ESSAYS IN BUSINESS-TO-BUSINESS CUSTOMER RELATIONSHIPS

By

ASHISH SHARMA

(Under the Direction of Sundar G. Bharadwaj)

ABSTRACT

My dissertation focuses on effective management of Business-to-Business (B2B) relationships for better supplier innovation performance and customer engagement. I examine these relationships from the supplier firm's perspective. In the first essay, I investigate the effect of multiple B2B ties (ie., relationship multiplexity) between customer and supplier firms on supplier firm innovation. Unlike Business-to-customer domain, the revenues and relationships of a B2B firm are highly concentrated among fewer customers, who also affect the firm's ability to innovate. In examining these B2B relationships, I find that relationship multiplexity with a firm's major customers has a significant adverse effect on its innovation. Furthermore, I propose and find support for several supplier firm strategies to overcome the adverse effects of relationship multiplexity on supplier innovation. In the second essay, I examine the combined role of personal selling, digital marketing and social media channels in enhancing customer engagement across different buying stages. Using a combination of exploratory and confirmatory research, I identify preferences for communication channels across buying stages, together with important attributes underlying effective utilization of a communication channel.

INDEX WORDS: Business-to-Business Marketing, Innovation, Relationship Multiplexity, Personal Selling, Digital Marketing, Social Media.

ESSAYS IN BUSINESS-TO-BUSINESS CUSTOMER RELATIONSHIPS

By

ASHISH SHARMA

B.B.A. (Hons.), Guru Gobind Singh Indraprastha University, India, 2004

M.B.A., Guru Gobind Singh Indraprastha University, India, 2006

M.Fin., University of Glasgow, United Kingdom, 2008

A Dissertation Submitted to the Graduate Faculty of the University of Georgia in Partial

Fulfillment of the Requirements for the Degree

DOCTOR OF PHILOSOPHY

ATHENS, GEORGIA

2018

ESSAYS IN BUSINESS-TO-BUSINESS CUSTOMER RELATIONSHIPS

by

ASHISH SHARMA

Major Professor: Sundar G. Bharadwaj

Committee: Son K. Lam
Anindita Chakravarty

Electronic Version Approved:

Suzanne Barbour
Dean of the Graduate School
The University of Georgia
May 2018

ACKNOWLEDGEMENTS

First, I would like to thank my advisor, Sundar Bharadwaj, for all his guidance and support. This dissertation would not have been possible without the countless discussions and deliberation of ideas with him over the course of the last five years.

Additionally, I could not have successfully completed my thesis without the guidance and support of my committee members – Son K. Lam and Anindita Chakravarty. I have learned a lot from them about academic research and cannot thank them enough for their advice and support as my coauthors.

I am also grateful to my fellow graduate students – Aray Chen, Jessica Babin, Kevin Sample and Kaushik Jayaram. My early years as a graduate student would not have been half as enjoyable without Nik Nikolov’s company.

Much of this work would not have been possible without the financial support from National Center for the Middle Market and the Sales Education Foundation. Also, A heartfelt thanks to all faculty members and staff at the Department of Marketing at UGA for all their support.

Finally, I am grateful to my family for all their love, support and patience.

TABLE OF CONTENTS

CHAPTER 1

INTRODUCTION AND OVERVIEW OF THE DISSERTATION

Business-to-business (B2B) markets are responsible for almost 90% of the total world trade. According to a report published by the World Trade Organization, the global B2B e-commerce amounted to US$ 12.4 trillion at the end of 2012. In essence, B2B comprises a larger portion of total world trade than is visible to the eye. This is so because each business-to-consumer (B2C) transaction is preceded by a number of transactions between different business firms to transform raw materials and other production inputs into products and brands that are bought by consumers (Olivia 2012). Additionally, in comparison to B2C markets, B2B markets have a highly complex decision-making process, which involves multiple stakeholders and longer time periods, making B2B marketing even more challenging.

Traditionally, the role of marketing function in B2B domain was limited to providing sales support and basic marketing communication activities, rendering marketing as a mere 'SG&A' expense head, which was further marginalized in times of financial stress (Webster, Malter, and Ganesan 2005). However, an increasing number of B2B firms are realizing that in order to stay relevant and competitive in the marketplace, they need to foster healthy relationships with upstream and downstream channel partners through relationship marketing, capitalize upon these relationships to become more innovative, and adopt modern communication channels to listen to their customers. Thus, B2B marketing is constantly evolving from being seen as merely an expense to a sustainable capability development exercise.

Increasing market and economic pressures are constantly commoditizing the brand offerings of the modern B2B enterprise, leading to lower margins and market share pressures. Such market threats require the firms to innovate in order to maintain differentiation and obtain a competitive advantage. In addition, the emergence of alternative communication platforms, such as social media and digital marketing, is progressively altering the communication preferences of buyers, and the ensuing need for a superior engagement model. In consideration of these challenges, my thesis focuses on managerial problems pertaining to effective management of B2B relationships for better business performance by focusing on two key issues – innovation and customer engagement.

My first dissertation essay investigates the effect of B2B relationship multiplexity (i.e., the presence of multiple ties between a supplier firm and its customer) on supplier firm innovation.

Unlike in B2C domain, the revenues and relationships of a B2B firm are highly concentrated among fewer customers, which also influence the firm's ability to innovate. I build on research in innovation and buyer-supplier relationships to hypothesize and find in an empirical examination of a panel data set of firms with B2B relationships that relationship multiplexity has a significant negative influence on the supplier firms' innovation. This is a critical finding for the supplier firms, because relationship multiplexity has been shown to aid better firm performance. However, my study also examines the influence of contextual factors, such as alternative firm strategies, and customer firm and supplier firm characteristics, which can help supplier firms' reduce the magnitude of the negative effect and insure against the downsides of relationship multiplexity.

In my second essay, I examine how alternative communication channels, such as digital marketing and social media, are changing the landscape of B2B buying.

Researchers in B2C domain have examined the increasing influence of social media outlets on firm performance and word-of-mouth publicity. Extant research notes the role of online consumer-generated content on firms' sales and marketing performance measures, such as the effect of online discussion forum activities on television show ratings (Godes and Mayzlin 2004); the impact of user-generated online reviews on product sales (Chevalier and Mayzlin 2006; Xiong and Bharadwaj 2014); the effect of referrals to join an online social network on website growth (Trusov et al. 2009); the effect of blog activity and TV advertising on sales (Onishi and Manchanda 2011); and the effect of traditional and social earned media on sales (Stephan and Gallack 2012). In sharp contrast, a recent review of the past 15 years of digital, social media and mobile marketing research (Lamberton and Stephen 2016) makes no mention of research in the B2B domain despite a quantum change in B2B customer engagement due to the change in composition and behavior of buying teams.

Digital marketing and social media channels are changing the model of information search. Hundreds of online communities serve as a platform for exchange of ideas, reviews, and feedbacks for business and non-business customers alike, who are now constantly connected and well informed, not only of their own business requirements, but also of available competing solutions, market pricing, and suppliers' costs as well, creating a strong push-back for the selling firms. Additionally, while industry trends reveal early signs of the influence of social media on organizational buying and other decisions of strategic importance in B2B format, academic research on the changing dynamics of business-to-business domain with respect to the same is virtually non-existent.

One primary factor responsible for this shift is the inclusion of a larger number of stakeholders, particularly the non-procurement functions, in B2B buying decision process. The same survey notes that although many B2B marketing campaigns are targeting the C-suite employees, 81% of non-C-suite employees have a say in purchase decisions and roughly a quarter of the final decisions are made by non-C-suite employees. In addition, 70% of the B2B buyers used video content to aid decision making.

Another factor driving this shift in B2B buying is the changing demographics of the key decision makers in buying organizations. An increasing number of millennials are joining the C-suite and they are influencing the way B2B buying decision processes. According to a study, (jointly conducted by Millward Brown Inc. and Google in 2014), millennials – those born during the 80s and 90s – now account for almost half of all B2B purchase decision makers, up from 27% in 2012. Furthermore, millennials are twice as likely as their counterparts in 45 – 55 year age bracket, and three times more likely than their counterparts over 55 years of age, to use mobile phone to conduct research for organizational buying decisions (Snyder and Hilal 2015). However, older B2B buyers are quickly adopting these habits of digital natives in their B2B buying research and decision-making (Almquist, Cleghorn, and Sherer 2018).

This seismic shift has pushed the traditional engagement with a sales representative to much later in the buying process, necessitating a review of the traditional engagement approach, utilized by marketers to identify the communication needs of the buying teams and establish more effective contact points. By investigating the actual buying stages traversed by B2B buyers in the buying process, and by identifying their communication needs at each stage in the process, I contribute to marketers' understanding of the process in light of altered customer behavior. Furthermore, by discovering customer preferences for a communication channel across buying stages, this essay aids marketing strategy formulation for higher customer engagement.

REFERENCES

Almquist Eric, Jamie Cleghorn, and Lori Schere (2018), “The B2B Elements of Value”, *Harvard Business Review*, March-April issue, available at - https://hbr.org/2018/03/the-b2b-elements-of-value.

Chevalier, Judith A. and Dina Mayzlin (2006), “The Effect of Word of Mouth on Sales: Online Book Reviews,” *Journal of Marketing Research,* 43 (3), 345–354.

Godes, David and Dina Mayzlin (2004), “Using Online Conversations to Study Word-of-Mouth Communication,” *Marketing Science,* 23 (4), 545–560.

Lamberton, C., & Stephen, A. T. (2016), “A Thematic Exploration of Digital, Social Media, and Mobile Marketing: Research Evolution from 2000 to 2015 and an Agenda for Future Inquiry,” *Journal of Marketing,* 80 (6), 146–172.

Ralph Oliva, (2012) “A high-level overview: a value perspective on the practice of business-to-business marketing,” in Handbook of Business-to-Business Marketing, 15-40

Onishi, H., & Manchanda, P. (2012), “Marketing Activity, Blogging and Sales,” *International Journal of Research in Marketing,* 29 (3), 221-234.

Snyder, Kelsey, and Pashmeena Hilal (2015), “The Changing Face of B2B Marketing,” Google/Milward Brown Digital, B2B Path to Purchase Study, available at https://www.thinkwithgoogle.com/consumer-insights/the-changing-face-b2b-marketing/

Stephen, A. T., & Galak, J. (2012), “The Effects of Traditional and Social Earned Media on Sales: A Study of a Microlending Marketplace,” *Journal of Marketing Research,* 49 (5), 624–639.

Trusov, Michael, Randolph Bucklin, and Koen Pauwels (2009), “Effects of Word-of-Mouth Versus Traditional Marketing: Findings from an Internet Social Networking Site,” *Journal of Marketing,* 73 (5), 90–102.

Webster, F., A. Malter and S. Ganesan (2005), “The Decline and Dispersion of Marketing Competence,” *Sloan Management Review,* 46 (4), 35–43.

CHAPTER 2

TIES THAT BLIND: MANAGING CUSTOMER RELATIONSHIPS FOR INNOVATION PERFORMANCE[1]

[1] Sharma, A., S.G. Bharadwaj, and K. Tuli. To be submitted to *Journal of Marketing Research*.

ABSTRACT

Business-to-business firms often have multi-dimensional relationships with their suppliers or customers. Extant literature on the relationship embeddedness-firm performance and innovativeness relationship suggest that it is a double-edged sword. Empirical studies and anecdotal evidence find that multiplex ties between a supplier and its customer act as a rare and inimitable resource and generate better firm performance. However, such relationship multiplexity can also give rise to knowledge redundancy, resource constraint, and customer opportunism in the relationship, negatively affecting supplier innovation and survival. Literature on tight-loose coupling indicates that loosely-coupled systems provide ease of localized adaptation and enable a firm to sustain novel solutions, through preserving higher diversity, to be drawn upon in times of radical changes. Applying knowledge-based and strength-of-ties perspectives, this study examines the effect of supplier firms' relationship multiplexity with focal customers on supplier innovation. Analyzing a unique hand-collected data set of customer-supplier relationships, the authors find that while supplier relationship multiplexity has been shown to improve supplier's sales performance, it hurts supplier innovation. Additionally, the authors examine relationship-specific and environmental factors that moderate the main effect on supplier innovation, and suggest countervailing strategies to mitigate the negative innovation consequences of relationship multiplexity with key customers.

INTRODUCTION

Supplier firms often dedicate valuable resources to establish diverse ties with their customers, i.e., relationship multiplexity, with the objective of obtaining relational and financial benefits (Ross and Robertson 2007). Indeed, extant research finds that such close multiplex relationships allow suppliers to obtain private information about customers (Uzzi 1997), enhance collaboration (Rindfleisch and Moorman 2001), establish long-term focus (Kilduff and Tsai 2003), and even achieve higher sales growth with lower volatility in sales to the customer (Tuli, Bharadwaj, and Kohli 2010).

Interestingly, prior literature focuses entirely on the consequences of relationship multiplexity (RM) for the supplier's relationship with the customer. Little attention, however, is directed towards systematically exploring the potential spillover effects of a suppliers RM with a customer, beyond this relationship.

