***
	(0.127)	(0.143)	(0.159)	(0.142)	(0.163)	(0.183)	(0.185)	(0.207)	(0.25)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log Likelihood	-72859	-62762	-53597	-32063	-27794	-23734	-21538	-18122	-15060
AIC	145769	125573	107239	64176	55637	47515	43125	36291	30165
BIC	145971	125764	107419	64358	55809	47677	43298	36454	30318
N	24401	21293	18550	11002	9669	8469	7551	6561	5670

Standard errors in parentheses; ^ $p<0.10$; * $p<0.05$; ** $p<0.01$; *** $p<0.001$.

APPENDIX B

ALTERNATIVE REGRESSION MODELS

Given that different regression models have different assumptions and varying levels of robustness to violation of assumptions, we check the results under alternative models. As shown in Table A2, the main conclusion holds under various distributional assumptions.

Table A2. Comparison of Results Under Various Models

$Patents_{it+1}$	Poisson	Negative Binomial	Panel Poisson		Panel Negative Binomial		
			RE	FE	RE	FE	Hybrid+
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	4.190***	3.932***	4.198***	- #	-1.328***	-1.237***	-1.457***
	(0.006)	(0.185)	(0.067)	-	(0.094)	(0.095)	(0.093)
RDInt	0.061***	0.037^	0.022***	0.022***	0.060***	0.048***	0.031*
	(0.002)	(0.019)	(0.002)	(0.002)	(0.013)	(0.014)	(0.013)
Assets	0.056***	0.110^	0.015***	0.014***	0.046***	0.040**	-0.018
	(0.000)	(0.061)	(0.002)	(0.002)	(0.014)	(0.015)	(0.021)
EMP	0.003***	0.009	0.005***	0.005***	0.011***	0.011***	-0.008^
	(0.000)	(0.012)	(0.000)	(0.000)	(0.002)	(0.003)	(0.004)
ROA	0.493***	0.174*	-0.014^	-0.015^	0.118*	0.126*	0.003
	(0.006)	(0.079)	(0.008)	(0.008)	(0.051)	(0.055)	(0.057)
ROS	0.053***	0.039*	0.010***	0.009***	0.038***	0.030**	0.018^
	(0.001)	(0.015)	(0.002)	(0.002)	(0.011)	(0.011)	(0.011)
SEMP	0.456***	0.454	-0.044^	-0.049^	-0.200	-0.316^	-0.432^
	(0.008)	(0.321)	(0.026)	(0.027)	(0.177)	(0.192)	(0.240)
Service	3.443***	5.587***	1.042***	1.041***	2.283***	2.164***	1.328***
	(0.007)	(0.461)	(0.020)	(0.020)	(0.192)	(0.203)	(0.224)
Group Means	-	-	-	-	-	-	Y
Year Dummies	Y	Y	Y	Y	Y	Y	Y
N	7265	7265	7265	5234	7265	5234	7265

Standard errors in parentheses; # this model does not have an intercept; ^ $p<0.10$; * $p<0.05$; ** $p<0.01$; *** $p<0.001$.

+ A note on the Hybrid model: The negative binomial panel models developed by Hausman et al. (1984) are commonly used for modeling patent data. However, Allison and Waterman (2002) argue that Hausman et al.'s (1984) fixed effects negative binomial model controls for the fixed effects on the dispersion factor but not on the conditional mean, and therefore, does not fully control for the time-invariant covariates. They suggest estimating a random effects model with a fixed effect estimator embedded to avoid potential heterogeneity bias. This method (here referred to as the hybrid method) involves centering all time-varying regressors around the unit mean and entering the unit mean into the model. Effectively, the hybrid method separates the within-unit and between-unit effects, and provides the benefits of both fixed effects and random effects models. The hybrid method is promising; however, its results should be treated with caution. Recent simulation studies have shown that in some cases, especially for non-linear models, it can produce biased results – although the observed biases have been small (Brumback, Dailey, Brumback, Livingston, & He, 2010; Goetgeluk & Vansteelandt, 2008).