Drawing on prior work, we propose that a supplier's RM with a customer can have a negative spillover effect on the supplier's innovation output. I focus on innovation as it is widely viewed as the primary avenue to drive successful firm financial performance (Borah and Tellis 2014; Rao, Chandy, and Prabhu 2008; Sorescu, Chandy, and Prabhu 2003). While a few studies have examined the role of supplier–customer relationships in fostering innovation, almost all have focused either on customer firm innovation or on relationship-specific co-developed innovation, providing limited insights into supplier innovation

Given the economic importance of innovation, firms have an impetus to drive innovation efforts. While internal knowledge is instrumental in development of core competencies, knowledge from external sources is critical for firms to capitalize on new technological and market developments and to adapt to changing environments (Grant 1996; Prabhu, Chandy, and Ellis 2005). One way firms obtain external knowledge is by establishing close relationships with other firms in the marketplace and by collaborating with their downstream or upstream channel partners (Roy, Sivakumar, and Wilkinson 2004; Sampson 2007; Sivadas and Dwyer 2000; Un, Cuervo-Cazurra, and Asakawa 2010; Wuyts and Dutta 2014).

Anecdotal evidence from the industry suggests that deep relations with customer firms may not necessarily aid supplier innovation. The relationship between Apple and Foxconn is a case in point. Apple is a major customer of Foxconn and the two share a significantly deep relationship that has changed the technology sector. The pair of firms has shared success and risks over the years strengthening the relationship and Apple continues to do so by investing in new R&D centers in China and Indonesia.[2] However, Apple does not let Foxconn in on its product development secrets.[3] Highly cautious about any knowledge spillover, Apple strictly controls all specifications and requires its suppliers to match production exactly to Apple's requirements (Gereffi and Lee, 2012). This lack of information sharing could put Foxconn at a disadvantage, if there are technological shifts in the market and Apple chooses to change its production strategy. Moreover, investments made by Foxconn in the Apple relationship is resources taken away from other technological investments. The dedication to technology that serves Apple's current needs may blind the firm to new technology paradigms that might emerge and the customer might shift towards. A case in point, Intel Inc. was the key supplier to Apple's MAC business with its expensive, but high performance chips created through its vertically integrated capital-intensive model. However, when Apple began production of the iPhone, its

---

[2] https://9to5mac.com/2016/12/26/apple-foxconn-partnership-china-indonesia/
[3] https://asia.nikkei.com/magazine/20170713/On-the-Cover/Foxconn-Apple-and-the-partnership-that-changed-the-tech-sector

requirement shifted away from chip performance to energy efficiency and specialized (as opposed to general architecture) chips that was inexpensive to produce. Intel Inc., whose technology investments were dedicated to general architecture chips, had not invested in this new chip technology for the smart phone and tablet business and eventually lost its business to ARM Holdings, a much smaller British firm.[4]

Consistent with the anecdotal business cases, Christensen (1997) suggests that a supplier firm, when closely embedded with its major customers, can become too focused on innovations specific to customers' pet projects and can often ignore or discontinue innovations that do not meet the needs of those customers (Christensen 1997). Although an increase in RM can facilitate better understanding and specification of customer's needs, an improved understanding may not necessarily benefit the supplier innovation. This is because a consequence of focusing of suppliers' focusing their innovation efforts on current customers' specifications discarding or lacking the resource to dedicate towards peripheral ideas that do not, irrespective of their potential outside the relationship.

While suppliers face this relational myopia as a consequence of relationship multiplexity with large customers, little academic research has focused on how suppliers can maintain their innovative ability in the presence of such ties, i.e., overcome relational myopia. I seek to address this important gap in the literature. Specifically, I study what impact does an increase in RM of a supplier with its focal customer firm have on the supplier's innovation. I draw on the knowledge-based view and strength-of-ties literature to identify firm-level and industry-level moderating factors that either counter or exacerbate the main effect of RM on supplier innovation.

[4] https://www.theatlantic.com/technology/archive/2013/05/paul-otellinis-intel-can-the-company-that-built-the-future-survive-it/275825/

Analyzing a unique hand-collected secondary data of over 2400 customer-supplier dyads from multiple industries, and close to 100,000 patent documents, I find that an increase in supplier firm's RM with its focal customers adversely affects supplier firm's innovation. A supplier firm's loosely coupled relationships with other firms in the marketplace and a product-centric organization structure are pivotal in mitigating this negative effect. I also find that an increase in supplier industry competitiveness weakens the negative effect of RM on supplier innovation. The results are robust to endogeneity correction and alternative measures.

The rest of the paper is as follows. I begin by surveying past literature and the theory underlining my conceptual framework. Next, I present the hypotheses about the direct and moderating effects of RM on supplier innovation. I then describe my empirical strategy, data and results, followed by a set of robustness tests. I then discuss the empirical results with an emphasis on theoretical and managerial implications of this research. I conclude with the limitations of the study and directions for further research.

THEORY AND HYPOTHSES

A growing number of academic literature in marketing and management has examined the role of knowledge in enhancing innovation and new product development (Atuahene-Gima 1995, 2005; Day 1994; Li and Calantone 1998; Moorman and Miner 1997), and while different knowledge types (explicit vs. tacit) may be more or less fluid with respect to their transferability, it is generally agreed that innovation requires many types of knowledge (Grant 1996; Kogut and Zander 1992; Nonaka 1994). Also, applying a knowledge-based view, scholars have examined the role of different dimensions (depth, breadth, and similarity) and sources (internal vs. external) of knowledge in innovation, and have established that knowledge breadth (and not only knowledge depth) is also critical for innovation (Prabhu, Chandy, and Ellis 2005), since diverse knowledge facilitates wider prospects and their absorption, preventing firms from getting locked in past knowledge (Cohen and Levinthal 1990; Wuyts, Dutta, and Stremersch 2004). Moreover, while internal knowledge is instrumental in development of core competencies, knowledge from external sources is critical for firms to capitalize on new technological and market developments and to adapt to changing environments (Grant 1996; Prabhu, Chandy, and Ellis 2005).

Following the knowledge-based view, existing research in marketing has focused on inter-firm relationships and relational embeddedness with other firms as external sources to gather knowledge resources for innovation (Cui and O'Connor 2012; Rindfleisch and Moorman 2001; Sampson 2007; Sivadas and Dwyer 2000; Un, Cuervo-Cazurra, and Asakawa 2010; Wuyts and Dutta 2014; Wuyts, Dutta, and Stremersch 2004). In doing so, majority of the research in this domain builds upon the structural and/or relational dimensions of social capital (e.g. Granovetter 1992; Nahapiet and Ghoshal 1998). While structural embeddedness focuses on the (impersonal) patterns of network ties between partners (Burt 1992), relational embeddedness focusses on particular relations (Granoveter 1992). Researchers examining B2B dyadic relationships have adopted the strength-of-ties perspective (Granovetter 1973, 1982; Hansen 1999; Uzzi 1999) to study the impact of strong or weak relational ties between two firms over the level of information sharing, reciprocity and solidarity in their relationship. While there is some debate over the respective advantages of each type of relational ties, the general consensus is that strong ties facilitate information sharing, whereas weak ties are pivotal in gaining access to diverse knowledge (Hansen 1999; Rindfleisch and Moorman 2001).

Previous literature examining the role of embedded ties between partner firms has argued for positive as well as negative effects on innovation. While embedded ties help in transfer of complex and private information (Hansen 1999), they also give rise to the issues of knowledge redundancy and opportunism (Anderson and Jap 2005; Grayson and Ambler 1999; Moorman, Zaltman, and Deshpande 1992). One special category of B2B dyadic relationships – supplier-customer relationship multiplexity, is the focus of this study as a source of innovation for the supplier firm. Adopting a knowledge-based view, RM of a supplier firm with a focal customer should lead to higher information exchange and generation of higher level of social capital in the relationship, thus aiding the innovation process. However, as Nahapiet and Ghoshal (1998: pg. 245) suggest "social capital is not a universally beneficial resource." A given type of social capital generated in a relationship to achieve certain objectives is not necessarily as useful, and may even be harmful, for other activities (Coleman 1990). For example, collective norms in a relationship, which facilitate better performance, can also limit the access to new information and generate knowledge redundancy, leading to adverse outcomes (Janis 1982; Nahapiet and Ghoshal 1998). The above arguments suggest that while RM between the customer and supplier firms may facilitate higher information sharing within the relationship and motivate the supplier firm to find new and efficient ways of addressing customer needs, it may not replicate outside the relationship and may actually harm the supplier firm's overall innovation capabilities. Despite the conceptual tension, systematic research in marketing on the role of customer-supplier collaborations in innovation is lacking, with the exception of a few studies (Arnold, Fang, and Palmatier 2011; Fang, Palmatier, and, Evans 2008; Fredberg and Piller 2011; Noordhoff et al. 2011; Roy, Sivakumar, and Wilkinson 2004; Un, Cuervo-Cazurra, and Asakawa 2010). Moreover, almost all of these studies (except Noordhoff et al. 2011) either focus on customer innovation or co-developed innovation, which is specific to the relationship, providing limited understanding of implications for supplier innovation.

Following previous literature, I apply a strength-of-ties perspective to study a supplier firm's relationships with focal customers and other firms in the marketplace. My predictions are summarized in Figure 2.1. I theorize that while supplier firms' RM with focal customers can facilitate information sharing and help generate social capital in the relationship, it can create knowledge redundancy and asset specificity in the relationship, negatively affecting the supplier firms' ability to innovate outside the relationship. However, applying a strength-of-weak-ties perspective, I propose that the supplier firms' relationships with other firms in the marketplace should provide an access to diverse knowledge and resources, creating a buffer against knowledge redundancy, resource specificity and potential opportunism in the focal relationship.

The Effect of RM on Supplier Innovation

Following Kenis and Knoke (2002) and Tuli, Bharadwaj and Kohli (2010), I define supplier-customer RM as a relationship comprising multiple diverse ties between the two parties, in addition to the core relationship, where each additional tie provides unique value to the partners. While RM may be helpful in information transfer within the relationship, access to customers' private information and enhancing solidarity, I propose that RM can be detrimental to supplier firm's innovation for the following primary reasons: 1) knowledge redundancy, 2) resource depletion, and 3) customer opportunism. I discuss these in detail below.

Market knowledge has been shown to boost innovation performance (Atuahene-Gima 1995; Day 1994). However, generating innovation requires faster access to new and diverse knowledge. Diversity or breadth of knowledge has also been identified as one of the key dimensions of market knowledge, required for innovation performance (e.g. see Luca and Atuahene-Gima 2007). Knowledge transfer and learning in markets is a function of type of exchange ties, i.e., while arm's-length ties facilitate drawing and transferring information from a broader pool, multiple ties from a focal customer draw from a limited pool of knowledge, but are better suited for exchange of private information (Tuli, Bharadwaj, and Kohli 2010; Uzzi and Lancaster 2003). While higher embeddedness between firms helps facilitate knowledge sharing, it also leads to higher knowledge redundancy (Granovetter 1973; Rindfleisch and Moorman 2001). Thus, I contend that because relationship multiplexity between a supplier and a customer firm should create higher embeddedness, it should boost knowledge sharing in the relationship and access to customer's private information, but at the cost of knowledge diversity. This is so because the scope of knowledge generated and exchanged in a multiplex relationship is generally restricted to customer's own needs and expertise, which limits the supplier firm's access to new knowledge created elsewhere in the network, thus leading to knowledge redundancy and homogeneity.

Second, RM can lead to locking and depletion of critical supplier resources, which could otherwise be used to generate innovation. The role of amount and diversity of resources in driving knowledge development and innovation is well established (Baum, Calabrese, and Silverman 2000; Cui and O'Connor 2012; Moorman and Miner 1997; Swaminathan and Moorman 2009; Wuyts, Dutta, and Stremersch 2004). In order to better service its key customers and achieve higher customer satisfaction in a multiplex relationship, a supplier firm needs to identify not only the current but also the latent needs (often indefinite and ambiguous) of the customer firm (Tuli, Bharadwaj and Kohli, 2010). However, in doing so, the supplier firm's critical resources get locked into that relationship, constraining the firm of resources to be deployed toward innovating more broadly. Moreover, increased focus of supplier firm on customer needs can lead it to lose the sight of peripheral market knowledge and technology opportunities, hampering its ability to innovate (Christensen and Bower 1996).

Third, RM with a focal customer can give rise to negative influence of customer opportunism, which should hinder supplier innovation. Research finds that longer relationships are more prone to negative influences that diminishes the effect of relational factors such as trust and commitment (Grayson and Ambler 1999; Moorman, Deshpande, and Zaltman, 1993). Similar to the influence of a long-term relationship, RM breeds improved experience of working with the other partner in relationship, and higher expectations, leading to increased likelihood of dissatisfaction and opportunism (Moorman, Deshpande, and Zaltman, 1993). Moreover, the process of creating RM with a customer is highly likely to involve asset specific investments on part of the supplier firm as the supplier's focus on achieving higher customization to enhance customer satisfaction. However, such asset specificity generates dependence asymmetry in the relationship, causing power imbalance and increasing the likelihood of customer opportunism (Anderson and Jap 2005; Jap 2003). While an increase in RM with the focal customer may benefit the supplier with the opportunity to test early knowledge, such innovation is specific to the focal customer needs and customer opportunism can hamper supplier's ability to learn and innovate in the long run (Noordhoff et al 2011). Such potential for customer expropriation and opportunism can increase the supplier firm's vulnerability, limiting its ability to take risks and experiment with new knowledge.

Thus, it can be logically concluded that RM hampers the supplier firm's ability to innovate by: 1) narrowing down the supplier's focus to the needs of the customer, often hampering its ability to identify and exploit emerging technological opportunities, i.e., creating *knowledge redundancy*, 2) depleting critical resources, otherwise required for innovation capabilities, i.e., creating *resource constraints* and 3) giving rise to *specific investments* and *customer opportunism*, negatively affecting supplier's ability to invest in innovation.

H1: An increase in RM between a supplier firm and its focal customers negatively affects supplier firm's (i) innovation scientific value, and (ii) exploratory innovation.

Moderators

The ability of supplier firms to mobilize their resources to achieve intended innovation goals is expected to be moderated by relationship-specific factors as well as factors that are external to the focal relationship. First, following the weak ties perspective, I argue that supplier firms' relationships with other firms in the marketplace should alter the impact of RM on supplier innovation by providing a buffer of diverse knowledge and resources. Second, organization structure of a firm has been shown to augment or impede knowledge transfer. I analyze how a supplier firms' product-centric structure can moderate the effect of RM on supplier firm's innovation outcomes. Third, the extent of supplier firms' business dependence on focal customers can increase or decrease the asymmetries and power imbalance in the relationship, altering the existing potential for opportunism in the relationship and subsequently affecting supplier innovation. Fourth, I argue that supplier firms' industry competitiveness can alter their ability to protect against and respond to potential customer opportunism. Moreover, industry competitiveness can also affect the ability of supplier firms to garner external buffer in the form of diverse knowledge and resources to be used against the negative influence of RM. In the following section, I examine the moderating effects of these relationship-specific and environmental influences.

Loose Coupling with Others

Scholars examining organizational design and studying the impact of environmental uncertainty on governance decisions suggest that formal arrangements and contracts become inefficient in managing uncertainty beyond a level in tight relationships and that market governance mechanisms, such as loosely coupled systems, provide a better alternative (Heidi and John 1990; Rindfleisch and Heide 1997). I draw on Weick (1976) and Danneels (2003) and define loose coupling in this context *as the supplier firm's relationships with non-focal customers and other firms in the network*. I propose that loose coupling with other firms should help the supplier firm create a buffer against the negative influence of RM on supplier innovation for the following reasons.

First, loosely coupled relationships are a source of diverse and peripheral knowledge, helping the supplier firm overcome knowledge redundancy emanating from RM with a focal customer. A loosely coupled system provides ease of localized adaptation and facilitates adaptation to a more diverse environment, allowing a firm to sustain more novel solutions and to preserve higher diversity (Weick 1976). Thus, by forming loosely coupled relationships with other firms, the supplier firm can overcome the lack of diversity and extramural knowledge in RM with a focal customer.

Second, loosely coupled relationships of the supplier firm also act as a channel of marketplace knowledge and technological resources, which are otherwise lacking in the relationship. Such access to diverse resources can help the supplier firm overcome resource constraints imposed by the focal relationship (Rothaermel 2001). In addition to facilitate accumulation of external resources from the network, loosely coupled relationships of the supplier firm also require less coordination (Weick 1976), thus facilitating cost reduction and efficient use of scarce resources.

Third, through access to network resources, markets and other opportunities outside the relationship, loosely coupled relationships of the supplier firm can also provide an insurance to be drawn upon to curb potential customer opportunism. Moreover, such relationships could also provide alternative revenue source, mitigating the dependence on the focal customer.

Thus, I propose that by creating loosely coupled relationships with other firms, the supplier firm can gain access to new and diverse knowledge (mitigating knowledge redundancy), overcome resource constraints, and insure against customer opportunism, thus mitigating the negative effects of RM on innovation. Formally,

H2: An increase in supplier firm's loose coupling with other firms can help mitigate the negative effect of RM on supplier (i) innovation scientific value, and (ii) exploratory innovation.

Product-centric Organization Structure

A meta-analytic review of the literature on innovation points to the importance of organization structure in generating innovation (Vincent, Bharadwaj, and Challagalla, 2017). For example, a product-centric structure focuses on generating new products and solutions. In contrast, a customer-centric structure is geared toward a relationship orientation and better understanding and service of customer needs (Shah et al. 2006). I contend that when a supplier firm has multiple ties with a focal customer firm, a product centric product-centric structure, counter-balances the focus on the focal customer and allows the supplier firm to create some slack, which should help it overcome the negative influence of RM on innovation for the following reasons.

First, a product-centric organizational design is more aligned toward knowledge creation, facilitating focus on issues such as new product development, product portfolio and profitability, which is critical for innovation. While RM with a focal customer can lead to an increase in supplier focus on servicing customer needs and a decrease in supplier objectivity and ability to generate peripheral knowledge, a product-centric structure can compensate for this loss of focus by making the supplier firm more internally focused and driving the supplier towards accumulation of newer technologies and market knowledge.

Second, the performance metrics in a product-centric structure are more likely to focus on product-related issues, such as profitability per product, width and depth or product portfolios, addition of new products and features, product-market share improvement, etc. An internal focus on performance tied to products and services should make the supplier firm more aware of its inefficiencies and facilitate efficient use of resources for generating new knowledge, thus mitigating the investment requirement and compensating for the resources devoted towards the focal customer as a result of RM.

Third, a product-centric structure promotes efficient transfer of tacit knowledge from external sources and across the organization. As a product-centric structure is more aligned toward designing more and better products and solutions, it provides an insurance against customer entitlement and is helpful in reducing the magnitude of damage in case of opportunism. Put together,

H3: A product-centric organization structure can help the supplier firm mitigate the negative effect of RM on supplier (i) innovation scientific value, and (ii) exploratory innovation.

Customer Importance

Customer importance refers to the extent of supplier firm's dependence on a focal customer for business, as measured by the proportion of revenue generated through that customer (Heide and John 1990). Because revenue generation in B2B industries is concentrated among fewer customers, loss of a customer, who is responsible for a larger share of revenue generation, can be detrimental for the supplier firm's business. I suggest that an increase in customer importance can amplify the negative effects of RM on supplier innovation for three main reasons.

First, an increase in business dependence of a supplier firm on a focal customer firm for revenue generation can lead to higher dependence asymmetry in the relationship. This in turn is likely to make the supplier provide greater attention, resources and support towards the focal customer. Such customers may even develop a sense of entitlement, gaining more bargaining power and increasing the potential for customer opportunism (Wetzel, Hammerschmidt, and Zablah 2014). Bargaining power of large customers has been shown to exert considerable influence on supplier performance, constraining the relationship (Hammervol 2005). While relationship specific investments by both partners in the relationship can help ease the negative effects of customer opportunism (Anderson and Jap 2005), such strategy is practically ineffective when the relationship is marked by dependence asymmetry in favor of the customer firm.

Second, greater dependence of the supplier firm on focal customer for revenue generation can also result in lesser resources devoted towards objective and peripheral knowledge due to the supplier firm's increased focus on servicing the customer to achieve higher customer satisfaction. Besides, dependence is also a function of product/service complexity, i.e., the product/service solution may be of highly complex and customized nature demanding specific set of skills on part of the supplier to deliver it. Such complexity may further drive the supplier firm to accumulate knowledge and skills that are specific to addressing the needs of the customer, thus leading to a lack of knowledge heterogeneity.

Third, a supplier firm that has established RM with an important customer, can easily lose sight of the changing dynamics of the business and industry, and may be unable to exploit any new opportunities in the business and technological environment due to considerable resources locked in serving the major customer, hampering the supplier's ability to innovate. Hamel and Prahalad (1991) label such a restriction in the range of opportunities a 'contraction of the opportunity horizon.' Moreover, customer expectation and demands can quickly stack up with an increase in business share, requiring the supplier to invest more resources in servicing the relationship, thus constraining its ability to simultaneously exploit other potential opportunities.

In summary, I expect that the negative effect of RM on supplier innovation should be further strengthened due to the enhanced customer opportunism, knowledge redundancy and resource constraints engendered by a customer of high importance. Formally,

H4: An increase in customer importance can exacerbate the negative effect of RM on supplier (i) innovation scientific value, and (ii) exploratory innovation.

Supplier Industry Competitive Intensity

External environment and industry conditions have been shown to affect the innovation performance of a firm (Meyer and Goes 1988; Nohria and Gulati 1996; Vincent, Bharadwaj, and Challagalla, 2017). An increase in the competitive intensity in a supplier firm's industry can add to environmental hostility (Zahra and Covin 1995) and lead to lower margins, higher commoditization, and fierce competition for scarce resources. Also, an increase in competitive intensity can increase a supplier firm's dependence on its collaborative partners, while reducing its attractiveness in the relationship due to a lack of key resources. I posit that the competitive intensity in supplier's industry can negatively moderate the relationship between supplier-customer RM and supplier innovation.

First, when the competitive intensity in a supplier firm's industry is high, customers get access to an increasing number of alternative solutions to their needs since a firm's offerings can quickly be matched by other competing firms (Jaworski and Kohli 1993; Kumar et al. 2011). Further, as competitive intensity increases, it drives down the rate of return toward the competitive floor rate of return (Porter 1996) and reduces a firm's ability to alter the balance of power among supplier firms (Slater and Narver 1994). To remain successful in such environment, the supplier needs to increase its focus on its customer firms (Narver and Slater 1994) creating more asset-specificity and increasing dependence asymmetry in the relationship. Also, access to ample alternatives for new and potential technologies in a competitive marketplace may result in lower motivation for the customer firm to co-develop with and invest in the supplier firm (Wang, Lee, and Fang 2015).

Second, while new product introductions and other technological innovations are one source of differentiation in highly competitive markets, time and market pressures often cause firms to shift focus from long-term value creation to short-term value expropriation. Research also shows that competitive intensity weakens the effect of functional collaboration on new product performance (Tsai and Hsu 2013). In order to remain competitive in the marketplace, the supplier firm engages in pricing and promotion wars, creating further resource constraints and reducing its access to new and diverse knowledge.

Based on above arguments, I propose that an increase in competitive intensity in supplier's industry should further increase asset specificity and the issue of knowledge redundancy, consequently increasing the dependence asymmetry in the relationship, thus strengthening the negative influence of RM on supplier innovation.

H5: An increase in competitive intensity in supplier industry can exacerbate the negative effect of RM on supplier (i) innovation scientific value, and (ii) exploratory innovation.

SAMPLE AND MEASURES

Sample

In constructing the dataset to test the proposed hypotheses, I follow prior literature and focus on industries where scientific knowledge plays an important role. Specifically, I focus on firms operating in pharmaceuticals and diagnostic substances, manufacturing, communication equipment and electronics, and transport equipment manufacturing (e.g., Mishra and Slotegraaf 2013; sivakumar et al. 2011; Sood and Tellis 2011; Un, Cuervo-Cazurra and Asakawa 2010; Wuyts and Dutta 2010). As such, I complement prior studies that focus on single industries (e.g., Prabhu, Chandy, and Ellis 2005; Sorescu, Chandy, and Prabhu 2007). Importantly, this focus on multiple industries increases the potential generalizability of my findings.

I try to remove as much potential selection bias as possible by drawing a stratified random sample from each SIC category in my study to ensure that the number of firms in each SIC category in my sample represent the actual number of firms operating in respective SIC categories. This way, my chosen sample represents the actual population distribution of firms across selected SIC categories. I arrive at my final sample by doing the following: I start with all of the 1115 firms, operating in all of the selected SIC categories. 310 of these supplier firms either did not report any major customers or did not clearly identify their major customers in their SEC filings, hence I drop them from the study. Next, I assign weights to each SIC category in my sample on the basis of the proportion of firms in that SIC to that of the total firms in all

SIC categories. Then, I calculate a selection factor *s*, based on the weight assigned to each SIC in my sample and randomly select every s^{th} firm from that SIC for a total of 240 firms. I combined the dataset from Kogan et al. (2016) with patent data from USPTO, Google Patents and NBER to construct the dataset for my two innovation outcome variables. I eliminated 23 supplier firms that could not clearly be matched with patent data. Further, I drop 16 firms for which complete data on other variables was not available in COMPUSTAT. My final sample comprises of 171 publicly listed supplier firms and 231 customer firms, representing 77 four-digit SIC codes. Overall, my dataset spans a period of 13 years (1998 - 2010), capturing 2458 unique supplier-customer relationship dyads for innovation scientific value and 1532 dyads for exploratory innovation.

Measures

Table 2.1 lists the measures and data sources for the variables used in this study.

Dependent variables. I use two measures to evaluate two complementary dimensions of supplier innovation. My first measure, *innovation scientific value*, is forward looking and captures the potential value and importance of a firm's innovation in the future by accounting for the forward citations to that innovation. The second measure, *exploratory innovation*, complements the first measure by providing historical information in the form of reverse citations, highlighting whether the knowledge underlying an innovation already existed within the firm or was acquired from an external source. By employing these two measures, I add to the existing literature on innovation by studying not only a firm's ability to generate higher value innovations but also its ability to be more exploratory.

I measure innovation scientific value, by using citation-weighted patents (see Table 2.1). I adopt this measure because it allows us to assign more weight to innovations of a firm that have greater impact and therefore are instrumental in generating high scientific value (see for e.g., Hall, Jaffe, and Trajtenberg 2005; Kogan et al. 2016). I measure exploratory innovation by the degree to which the current innovation is based on prior innovations by the firm (see Benner and Tushman 2002). Specifically, I construct my measure of exploratory innovation based on the percentage to which the knowledge underlying an innovation is generated by sources external to the firm.