APPENDIX C

GRANGER CAUSALITY TEST

Granger causality test is a data-driven method developed to investigate some aspects (i.e. the necessary conditions) of causality (Granger, 1969). The core idea of Granger causality is that if the variable X causes the variations in the variable Y, it is necessary that X contain unique information about Y not found in the past of Y or elsewhere. Consequently, the past values of X must be able to predict Y over and above the past values of Y and any other influential variable (Granger, 1988). In a regression context, a test of joint significance of the past values of X would be a direct test of Granger causality (Freeman, 1983). Of course, Granger causality does not imply true causality (by the *post hoc ergo propter hoc* fallacy); rather, it only establishes "predictive causality" – a necessary condition for true causality (Diebold, 2001). Following the literature (Stock & Watson, 2003; Wooldridge, 2012) we regressed our dependent variable on the multiple lagged values of itself as well as of the other regressors. The general form of the model is given below:

$$PatentsCCW_{it} = f\{PatentsCCW_{it-l}, Service_{it-l}, Ctrl_{it-l}, Time\ Dummies \mid l = 1,2,\ldots,L\}$$

Where, L is the number of lagged values included in the model for each regressor. Proper selection of lag number is important in testing Granger causality because including very few lags can lead to spurious significance and including too many lags reduces the power of the test. Wooldridge (2012) suggests that for annual data, typically 1 or 2 lags are used. To cover a wide range of L values we estimated multiple models with values of L from 1 to 4. In each model, we tested the joint significance of lagged versions of *Service*. All the tests were significant ($p<0.001$) indicating that *Service* Granger-causes *Patents*. Engle and Granger (1987) also suggest first-differencing the variables (i.e. using changes instead of levels) prior to estimating regression models to ensure stationarity and improve accuracy of the test. Differencing increased the statistical significance in all models further confirming Granger causality.

APPENDIX D

TRIANGULATION OF FINDINGS USING TEXT ANALYSIS

To triangulate our results, we measured service offering of manufacturers in a different way, using a distinct data set. We drew a random sample of 1000 manufacturing firms with full panels (i.e. for each sampled firm all available years were included) and employed computerized text analysis to the Business Description section of the firm's 10-K reports. Our metric for service offering was the frequency count of the word "service(s)" divided by the number of all words in that section. The assumption here is that the frequency with which a manufacturer mentions "service" in the business description is indicative of how important and significant services are for its business. Strategy investigation using text analysis on corporate filings has been used in business studies very recently (Hoberg & Phillips, 2010; Li, Lundholm, & Minnis, 2013; Loughran & McDonald, 2011). For instance, Li et al. (2013) measures a firm's competitive environment as the frequency of references to competition in the firm's 10-K filing. For 647 firms, we found the corresponding 10-K filings in the Edgar database. Through various quality assurance steps, we had to eliminate several observations, e.g., due to inconsistent structure of the report leading to incorrect parsing. The final sample included 556 firms and 2770 firm-year observations.

Word counts can be quite noisy, especially within a single limited document, and so we did not want to directly include the proportion into the model. Rather, we used a binary indicator, where the indicator was positive if the proportion was above the median proportion for the entire sample. Using this measure (instead of *Service*) in our random effects negative binomial models, we find that patent activity is stronger in the group with high frequency of the word "service" in their 10-K report (Table A3). Not surprisingly, using the textual measure the effect is weaker, but, the pattern of estimates confirms our previous results. We also used a three-level measure (with low, medium and high levels split based on the 33^{rd} and 66^{th} percentiles) instead of the binary variable and observed a similar pattern – medium and high frequencies of "service" were associated with higher number of patents.

Table A3. Random Effects Negative Binomial Regression Using Textual Measure of Service Offering

	$Patents_{it+1}$	$Patents_{it+2}$	$Patents_{it+3}$
	Lag 1	Lag 2	Lag 3
	(1)	(2)	(3)
Constant	-0.694**	-0.843*	-0.190
	(0.223)	(0.420)	(0.284)
RDInt	0.090	-0.017	0.415
	(0.066)	(0.066)	(0.296)
Assets	-0.026	0.021	0.139
	(0.042)	(0.064)	(0.104)
EMP	0.035***	0.023^	0.020
	(0.009)	(0.013)	(0.015)
ROA	0.166	0.371	0.278
	(0.229)	(0.298)	(0.679)
ROS	0.069	-0.016	0.341
	(0.045)	(0.038)	(0.244)
SEMP	1.234**	1.621**	1.398^
	(0.402)	(0.512)	(0.724)
ServiceFreq	0.217^	0.273*	0.171
	(0.117)	(0.133)	(0.177)
Year Dummies	Y	Y	Y
Log Likelihood	-3464	-2475	-1697
AIC	6969	4989	3432
BIC	7079	5090	3522
N	1421	1113	854

Standard errors in parentheses; ^ $p<0.10$; * $p<0.05$; ** $p<0.01$; *** $p<0.001$.