I collected data from The US Patent and Trademark Office (USPTO) for the two measures. USPTO publishes data on applied and granted patents, available through bulk patent data files. I supplement this data with data from Google Patents and National Bureau of Economic Research (NBER). I collected information on all patents successfully filed by the firms in my sample over a period of 13 years. I coded patent specific information, such as assignee details, filing and grant date, forward and reverse citations, self-citations, classification, etc. for each of the patents filed. After removing non-usable patent information (due to missing data, errors in assignee names, etc.), I was able to match 93,194 patents to the supplier firms in my database.

I performed an extensive sequential process to identify each patent, successfully filed by a supplier firm each year during the sample period, and then identify and classify the reverse citations (existing patents cited by this patent) used to construct that knowledge. To do so, first, I retrieved all reverse citations from the abstract section of all patents. Second, I recorded the publication numbers of all reverse citations for each of the patents. The publication number of a patent uniquely identifies each patent in the USPTO database. Third, I used the publication numbers of each citation to identify: 1) whether the cited patent is assigned to the same supplier firm or a different firm, and 2) whether that cited patent was cited for the first time by the supplier firm. Thus, I classify all reverse citations to that patent into two categories: 1) existing knowledge, based on whether the cited patent is owned by the same supplier firm and/or has been cited by the supplier previously, or 2) new knowledge, if the cited patent is neither owned by the supplier firm nor cited by the supplier firm before.

Fourth, based on this classification, I calculated the proportion of new and existing supplier knowledge that each patent is built upon. I repeat this process for each patent for each year for each supplier firm in my sample. Finally, I aggregate the number of patents, which are built on 100% exploratory knowledge (i.e. citing previously published patents not owned by the supplier firm and cited for the first time) at firm-year level to arrive at a measure of exploratory innovation and use a log transformation of this measure.

Relationship multiplexity. I measure RM as the log of the sum of different types of ties between the supplier firm and the focal customer firm (Kilduff and Tsai 2003; Tuli, Bharadwaj, and Kohli 2010). Following Tuli, Bharadwaj, and Kohli (2010), I include the following types of ties: (1) board interlocks, (2) marketing alliances, (3) R&D alliances, (4) licensing agreements, (5) joint ventures, (6) equity investments, and (7) customer as a supplier. On average, a supplier firm in my sample has 1.35 ties with the focal customer.

I manually obtain the data for relationship multiplexity measure from the Securities and Exchange Commission (SEC) filings of publicly listed firms. SEC requires all publicly listed firms to report major customers (10% or more of operating revenues). Major customers of a firm and subsequent sales to those customers can be identified by tracking various SEC filings. I search through the 10-K (annual reports), 10-Q (quarterly reports), and 8-K (current reports) filings of all firms and for each year in my sample to identify the major customers of a supplier firm, the share of revenue generated by those customers, and the number of relationship ties between the supplier firms and their major customers. I supplement this data by searching through supplier firms' websites and the web.

Loose coupling. Similar to the RM measure, I construct loose coupling as log of the aggregate of different types of alliances of a supplier firm with all non-focal customer and other firms. To collect information on loose coupling measure, I first used Securities Data Company (SDC) database to gather information on various alliances between the supplier firms and other firms (non-major customers). However, I supplement SDC data by conducting a thorough search through the Exhibits and Financial Statement Schedules reported in the 10-K and 10-Q reports of supplier firms and record various alliances between the supplier and other firms.

Customer importance. This variable is measured as log of the proportion of supplier firm's revenues generated from a focal customer. I obtained customer level revenue information from the segment filings in 10-K of supplier firms.

Product-centric structure. This is a dummy variable. I code this measure as 1 if the organization structure of the supplier firm is identifiable as product-centric and 0 otherwise. To obtain information on organization structure of the supplier firm, I searched for segment reporting information and company business section in 10-K and 10-Q filings of supplier firms. The Statement of Financial Accounting Standards (SFAS) requires all publicly traded firms to disclose information about their operating segments corresponding to their reporting structure. After collecting all information on segment reporting, the first two authors independently reviewed the information contained in the section and classified the organization structure of the supplier firm as product-centric or non-product-centric based on whether the information contained matching keywords. All disagreements were resolved after a discussion.

Industry competitive intensity. I calculate the Herfindahl-Hirchman index in supplier firm's industry at the four-digit SIC level at time *t* to measure the competitive intensity in supplier firm's industry.

Control variables. I include several control variables in my model. First, I include the log of supplier firm's revenues to control for the effect of supplier firm size on its innovation efforts. Past research suggests that firm size can affect its innovation outcomes as larger firms have significantly more resources available for innovation (Vincent, Bharadwaj, Challagalla 2017). Second, I also include the log of customer firm's revenues to account for the effect of the size of the focal customer in the relationship. Third, to account for the effect of research and development projects undergoing at the supplier firm, I include a log of supplier R&D expenditure, scaled for the size of the firm because research shows that a firm's R&D budget can affect its capability to undertake novel projects and innovate (Ahuja and Katila 2001). Fourth, I include a ratio of selling, general and administrative expenses (SG&A) to sales to control for supplier firms' resource slack (Bromiley 1991). A firm's resource slack can provide a buffer against environmental uncertainty, to be drawn upon during difficult times (e.g. see Cyert and March 1963; Thompson 1967). Organizational slack is also correlated with risk taking (Bromley 1991) and can affect a firm's innovation performance (Cui and O'Connor 2012).

Fifth, I control for the innovation intensity of the focal customer firms as a focal customer firm with high innovation intensity is more likely to affect the motivation and capabilities of a supplier firm to innovate (e.g., see Noordhoff et al. 2011). I use the number of patents successfully filed by the focal customer firm as a proxy for its innovation intensity. Since patents reflect a firm's technological capabilities that are externally validated through examination (Griliches 1990; Narin, Noma, and Perry 1987), they are an objective measure of a firm's innovation intensity. To construct this measure, I draw on similar data sources as described in the supplier innovation measures. Customer innovation intensity is log of the count of patents filed by the customer firm in a given time period *t*.

Finally, I include year dummies to control for global shocks that can affect supplier firm innovation. I log transform all variables, except product-centric structure, to address the skewness in my unbalanced panel data.

MODEL AND ESTIMATION

I use the following two equations to measure the scientific value and type of supplier innovation, respectively.

(1) $\text{Log}\,(SIV_{it} + 1) = \beta_0 + \beta_1 RM_{it} + \beta_2 LCO_{it} + \beta_3 PCS_{it} + \beta_4 CI_{it} + \beta_5 SICI_{it}$

$+ \beta_6 RM_{it} \text{ X } LCO_{it} + \beta_7 RM_{it} \text{ X } PCS_{it} + \beta_8 RM_{it} \text{ X } CI_{it} + \beta_9 RM_{it} \text{ X } SICI_{it}$

$+ \sum_{k=1}^{K} C_k\, CONTROL_{itk} + \delta_t + \phi_i + \varepsilon_{it}$

(2) $\text{Log}\,(SEI_{it} + 1) = \beta_0 + \beta_1 RM_{it} + \beta_2 LCO_{it} + \beta_3 PCS_{it} + \beta_4 CI_{it} + \beta_5 SICI_{it}$

$+ \beta_6 RM_{it} \text{ X } LCO_{it} + \beta_7 RM_{it} \text{ X } PCS_{it} + \beta_8 RM_{it} \text{ X } CI_{it} + \beta_9 RM_{it} \text{ X } SICI_{it}$

$+ \sum_{k=1}^{K} C_k\, CONTROL_{itk} + \delta_t + \phi_i + \varepsilon_{it}$

where

SIV_{it} is the log of supplier i's innovation value at time t

SEI_{it} is the log of supplier i's exploratory innovation at time t

RM_{it} is the log of supplier i's multiplexity with focal customer at time t

LCO_{it} is the log of loose coupling of supplier i with other firms at time t

PCS_{it} is the dummy for product-centric structure of supplier i at time t

CI_{it} is the log of importance of focal customer in relationship with supplier i at time t

SICI_{it} is the log of competitive intensity in supplier i's industry at time t

$\mathrm{CONTROL}_{itk}$ is a vector of k control variables

δ_t is year dummies

ϕ_i is firm fixed effects, and

ε_{it} is the error term

Identification Strategy

The models depicted in equations (1) and (2) control for idiosyncratic firm characteristics and time effects, which can affect my outcome variables. However, the models still raise two challenges that could render my estimates biased and inconsistent. First, supplier innovation depends on a number of factors including firm-specific characteristics and marketplace factors (e.g., see Vincent, Bharadwaj, and Challagalla, 2017). The inclusion of competitive intensity and other control variables serve to address alternative explanations. Second, supplier firms' RM and LCO decisions may be made strategically, anticipating actual performance or driven by unobserved competitive actions. To the extent that the non-modelled unobserved variables are correlated with the error terms in equations (1) and (2), RM and LCO are endogenous to supplier innovation. (e.g., see Sridhar et al. 2016). Additionally, not controlling for the omitted variables that may drive strategic decisions can create first-order endogeneity in my model (Rossi 2014). Thus, I use a control function approach to avoid potential bias by accounting for unobservable factors (Petrin and Train 2010).

Control Function Approach

I introduce control function corrections with respect to the two endogenous regressors (RM and LCO) in equations (1) and (2) in order to establish that the endogenous regressors are no longer correlated with the error term and can invoke the assumption of independence (Sridhar et al. 2016).

In order to obtain the control function for RM and LCO, I first regress my two endogenous variables, RM and LCO, on their respective instruments and other exogenous variables to estimate the residuals, which provide a control function correction in the main estimation. In order to create instruments, I measure the average RM and LCO established by other firms in the same four-digit SIC code as the supplier firm and call them SICRM and SICLCO. I then use SICRM and SICLCO as the exclusion restrictions in first stage regressions to address the endogeneity concern in my model.

Prior research using similar instruments argues that firms that compete in similar industry conditions and share similar expectations are likely to be mimetic and adopt prevalent industry practices (Chintagunta, Gopinath, and Venkatraman 2010; Xiong and Bharadwaj 2014; Sridhar et al. 2016). Supplier-firm level idiosyncratic shocks should not affect industry average RM and LCO. The two industry level instruments reflect the probability of a supplier firm creating RM or LCO if the other firms in the industry do so as well. However, there is no underlying rationale for these instruments to be related to the innovation outcome of the supplier firm. It is also unlikely that my instrumental variables would relate to a focal firm's omitted variables (e.g., customer orientation or organizational culture, both potential antecedents) because such variables may be difficult to assess from the outside and it is very difficult for competitors to act collectively against a single firm. Therefore, the instrument should be uncorrelated with the omitted variable and consequently the error term that contains the omitted variable, thereby meeting the exclusion restriction.

Precisely, I estimate equations (3a) and (3b) as below:

(3a) $\mathrm{RM_{it}} = \alpha_{0,\mathrm{RM}} + \alpha_{1,\mathrm{RM}}\mathrm{SICRM_{it}} + \sum_{k=1}^{K} \alpha_{k,\mathrm{RM}} \times \mathrm{Exogenous_{itk}} + u_{it,\mathrm{RM}}$

(3b) $\mathrm{LCO_{it}} = \alpha_{0,\mathrm{LCO}} + \alpha_{1,\mathrm{LCO}}\mathrm{SICLCO_{it}} + \sum_{k=1}^{K} \alpha_{k,\mathrm{LCO}} \times \mathrm{Exogenous_{itk}} + u_{it,\mathrm{LCO}}$

Where, $SICRM_{it}$ and $SICLCO_{it}$ are the two industry level instruments for RM and LCO, respectively. $Exogenous_{itk}$ is the vector of exogenous variables, including control variables, firm fixed effects, and time fixed effects. Next, I obtain the predicted residuals from equation (3a) and (3b), respectively and include these residuals in the second stage as control function. Also, in order to correct for slope endogeneity issues, I include the interactions between the residuals and respective endogenous regressors (e.g., Luan and Sudhir 2010). My final models are summarized below:

(1) $\mathrm{Log}\ (\mathrm{SIV_{it}} + 1) = \beta_0 + \beta_1\mathrm{RM_{it}} + \beta_2\mathrm{LCO_{it}} + \beta_3\mathrm{PCS_{it}} + \beta_4\mathrm{CI_{it}} + \beta_5\mathrm{SICI_{it}}$

$+ \beta_6\mathrm{RM_{it}}\ \mathrm{X}\ \mathrm{LCO_{it}} + \beta_7\mathrm{RM_{it}}\ \mathrm{X}\ \mathrm{PCS_{it}} + \beta_8\mathrm{RM_{it}}\ \mathrm{X}\ \mathrm{CI_{it}} + \beta_9\mathrm{RM_{it}}\ \mathrm{X}\ \mathrm{SICI_{it}}$

$+ \sum_{k=1}^{K} C_k\ \mathrm{CONTROL_{itk}} + \delta_t + \phi_i + \varepsilon_{it} + \sum_{m=1}^{4} \zeta_m \begin{pmatrix} \hat{u}_{it,\mathrm{RM}} \\ \hat{u}_{it,\mathrm{LCO}} \\ \hat{u}_{it,\mathrm{RM}} \times \mathrm{RM_{it}} \\ \hat{u}_{it,\mathrm{LCO}} \times LCO_{it} \end{pmatrix}$

(2) $\mathrm{Log}\ (\mathrm{SEI_{it}} + 1) = \beta_0 + \beta_1\mathrm{RM_{it}} + \beta_2\mathrm{LCO_{it}} + \beta_3\mathrm{PCS_{it}} + \beta_4\mathrm{CI_{it}} + \beta_5\mathrm{SICI_{it}}$

$+ \beta_6\mathrm{RM_{it}}\ \mathrm{X}\ \mathrm{LCO_{it}} + \beta_7\mathrm{RM_{it}}\ \mathrm{X}\ \mathrm{PCS_{it}} + \beta_8\mathrm{RM_{it}}\ \mathrm{X}\ \mathrm{CI_{it}} + \beta_9\mathrm{RM_{it}}\ \mathrm{X}\ \mathrm{SICI_{it}}$

$$+ \sum_{k=1}^{K} C_k \text{ CONTROL}_{itk} + \delta_t + \phi_i + \varepsilon_{it} + \sum_{m=1}^{4} \zeta_m \begin{pmatrix} \hat{u}_{it,RM} \\ \hat{u}_{it,LCO} \\ \hat{u}_{it,RM} \times RM_{it} \\ \hat{u}_{it,LCO} \times LCO_{it} \end{pmatrix}$$

Where $\hat{u}_{it,RM}$ and $\hat{u}_{it,LCO}$ are the residuals from equation 3(a) and 3(b) and ζ_m captures the coefficients of residuals and their interactions.

RESULTS

I report the descriptive statistics and correlation matrix of main variables in my model in Table 2.2. The inter-item correlations suggest that multi-collinearity is unlikely to impact the results. Also, on average, supplier firms in my sample are much smaller than customer firms, suggesting potential for power imbalance in their relationships.

Table 2.3 reports the results from the first stage of the control function regression, based on Equation 3a and 3b. As can be seen from the first stage results, the SIC level instruments for RM and LCO are significant, suggesting that industry average RM and LCO are significantly relevant drivers of supplier RM and LCO. The main regression results for supplier innovation value and exploratory innovation are reported in Table 2.4. As hypothesized in H1, the main effect of RM on supplier innovation is negative and significant for both dependent variables – innovation value and exploratory innovation. Precisely, I find strong support that supplier firms' RM with their focal customers not only negatively affects supplier overall innovation but also brings down exploratory innovation. In H2, I posit that loose coupling should weaken the main negative effect of RM on supplier innovation. This is also strongly supported for innovation value and exploratory innovation. Also, as predicted in H3, I find support for the moderating effect of a product-centric structure for exploratory innovation. However, this is not supported for innovation value. In H4 I hypothesize that customer importance should further strengthen the main negative effect of RM on supplier innovation. While this hypothesis is supported for exploratory innovation, I find the opposite effect for innovation value, i.e. customer importance mitigates the original negative impact of RM on citation-weighted patents. I explore the possible causes of this anomalous finding in the discussion section. Consistent with H5, the moderating effect of supplier industry competitive intensity is in expected direction and significant for innovation value. However, this effect is not significant for exploratory innovation.

Sensitivity Analyses

I also conduct several additional analyses, using alternative empirical modelling strategies and measures, to check the robustness of my results. The results of these robustness checks are reported in the Appendix.

2SLS-IV. Table 2.5 reports the results a 2SLS-IV regression. I estimate a two-stage least-squares instrumental variable (2SLS-IV) fixed effects model. I prefer a fixed effects estimator over a random effects estimator as the former can account for time-invariant firm-specific factors, which can be correlated with the regressors. The first two columns of Table 2.5 report the regression results for innovation value and exploratory innovation, respectively. These models are estimated by using the same measures as in my main model. In the last two column of Table 2.5, I report the results for innovation value and exploratory innovation by examining the effect of removing potential outliers by using winsorized variables (± 10^{th} percentile of residuals). The results are similar to that of my main model. For winsorized variables, the results are similar and even stronger. All models pass the test of underidentification for the relevance condition of excluded instruments[5]. The null hypothesis is that the equation is underidentified. I reject the null and conclude that my equations are of full rank and that my model is not underidentified. Also, my instruments pass the weak instrument test.[6]

Alternative measures. As additional robustness checks, I estimate my model with alternative measures of RM by excluding a single type of tie. The results for these additional analyses for citation-weighted patents and for exploratory innovation remain unchanged and are presented in the top-half and bottom-half of Table 2.6, respectively.

Random effects and sample subset. Further, I conduct additional analyses by estimating a random effects model. The results are similar to those of my main model and are reported in the first and second column of Table 2.7 for innovation value and exploratory innovation, respectively. Also, I re-estimate my main model after dropping the first two years (Column 3 and 4) and last two years (Column 5 and 6) from my sample. The results from these analyses are also similar to my main estimation results for both of the dependent variables.

Seemingly Unrelated Regression. Finally, it could be argued that the underlying capabilities required by a firm to generate innovation of higher significance and exploratory nature are common. While the two linear equations (innovation value and exploratory innovation) do not appear related, they could be related through correlation in the error terms. To address the concern of potentially correlated errors in the two models, I performed a seemingly unrelated regression. The results are reported in Table 2.8(a) and are similar to those of my main model.

---

[5] As our equations are exactly identified, the Hansen statistics of model overidentification cannot be used for model interpretation.
[6] Cragg-Donald Wald F statistics for the weak instrument identification test exceed the Stock-Yogo critical values at 20% ($n = 2$, $K_2 = 4$).

Additionally, Table 2.8(b) reports the error correlation matrix. As we can see from the table, the two error terms are not correlated.

DISCUSSION

Building upon inter-firm relationships and innovation literature, this study improves my understanding by exploring the effect of customer-supplier RM on supplier firm innovation in a B2B context. In addition to examining a multi-industry, longitudinal panel data to study the relationship between customer-supplier RM and innovation, this study adds to my understanding of RM's effect on innovation by examining multiple measures of innovation - innovation importance and type.

The results of the study indicate that RM with a focal customer firm hurts supplier innovation. This is an interesting finding, given that RM between customer and supplier firms is seen as a market-based asset (Srivastava, Shervani, and Fahy 1998) and has previously been shown to help increase supplier firms' sales to a customer firm and reduce the volatility in sales to that customer (Tuli, Bharadwaj, and Kohli 2010). These findings corroborate previously established arguments related to knowledge redundancy, resource constraints and customer opportunism in inter-firm relationships, suggesting that while RM between customer and supplier firms may help boost supplier firm performance within that relationship, it may not be equally stimulating for overall firm-level innovation outcomes. Additionally, arguments for access to private customer information in a multiplex relationship point toward collaboration and co-development in the relationship to better understand and serve the customer firm's needs, thus motivating the customer firm to buy more from the supplier (Tuli, Bharadwaj, and Kohli 2010).

While these arguments support innovation within the relationship, such innovations appear specific to customer needs and do not necessarily pan out of the relationship, thus creating the challenges of lack of knowledge heterogeneity, resource specificity and potential for customer opportunism. In addition to improve my understanding of the divergent effects of RM for supplier sales versus supplier innovation, these findings are of significant value for business managers to make a choice to establish RM with customer firms given the end objectives of the firm.

The study also examines important relationship-specific and environmental factors to understand how these factors moderate the role of RM on supplier innovation. I find that a supplier firm’s loosely coupled relationships with other firms help the supplier firm mitigate the negative effect of RM on innovation. This finding provides an empirical confirmation that weak ties are a source of knowledge and technological resources for a supplier firm, helping it overcome the resource constraints imposed by the focal relationship (Rothaermel 2001). Also, I find that a product-centric organization structure is instrumental in reducing the negative effect of RM on supplier exploratory innovation. This finding suggests that while RM can drain a supplier firm of its resources and restrict its ability to explore and invest in new ideas, a product-centric structure creates higher efficiencies in knowledge generation and transfer, and use of resources. A product-centric structure is instrumental in helping the supplier firm to retain its focus on generating novel products and ideas while using relatively fewer resources.

The findings of this study contribute to theory significantly by improving the understanding of the alternative strategies to overcome the negative effects of RM on supplier innovation. Moreover, the findings contribute significantly to managerial decision making, particularly for supplier firms that have already established RM with focal customers, since such supplier firms can manage these characteristics to mitigate the negative effect of RM on own innovation. RM with focal customers presents a paradox to the supplier firm where, on one hand, RM is a market-based asset that allows a supplier firm to generate higher sales to a customer and reduce the sales volatility to that customer (Tuli, Bharadwaj, and Kohli 2010), while on the other hand, RM can negatively affect supplier innovation. This study helps resolve this paradox by allowing the supplier firm to undertake alternative strategies to reduce the negative impact of RM on innovation, while still enjoying its performance benefits. Supplier firms that have RM with focal customers can establish loosely coupled relationships with other firms in the marketplace to access new knowledge and resources, which can provide the supplier firm with enough slack to overcome the resource constraints, knowledge redundancy and customer opportunism in RM. Similarly, a change in organization structure to reflect a product-centric focus can help the supplier firm achieve higher resource efficiency and R&D capabilities. This is helpful in creating a safeguard against the downside of extensive customer focus, which can significantly impact a supplier firm’s resources, its ability to respond to shocks, and capacity to exploit potential technological opportunities.

Examining the supplier industry environment as a moderator, the study finds that the negative effect of RM on supplier innovation importance becomes weaker as the supplier industry becomes more competitive. This result supports the rationale that as industries become more competitive, supplier firms have higher motivations to explore newer and more efficient ways of doing business in order to remain competitive, manage shrinking margins and retain their customers. Managers thus need to evaluate industry concentration and their firm’s relative position before establishing RM with focal customers, since it can change the magnitude of

RM's negative effect on innovation value and quality. However, I do not find support for the moderating effect of industry competitiveness on supplier innovation type.

Finally, I find mixed results for the moderating effect of customer importance. These findings about the moderating effect of customer importance on supplier innovation value and exploratory innovation are interesting. I find that customer importance further strengthens the negative effect of RM on exploratory innovation. This confirms the expectation that as the business of a supplier firm becomes increasingly concentrated among fewer focal customers, customer firms enjoy greater bargaining power and drive the supplier firm away from exploratory innovation. However, I also find that customer importance attenuates the negative effect of RM on supplier innovation importance. One possible explanation for this effect is that as customer firms enjoy greater bargaining power, they drive the supplier firms to focus on becoming innovative within the relationship. In such situations, while the supplier firms might still innovative more, their innovation efforts might be tied to specific needs of focal customers.

LIMITATIONS AND FUTURE RESEARCH

While the results from this study suggest that RM with customer firms can have negative implications for a supplier firm's innovation efforts, I do not imply that supplier firms should or should not establish RM with their customers without considering other benefits and costs associated with such embedded relationships.

One possible limitation of this study emanates from the endogenous nature of customer-supplier RM and loosely coupled relationships with other firms as these are strategic choices made by the supplier firm. While I treat these two variables as endogenous and use supplier industry level instruments to correct for possible endogeneity, it would be useful to employ multiple instruments in the analyses in future research.

Although this study is among the first in marketing to examine the effect of RM on supplier firm innovation scientific value and exploratory innovation, further research can look into the effect on how general or specific to a class an innovation is by examining patent classifications to measure an innovation's usefulness beyond its own class. Also, while this study examines the contextual effect of customer firm, supplier firm and environmental variables on the main relationship, other network level contextual factors that can affect this relationship remain to be explored.

REFERENCES

Ahuja, Gautam and Riitta Katila (2001), "Technological Acquisitions and the Innovation Performance of Acquiring Firms: A Longitudinal Study," *Strategic Management Journal,* 22 (3), 197—220.

Anderson, Erin and Sandy D. Jap (2005), "The Dark Side of Close Relationships," *MIT Sloan Management Review*, 46 (3), 75—82.

Arnold, Todd J., Eric E. Fang, and Robert W. Palmatier (2011), "The Effects of Customer Acquisition and Retention Orientations on a firm's Radical and Incremental Innovation Performance," *Journal of the Academy of Marketing Science,* 39 (2), 234—51.

Arora, Ashish and Alfonso Gambardella (1990), "Complementarity and External Linkages: The Strategies of the Large Firms in Biotechnology," *The Journal of Industrial Economics,* 38 (4), 361—379.

Atuahene-Gima, Kwaku (1995), "An Exploratory Analysis of the Impact of Market Orientation on New Product Performance a Contingency Approach," *Journal of Product Innovation Management,* 12 (4), 275—93.

——— (2005), "Resolving the Capability-Rigidity Paradox in New Product Innovation," *Journal of Marketing,* 69 (4), 61—83.

Barney, Jay (1991), "Firm Resources and Sustained Competitive Advantage," *Journal of Management,* 17 (1), 99—120.

Baum, Joel A., Tony Calabrese, and Brian S. Silverman (2000), "Don't Go it Alone: Alliance Network Composition and Startups' Performance in Canadian Biotechnology," *Strategic Management Journal,* 21 (3), 267—294.

Benner, Mary J. and Michael Tushman (2002), "Process Management and Technological Innovation: A Longitudinal Study of the Photography and Paint Industries," *Administrative Science Quarterly,* 47 (4), 676—707.

Borah, Abhishek and Gerard J. Tellis (2014), "Make, Buy, Or Ally? Choice of and Payoff from Announcements of Alternate Strategies for Innovations," *Marketing Science,* 33 (1) 114—33.

Bromley, Daniel W. (1991), "*Environment and Economy: Property Rights and Public Policy,"* Cambridge: Basil Blackwell Ltd.

Burt, Ronald S. (1992), “Structural Holes: The Social Structure of Competition,” Cambridge, MA: Harvard University Press.

Chandy, Rajesh K. and Gerard J. Tellis (2000), "The Incumbent’s Curse? Incumbency, Size, and Radical Product Innovation," *Journal of Marketing,* 64 (3), 1—17.

Chintagunta, Pradeep K., Shyam Gopinath, and Sriram Venkataraman (2010), "The Effects of Online User Reviews on Movie Box Office Performance: Accounting for Sequential Rollout and Aggregation Across Local Markets," *Marketing Science* 29 (5), 944—957.

Christensen, Clayton M. and Joseph L. Bower (1996), "Customer Power, Strategic Investment, and the Failure of Leading Firms," *Strategic Management Journal,* 17 (3) 197—218.

Cohen, Wesley M. and Daniel A. Levinthal (1990), "Absorptive Capacity: A New Perspective on Learning and Innovation," *Administrative Science Quarterly,* 35 (1), 128—152.

Coleman, J. (1990), "Foundations of Social Theory,” Cambridge, MA: Belknap Press of Harvard University Press.

Colt, Sam (2014a), “Ex-Apple Supplier Says a Soured Deal with Apple Forced it into Bankruptcy,” *Business Insider*, (accessed June 15, 2016), Retrieved from http://www.businessinsider.com/gtat-reveals-how-went-bankrupt-2014-10.

——— (2014b), “Here’s The Real Reason Apple’s Sapphire Supplier Went Bankrupt,” *Business Insider*, (accessed June 15, 2016), Retrieved from http://www.businessinsider.com/the-real-reason-apple-sapphire-supplier-gtat-went-bankrupt-2014-11.

Cui, Anna S. and Gina O'Connor (2012), "Alliance Portfolio Resource Diversity and Firm Innovation," *Journal of Marketing,* 76 (4), 24—43.

Cyert, Richard M., and James G. March (1963), "A Behavioral Theory of the Firm," Malden, MA: Blackwell Publishers.

Danneels, Erwin (2003), "Tight-loose Coupling with Customers: The Enactment of Customer Orientation," *Strategic Management Journal,* 24 (6) 559—76.

Day, George S. (1994), "The Capabilities of Market-Driven Organizations," *The Journal of Marketing,* 58 (4), 37—52.

Dwyer, F. R., Paul H. Schurr, and Sejo Oh (1987), "Developing Buyer-Seller Relationships," *Journal of Marketing,* 51 (2), 11—27.

Fang, Eric, Robert W. Palmatier, and Kenneth R. Evans (2008), "Influence of Customer Participation on Creating and Sharing of New Product Value," *Journal of the Academy of Marketing Science,* 36 (3), 322—36.

Fredberg, Tobias and Frank T. Piller (2011), "The Paradox of Tie Strength in Customer Relationships for Innovation: A Longitudinal Case Study in the Sports Industry," *R&D Management,* 41 (5), 470—84.

Germann, Frank, Peter Ebbes, and Rajdeep Grewal (2015), "The Chief Marketing Officer Matters!" *Journal of Marketing,* 79 (3) 1—22.

Granovetter, Mark S. (1973), "The Strength of Weak Ties," *American Journal of Sociology,* 78 (6), 1360—80.

——— (1982), "Alienation Reconsidered: The Strength of Weak Ties," *Connections,* 5(2) 4—16.

——— (1992), "Economic Institutions as Social Constructions: A Framework for Analysis," *Acta Sociologica,* 35 (1) 3—11.

Grant, Robert M. (1996), "Toward a Knowledge-Based Theory of the Firm," *Strategic Management Journal,* 17 (S2), 109—22.

Grayson, Kent and Tim Ambler (1999), "The Dark Side of Long-Term Relationships in Marketing Services," *Journal of Marketing Research,* 36 (1), 132—141.

Griliches, Z. (1990), "Patent Statistics as Economic Indicators: A Survey," *Journal of Economic Literature,* 28 (4), 1661—1707.

Hall, Bronwyn H., Adam Jaffe, and Manuel Trajtenberg (2005), "Market Value and Patent Citations," *RAND Journal of Economics,* 36 (1), 16—38.

Hamel, Gary and C. K. Prahalad (1991), "Corporate Imagination and Expeditionary Marketing," *Harvard Business Review,* 69 (Jul—Aug), 81—92.

Hammervol, T. (2005), "Customer Categorization: ABC-Analysis," *Norway: Harstad University College.*

Hansen, Morten T. (1999), "The Search-Transfer Problem: The Role of Weak Ties in Sharing Knowledge Across Organization Subunits," *Administrative Science Quarterly,* 44 (1), 82—111.

Heide, Jan B. and George John (1990), "Alliances in Industrial Purchasing: The Determinants of Joint Action in Buyer-Supplier Relationships," *Journal of Marketing Research*, 27 (1), 24—36.

Inemek, Aydin and Paul Matthyssens (2013), "The Impact of Buyer–Supplier Relationships on Supplier Innovativeness: An Empirical Study in Cross-Border Supply Networks," *Industrial Marketing Management*, 42 (4), 580—94.

Janis, Irving L. (1982), "Groupthink: Psychological Studies of Policy Decisions and Fiascoes," New York (NY): Houghton Mifflin Company.

Jap, Sandy D. (2003), "An Exploratory Study of the Introduction of Online Reverse Auctions," *Journal of Marketing*, 67 (3), 96—107.

Joshi, Amol M. and Atul Nerkar (2011), "When do Strategic Alliances Inhibit Innovation by Firms? Evidence from Patent Pools in the Global Optical Disc Industry," *Strategic Management Journal*, 32 (11), 1139—1160.

Kalaignanam, Kartik, Venkatesh Shankar, and Rajan Varadarajan (2007), "Asymmetric New Product Development Alliances: Win-Win or Win-Lose Partnerships?" *Management Science*, 53 (3), 357—374.

Kenis, Patrick and David Knoke (2002), "How Organizational Field Networks Shape Interorganizational Tie-Formation Rates," *Academy of Management Review*, 27 (2), 275—293.

Kilduff, Martin and Wenpin Tsai (2003), *Social Networks and Organizations.* London: Sage.

Kogan, Leonid, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman (2016), "Technological Innovation, Resource Allocation, and Growth," *The Quarterly Journal of Economics*, 132 (2), 665—712.

Kogut, Bruce and Udo Zander (1992), "Knowledge of the Firm, Combinative Capabilities, and the Replication of Technology," *Organization Science*, 3 (3), 383—97.

Kumar, V., Eli Jones, Rajkumar Venkatesan and Robert P. Leone (2011), “Is Market Orientation a Source of Sustainable Competitive Advantage or Simply the Cost of Competing?” Journal of Marketing, 75 (1), 16–30.

Lee, Ju-Yeon, Shrihari Sridhar, Conor M. Henderson, and Robert W. Palmatier (2014), "Effect of Customer-Centric Structure on Long-Term Financial Performance," *Marketing Science*, 34 (2), 250—268.

Li, Tiger and Roger J. Calantone (1998), "The Impact of Market Knowledge Competence on New Product Advantage: Conceptualization and Empirical Examination," *Journal of Marketing,* 62 (4), 13—29.

Lilien, Gary L., Pamela D. Morrison, Kathleen Searls, Mary Sonnack, and Eric von Hippel (2002), "Performance Assessment of the Lead User Idea-Generation Process for New Product Development," *Management Science* 48 (8), 1042—1059.

Luca, Luigi M. D. and Kwaku Atuahene-Gima (2007), "Market Knowledge Dimensions and Cross-Functional Collaboration: Examining the Different Routes to Product Innovation Performance," *Journal of Marketing,* 71 (1), 95—112.

Lusch, Robert F., Stephen L. Vargo, and Matthew O'Brien (2007), "Competing through Service: Insights from Service-Dominant Logic," *Journal of Retailing,* 83 (1), 5—18.

Meyer, Alan D. and James B. Goes (1988), "Organizational Assimilation of Innovations: A Multilevel Contextual Analysis," *Academy of Management Journal,* 31 (4), 897—923.

Mishra, Saurabh and Rebecca J. Slotegraaf (2013), "Building an Innovation Base: Exploring the Role of Acquisition Behavior," *Journal of the Academy of Marketing Science,* 41 (6), 705—721.

Moorman, Christine and Anne S. Miner (1997), "The Impact of Organizational Memory on New Product Performance and Creativity," *Journal of Marketing Research*, 34 (1), 91—106.

Moorman, Christine, Gerald Zaltman, and Rohit Deshpande (1992), "Relationships between Providers and Users of Market Research: The Dynamics of Trust within and between Organizations," *Journal of Marketing Research,* 29 (3), 314—328.

Moorman, Christine, Rohit Deshpande, and Gerald Zaltman (1993), "Factors Affecting Trust in Market Research Relationships," *Journal of Marketing,* 57 (1), 81—101.

Morgan, Robert M. and Shelby D. Hunt (1994), "The Commitment-Trust Theory of Relationship Marketing," *Journal of Marketing,* 58 (3), 20—38.

Nahapiet, Janine and Sumantra Ghoshal (1998), "Social Capital, Intellectual Capital, and the Organizational Advantage," *Academy of Management Review,* 23 (2), 242—266.

Narin, Francis, Elliot Noma, and Ross Perry (1987), "Patents as Indicators of Corporate Technological Strength," *Research Policy,* 16 (2-4), 143—155.

Nohria, Nitin and Ranjay Gulati (1996), "Is Slack Good or Bad for Innovation?" *Academy of Management Journal,* 39 (5), 1245—1264.

Nonaka, Ikujiro (1994), "A Dynamic Theory of Organizational Knowledge Creation," *Organization Science,* 5 (1), 14—37.

Noordhoff, Corine S., Kyriakos Kyriakopoulos, Christine Moorman, Pieter Pauwels, and Benedict GC Dellaert (2011), "The Bright Side and Dark Side of Embedded Ties in Business-to-Business Innovation," *Journal of Marketing,* 75 (5), 34—52.

Petrin, Amil, and Kenneth Train (2010), "A Control Function Approach to Endogeneity in Consumer Choice Models," *Journal of Marketing Research,* 47 (1), 3—13.

Prabhu, Jaideep C., Rajesh K. Chandy, and Mark E. Ellis (2005), "The Impact of Acquisitions on Innovation: Poison Pill, Placebo, Or Tonic?" *Journal of Marketing,* 69 (1), 114—130.

Rao, R. S., Chandy, R. K., and Prabhu, J. C. (2008), “The Fruits of Legitimacy: Why Some New Ventures Gain More from Innovation than Others,” *Journal of Marketing*, 72 (4), 58—75.

Rindfleisch, Aric and Christine Moorman (2001), "The Acquisition and Utilization of Information in New Product Alliances: A Strength-of-Ties Perspective," *Journal of Marketing,* 65 (2), 1—18.

Rindfleisch, Aric, and Jan B. Heide (1997), "Transaction Cost Analysis: Past, Present, and Future Applications," *Journal of Marketing,* 61 (4), 30–54.

Rossi, Matteo (2014), "Capital Budgeting in Europe: Confronting Theory with Practice," *International Journal of Managerial and Financial Accounting,* 6 (4), 341—356.

Rothaermel, Frank T. (2001), "Incumbent's Advantage Through Exploiting Complementary Assets Via Interfirm Cooperation," *Strategic Management Journal* 22 (6/7), 687—699.

Roy, Subroto, Kumaraswamy Sivakumar, and Ian F. Wilkinson (2004), "Innovation Generation in Supply Chain Relationships: A Conceptual Model and Research Propositions," *Journal of the Academy of Marketing Science,* 32 (1), 61—79.

Samaha, Stephen A., Robert W. Palmatier, and Rajiv P. Dant (2011), "Poisoning Relationships: Perceived Unfairness in Channels of Distribution," *Journal of Marketing,* 75 (3), 99—117.

Sampson, Rachelle C. (2007), "R&D Alliances and Firm Performance: The Impact of Technological Diversity and Alliance Organization on Innovation," *Academy of Management Journal,* 50 (2), 364—386.

Schilling, Melissa A. and Corey C. Phelps (2007), "Interfirm Collaboration Networks: The Impact of Large-Scale Network Structure on Firm Innovation," *Management Science*, 53 (7), 1113—1126.

Seggie, Steven H., David A. Griffith, and Sandy D. Jap (2013), "Passive and Active Opportunism in Interorganizational Exchange," *Journal of Marketing*, 77 (6), 73—90.

Shah, Denish, Roland T. Rust, Ananthanarayanan Parasuraman, Richard Staelin, and George S. Day (2006), "The Path to Customer Centricity," *Journal of Service Research*, 9 (2), 113—124.

Sivadas, Eugene and F. R. Dwyer (2000), "An Examination of Organizational Factors Influencing New Product Success in Internal and Alliance-Based Processes," *Journal of Marketing*, 64 (1), 31—49.

Slotegraaf, Rebecca J., Christine Moorman, and J. J. Inman (2003), "The Role of Firm Resources in Returns to Market Deployment," *Journal of Marketing Research*, 40 (3), 295—309.

Sorescu, Alina B., Rajesh K. Chandy, and Jaideep C. Prabhu (2003), "Sources and Financial Consequences of Radical Innovation: Insights from Pharmaceuticals," *Journal of Marketing*, 67 (4), 82—102.

——— (2007), "Why Some Acquisitions Do Better Than Others: Product Capital as Driver of Long-Term Stock Returns," *Journal of Marketing Research*, 44 (1), 57—72.

Sridhar, Shrihari, Frank Germann, Charles Kang, and Rajdeep Grewal (2016), "Relating Online, Regional, and National Advertising to Firm Value," *Journal of Marketing*, 80 (4), 39—55.

Srivastava, Rajendra K., Tasadduq A. Shervani, and Liam Fahey (1998), "Market-Based Assets and Shareholder Value: A Framework for Analysis," *Journal of Marketing* 62 (1), 2—18.

Stock, James H. and Motohiro Yogo (2002), "Testing for Weak Instruments in Linear IV Regressions." In *Identification and Inference for Econometric Models*, ed. Andrews Donald W.K., Stock James H., 80—108. Cambridge: Cambridge University Press

Swaminathan, Vanitha and Christine Moorman (2009), "Marketing Alliances, Firm Networks, and Firm Value Creation," *Journal of Marketing*, 73 (5), 52—69.

Szymanski, David M., Sundar G. Bharadwaj, and P. R. Varadarajan (1993), "An Analysis of the Market Share-Profitability Relationship," *Journal of Marketing*, 57 (3), 1—18.

Thompson, James D. (1967), “*Organizations in Action: Social Science Bases of Administrative Theory,”,* New Brunswick (NJ): Transaction Publishers.

Tsai, Kuen-Hung, and Teresa Tiaojung Hsu (2014), "Cross-Functional Collaboration, Competitive Intensity, Knowledge Integration Mechanisms, and New Product Performance: A Mediated Moderation Model," *Industrial Marketing Management*, 43 (2), 293–303.

Tuli, Kapil R., Sundar G. Bharadwaj, and Ajay K. Kohli (2010), "Ties that Bind: The Impact of Multiple Types of Ties with a Customer on Sales Growth and Sales Volatility," *Journal of Marketing Research,* 47 (1), 36—50.

Un, C. A., Alvaro Cuervo-Cazurra, and Kazuhiro Asakawa (2010), "R&D Collaborations and Product Innovation," *Journal of Product Innovation Management,* 27 (5), 673—689.

Urban, Glen L. and Eric Von Hippel (1988), "Lead User Analyses for the Development of New Industrial Products," *Management Science,* 34 (5), 569—582.

Uzzi, Brian (1997), "Social Structure and Competition in Interfirm Networks: The Paradox of Embeddedness," *Administrative Science Quarterly,*42 (1), 35—67.

——— (1999), "Embeddedness in the Making of Financial Capital: How Social Relations and Networks Benefit Firms Seeking Financing," *American Sociological Review,* 64 (4), 481—505.

——— and Ryon Lancaster (2003), "Relational Embeddedness and Learning: The Case of Bank Loan Managers and their Clients," *Management Science*, 49 (4), 383—399.

Wakayabashi, Daisuke (2014), “Inside Apple’s Broken Sapphire Factory,” *The Wall Street Journal*, (accessed June 15, 2016), Retrieved from https://www.wsj.com/articles/inside-apples-broken-sapphire-factory-1416436043.

Wang, Yonggui, Jongkuk Lee, Er Eric Fang, and Shuang Ma (2017), "Project Customization and the Supplier Revenue–Cost Dilemmas: The Critical Roles of Supplier–Customer Coordination." *Journal of Marketing*, 81 (1), 136—154.

Wathne, Kenneth H. and Jan B. Heide (2000), "Opportunism in Interfirm Relationships: Forms, Outcomes, and Solutions," *Journal of Marketing*, 64 (4), 36—51.

Weick, Karl E. (1976), "Educational Organizations as Loosely Coupled Systems," *Administrative Science Quarterly*, 21 (1), 1—19.

Wetzel, Hauke A., Maik Hammerschmidt, and Alex R. Zablah (2014), "Gratitude Versus Entitlement: A Dual Process Model of the Profitability Implications of Customer Prioritization," *Journal of Marketing*, 78 (2), 1—19.

Wuyts, Stefan, and Shantanu Dutta (2014), "Benefiting from Alliance Portfolio Diversity: The Role of Past Internal Knowledge Creation Strategy," *Journal of Management* 40 (6): 1653—1674.

———, Shantanu Dutta, and Stefan Stremersch (2004), "Portfolios of Interfirm Agreements in Technology-Intensive Markets: Consequences for Innovation and Profitability," *Journal of Marketing*, 68 (2), 88—100.

Xiong, Guiyang and Sundar Bharadwaj (2011), "Social Capital of Young Technology Firms and their IPO Values: The Complementary Role of Relevant Absorptive Capacity," *Journal of Marketing*, 75 (6), 87—104.

——— (2014), "Prerelease Buzz Evolution Patterns and New Product Performance," *Marketing Science* 33 (3), 401—421.

Zahra, Shaker A., and Jeffrey G. Covin (1995), "Contextual Influences on The Corporate Entrepreneurship–Performance Relationship: A Longitudinal Analysis," Journal of Business Venturing, 10 (1), 43–58.

TABLES

Table 2.1
SUMMARY OF MEASURES AND DATA SOURCES

Variable	***Measure***	***Source***	***Literature***
Dependent variables			
Supplier innovation:			
Innovation scientific value	log (citation-weighted patents)	Kogan et al. 2016, USPTO, NBER,	Kogan et al. 2016
Exploratory innovation	log (number of patents based on new knowledge)	Google patents	Benner and Tushman 2002
Independent variables			
Relationship multiplexity	log (number of ties between a supplier and its focal customer)	SEC filings (10-K, 10-Q, 8-k, DEF 14A), company website	Kilduff and Tsai 2003; Tuli, Bharadwaj, and Kohli 2010
Loose coupling	log (number of ties between a supplier and other firms)	SEC filings (10-K, 10-Q, 8-k, DEF 14A), company website	Daneels 2003
Customer importance	log (revenue proportion tied to the customer)	SEC filings (10-K, 10-Q)	Heide and John 1990
Product-centric structure	Dummy: 1 – product-centric, 0 – other	SEC filings (10-K, 10-Q)	Lee et al., 2015; Day, 2006
Supplier industry competitive intensity	Herfindahl-Hirschman Index	COMPUSTAT	Szymanski, Bharadwaj and Varadarajan 1993; Tellis and Chandy 1999
Control variables	Supplier firm size Supplier firm R&D expenditure Customer firm size Supplier resource slack Customer innovation intensity	COMPUSTAT, USPTO, NBER, Google patents	Joshi and Nerkar 2011; Wuyts and Dutta 2014

Table 2.2

DESCRIPTIVE STATISTICS FOR INNOVATION SCIENTIFIC VALUE AND EXPLORATORY INNOVATION

Correlation matrix: Innovation scientific value

		M	SD	1	2	3	4	5	6	7	8	9	10	11
1	Innovation scientific value	49.23	316.30	1.00										
2	Relationship multiplexity	1.35	.67	**.12**	1.00									
3	Loose coupling	1.14	1.51	.03	.03	1.00								
4	Customer innovation intensity	268.71	740.72	**.11**	**.14**	**-.08**	1.00							
5	Customer importance	.20	.15	-.03	**.22**	.04	**.08**	1.00						
6	Customer size ($M)	49487.84	61032.93	.01	**-.08**	.02	**.14**	**.12**	1.00					
7	Ind. competitive intensity	.16	.14	**-.07**	**.19**	**-.19**	**.24**	.00	**-.15**	1.00				
8	Product-centric structure	.25	.43	**.10**	-.03	-.02	**-.06**	-.03	**.18**	**-.16**	1.00			
9	Supplier size ($M)	1002.23	2541.47	**.15**	.01	**.05**	**-.04**	**.10**	**.32**	**-.16**	**.30**	1.00		
10	Supplier R&D (%)	.14	.16	**-.05**	**.11**	.00	**.08**	**.12**	**-.16**	**.13**	**-.12**	**-.17**	1.00	
11	Supplier resource slack	.50	.98	-.03	.02	**.09**	.00	**.04**	**-.04**	.02	**-.09**	**-.11**	**.18**	1.00

Correlation matrix: Exploratory innovation

		M	SD	1	2	3	4	5	6	7	8	9	10	11
1	Exploratory innovation	13.57	31.27	1.00										
2	Relationship multiplexity	1.35	67	**.09**	1.00									
3	Loose coupling	1.14	1.51	-.02	.03	1.00								
4	Customer innovation intensity	268.71	740.72	.03	**.14**	**-.08**	1.00							
5	Customer importance	.20	.15	-.02	**.22**	.04	**.08**	1.00						
6	Customer size ($M)	49487.84	61032.93	.04	**-.08**	.02	**.14**	**.12**	1.00					
7	Ind. competitive intensity	.16	.14	**-.10**	**.19**	**-.19**	**.24**	.00	**-.15**	1.00				
8	Product-centric structure	.25	.43	**.25**	-.03	-.02	**-.06**	-.03	**.18**	**-.16**	1.00			
9	Supplier size ($M)	1002.23	2541.47	**.32**	.01	**.05**	**-.04**	**.10**	**.32**	**-.16**	**.30**	1.00		
10	Supplier R&D (%)	.14	.16	**-.12**	**.11**	.00	**.08**	**.12**	**-.16**	**.13**	**-.12**	**-.17**	1.00	
11	Supplier resource slack	.50	.98	**-.07**	.02	**.09**	.00	**.04**	**-.04**	.02	**-.09**	**-.11**	**.18**	1.00

Correlations in bold are significant at $p < .05$

Table 2.3
CONTROL FUNCTION FIRST STAGE REGRESSION

	Relationship multiplexity (*Eq. 3a*)	*Loose coupling* (*Eq. 3b*)
Industry average	.34***	.24***
	(.05)	(.02)
Customer size	.00	-.01
	(.00)	(.01)
Customer importance	.12*	-.08
	(.05)	(.09)
Customer innovation intensity	-.01*	.04*
	(.01)	(.02)
Supplier industry competitive intensity	-.37***	.44*
	(.10)	(.19)
Supplier size	.00	-.01
	(.01)	(.02)
Supplier R&D	-.04***	.02
	(.01)	(.02)
Supplier resource slack	-.10***	-.04
	(.02)	(.04)
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Intercept	-.06***	-.06
	(.02)	(.04)
N	2458	2458

Two-tailed tests: * $p < .05$; ** $p < .01$; *** $p < .001$; SE in parentheses

Table 2.4
MAIN MODEL ESTIMATION RESULTS (CONTROL FUNCTION APPROACH)

	Innovation scientific value	*Exploratory innovation*
Relationship multiplexity (*H1*)	-2.73***	-2.72**
	(.70)	(.88)
Multiplexity X Loose coupling (*H2*)	.29**	.29**
	(.11)	(.11)
Multiplexity X Product-centric structure (*H3*)	.06	.29*
	(.13)	(.14)
Multiplexity X Customer importance (*H4*)	1.39**	-1.03*
	(.45)	(.55)
Multiplexity X Supplier industry competitive intensity (*H5*)	-1.79***	.42
	(.51)	(.53)
Main effects		
Loose coupling	.24	-.54*
	(.21)	(.25)
Product-centric structure	.14*	-.14
	(.06)	(.07)
Customer importance	.52*	.57
	(.24)	(.30)
Supplier industry competitive intensity	-1.70**	2.57**
	(.62)	(.78)
Control variables		
Supplier size	.17***	.41***
	(.04)	(.04)
Supplier R&D	-.03	-.08
	(.05)	(.06)
Supplier resource slack	-.46***	.15
	(.11)	(.14)
Customer size	-.03	-.02
	(.02)	(.02)
Customer innovation intensity	-.09**	-.04
	(.04)	(.04)
Residuals $_{RM}$	2.88***	2.87**
	(.70)	(.90)
Residuals $_{LCO}$	-.21	.41
	(.21)	(.26)
Residuals $_{RM}$ X Relationship multiplexity	.06	.03
	(.25)	(.26)
Residuals $_{LCO}$ X Loose Coupling	.02	-.14
	(.08)	(.09)
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Intercept	-.38***	-.16
	(.11)	(.12)
N	2458	1532
R-square	.11	.41

Overall test of significance	7.32 (F-test)	7.13 (F-test)
Test of significance	<.001	<.001

Two-tailed tests: * *p < .05; *** *p < .01; **** *p < .001*; SE in parentheses; [a]Residuals obtained from auxiliary regression in Table 2.3.

Table 2.5
ROBUSTNESS CHECKS (2SLS-INSTRUMENTAL VARIABLE ESTIMATION)

	Innovation scientific value	*Exploratory innovation*	*Innovation scientific value (winsorized)*	*Exploratory innovation (winsorized)*
Relationship multiplexity *(H1)*	-3.45*	-2.37*	-3.45*	-2.17*
	(1.52)	(1.06)	(1.45)	(.98)
Multiplexity X Loose coupling *(H2)*	.59*	.77**	.60*	.75**
	(.31)	(.25)	(.30)	(.24)
Multiplexity X Product-centric structure *(H3)*	1.14*	.78**	1.21*	.78**
	(.53)	(.29)	(.53)	(.27)
Multiplexity X Customer importance *(H4)*	3.71*	1.10	3.84**	.92
	(1.47)	(1.54)	(1.46)	(1.45)
Multiplexity X Supplier industry competitive intensity *(H5)*	-7.52**	-4.10*	-7.62**	-3.86*
	(2.67)	(1.89)	(2.61)	(1.80)
Other Main Effects & Controls				
Loose coupling	.03	-.71*	.04	-.71*
	(.35)	(.33)	(.35)	(.32)
Product-centric structure	.08	-.17	.09	-.18
	(.10)	(.12)	(.10)	(.12)
Customer importance	.32	.07	.32	.05
	(.44)	(.50)	(.45)	(.48)
Supplier industry competitive intensity	-.49	-.04	-.35	-.02
	(.80)	(.86)	(.77)	(.78)
Supplier size	.12	.35***	.14	.35***
	(.08)	(.07)	(.08)	(.07)
Supplier R&D	.01	-.00	.03	.01
	(.07)	(.07)	(.06)	(.07)
Supplier resource slack	-.55	-.09	-.66	-.08
	(.31)	(.27)	(.35)	(.29)
Customer size	-.02	.00	-.02	.00
	(.03)	(.03)	(.03)	(.03)
Customer innovation intensity	-.07	-.04	-.08	-.04
	(.06)	(.07)	(.06)	(.07)
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Kleibergen-Paap rk LM stat	12.56***	10.06***	12.95***	10.79***
Cragg-Donald Wald F stat	18.84	17.08	20.27	17.29
Kleibergen-Paap rk Wald F stat	6.61	6.04	6.93	6.44
N	2420	1463	2420	1463

Two-Tailed Tests: ** p < .05; ** p < .01; *** p < .001*; SE in parentheses

Table 2.6
ROBUSTNESS CHECKS (ALTERNATIVE MEASURES OF RM)

Dependent variable – Innovation scientific value	*without Board Interlock*	*without R&D Alliance*	*without Marketing Alliance*	*without Customer as Supplier*	*without Equity Investment*	*without Joint Venture*	*without Licensing*
Relationship multiplexity *(H1)*	-3.02**	-5.36***	-5.36***	-1.61	-4.24**	-4.73***	-4.19***
Multiplexity X Loose coupling *(H2)*	.44*	.50**	.40*	.60**	.47**	.67***	.36*
Multiplexity X Product-centric structure *(H3)*	.12	.14	.01	.26	.15	.21	.21
Multiplexity X Customer importance *(H4)*	2.27**	2.40**	2.06*	2.35**	2.18**	1.73*	2.84***
Multiplexity X Supplier ind. comp. intensity *(H5)*	-2.81***	-2.84***	-3.03**	-3.11***	-2.58**	-3.03***	-3.85***
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2458	2458	2458	2458	2458	2458	2458
R-square	.09	.10	.11	.10	.10	.11	.09
Overall test of significance (F-stat)	7.48***	7.71***	7.40***	7.90***	7.33***	7.85***	7.82***
Dependent variable – Exploratory innovation	*without Board Interlock*	*without R&D Alliance*	*without Marketing Alliance*	*without Customer as Supplier*	*without Equity Investment*	*without Joint Venture*	*without Licensing*
Relationship multiplexity *(H1)*	-3.62*	-5.75***	-6.38**	-2.56	-5.63**	-3.75*	-5.79***
Multiplexity X Loose coupling *(H2)*	.47*	.47*	.46*	.41*	.44*	.45*	.46*
Multiplexity X Product-centric structure *(H3)*	.51*	.45*	.39	.65**	.51*	.59*	.51*
Multiplexity X Customer importance *(H4)*	-1.62	-1.83	-1.25	-2.02*	-1.25	-1.46	-1.73
Multiplexity X Supplier ind. comp. intensity *(H5)*	0.60	0.79	0.27	1.18	0.46	1.78	0.49
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1532	1532	1532	1532	1532	1532	1532
R-square	.39	.39	.41	.40	.40	.37	.41
Overall test of significance (F-stat)	7.43***	7.59***	7.20***	7.52***	7.46***	7.49	7.90***

* $p < .05$; ** $p < .01$; *** $p < .001$

Table 2.7
ROBUSTNESS CHECKS (RANDOM EFFECTS AND SAMPLE SUBSET)

	Random Effects		*without 1998-1999*		*without 2009-2010*	
	Citation-weighted Patents	*Innovation Type*	*Citation-weighted Patents*	*Innovation Type*	*Citation-weighted Patents*	*Innovation Type*
Relationship multiplexity *(H1)*	-2.44***	-2.35***	-4.30***	-3.65*	-2.18***	-2.66**
Multiplexity X Loose coupling *(H2)*	.27**	.44***	.28*	.33**	.32**	.36**
Multiplexity X Product-centric structure *(H3)*	.09	.44***	.04	.28	.19	.15
Multiplexity X Customer importance *(H4)*	.99*	-.62	1.68***	-.32	.91	-1.15*
Multiplexity X Supplier ind. comp. intensity *(H5)*	-1.22**	.33	-1.34*	.47	-2.38***	.67
Firm fixed effects	No	No	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	2458	1532	2204	1372	2091	1307
R-square	.24	.49	.06	.36	.08	.38
Overall test of significance	340*** (wald)	632.10*** (wald)	6.90*** (F-stat)	6.21*** (F-stat)	7.81*** (F-stat)	7.03*** (F-stat)

* *p* < .05; ** *p* < .01; *** *p* < .001

Table 2.8(a)
ROBUSTNESS CHECKS (SEEMINGLY UNRELATED REGRESSION)

	Citation-weighted Patents	*Innovation Type*
Relationship multiplexity *(H1)*	-5.37***	-2.68***
Multiplexity X Loose coupling *(H2)*	.23*	.28**
Multiplexity X Product-centric structure *(H3)*	.11	.29*
Multiplexity X Customer importance *(H4)*	2.56***	-.10*
Multiplexity X Supplier ind. comp. intensity *(H5)*	-2.16***	.37
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
N	1532	1532
R-square	.89	.85

* $p < .05$; ** $p < .01$; *** $p < .001$

Table 2.8(b)
CORRELATION MATRIX OF RESIDUALS

	Citation-weighted Patents	*Innovation Type*
Citation-weighted Patents	1.000	
Innovation Type	-.042	1.000

FIGURES

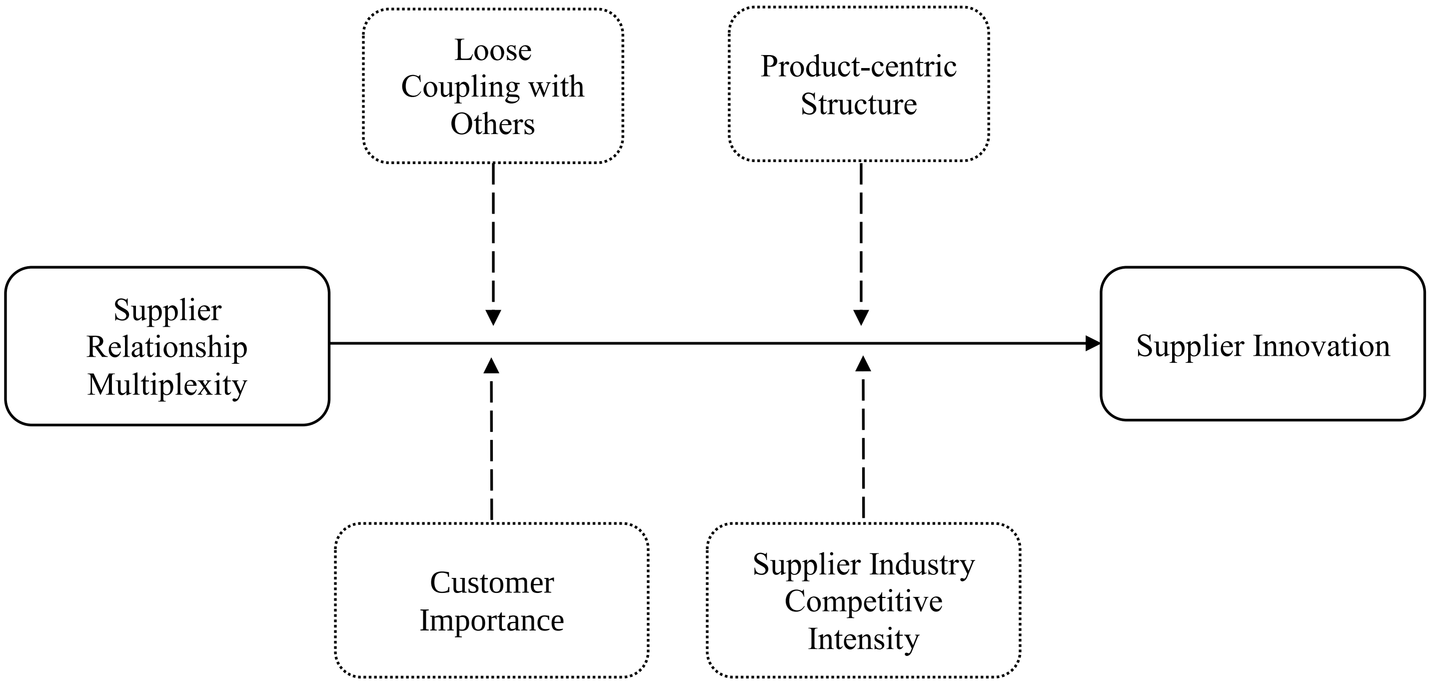

Figure 2.1
THE EFFECT OF RELATIONSHIP MULTIPLEXITY AND OTHER MODERATORS ON SUPPLIER INNOVATION

CHAPTER 3

BUSINESS-TO-BUSINESS MARKETING AND CUSTOMER ENGAGEMENT IN SOCIAL MEDIA AND DIGITAL ENVIRONMENTS[7]

[7] Sharma, A. and S.G. Bharadwaj. To be submitted to *Journal of Marketing*.

ABSTRACT

Traditional customer engagement practices (personal selling) in B2B are increasingly becoming less effective, when applied in isolation and without proper understanding of factors that influence buying behavior. The authenticity, reliability and ease of consumption of online content are making traditional engagement practices obsolete. Against this backdrop, through a combination of exploratory and confirmatory research, this study identifies the changes in the model of customer engagement in B2B markets and the role of marketing in establishing customer engagement. I find that the selection of a communication channel is contingent upon a number of underlying channel attributes, which make the communication between customers and sellers more or less engaging. I find that some of these attributes have a positive relationship whereas others have a negative relationship with the likelihood of selection of digital marketing and social media, as the preferred channel of communication, over personal selling. Additionally, I examine how channel preferences change at different buying stages.

INTRODUCTION

Business-to-Business (B2B) buying is complex and time consuming due to a larger number of stakeholders involved in the decision making process. Besides, economic pressures and market forces are increasingly commoditizing the salient features of most brand offerings, forcing businesses to develop deeper understanding of customer needs and devise novel ways of communicating the value of their offerings. Digital marketing and social media are changing the model of customer engagement and serve as a platform for the exchange of ideas, reviews, and feedback for business and non-commercial stakeholders alike.

In the B2C marketplace, it is common practice for customers to engage with the marketer through different marketing channels at different stages of the buying journey. For example, a customer looking to buy a car may first conduct their research through various company websites and independent review sites to make a brand choice, followed by the actual purchase at the selected brand’s dealership. Later, the customer may share their product review with other prospective buyers using social media.

Over the past few years, the B2B landscape is not too different from B2C. B2B buyers have also begun to utilize multiple channels to interact with marketers and other participants, such as other customers, industry experts, etc. (I refer to them as third-party in this essay) at different stages of their buying decision making process. This raises an important question – is it a strategic necessity for B2B marketers to follow buyers at these channels to be able to actively engage with them? The answer to these questions probably lies in the fact that channels such as digital marketing and social media have empowered B2B customers, shifting the power-dependence balance in favor of the customer. B2B customers now have access to a wealth of information through digital marketing and social media. Buyers are no longer dependent upon the communication from and expertise of sales teams alone. The timelines, relevance, authenticity, reliability and ease of consumption of online content, directed towards key pressing needs of B2B buyers, has a higher influence and appeal compared with that of traditional sales pitch and brochures (Kovac 2016). A fast growing segment of buyers, who rely increasingly on social media, thereby reducing the information asymmetry between B2B buyers and sellers, are drastically changing the engagement and negotiation process with higher buyer awareness and expectations (Grewal et al., 2015). It is not surprising that this increasing shift of preference of B2B buyers toward digital and social media is changing the traditional buying process and disrupting the selling process, requiring B2B marketers to adopt a new model of customer engagement.

Traditionally, B2B marketers have used the BuyGrid framework (Robinson, Farris and Wind 1967; Webster and Wind 1972) as the standard approach to identify the preparedness of various prospects and match their respective stage in the *buying cycle* with the *sales funnel* approach in order to generate business. Traditionally, personal selling served as the predominant form of customer engagement in B2B industries. However, digital marketing and social media are disrupting this engagement process by creating the possibility for constant interactions between the buyer, the seller and third-party actors throughout the customer journey. Industry surveys find that more than three quarters of B2B customers indicate a preference to interact with a salesperson only after they have conducted their own social media based research on product and solution offerings as well as potential suppliers (2012 Demand Gen Report). Consequently, a highly aware buyer now exerts more pressure through higher expectations, leading the seller to seek better expertise, more information on customer requirements and availability of competitive offers outside the firm. On the other hand, using data gathered through firm's own website and other embedded digital marketing features is on the rise to enable customer information search and consumption patterns at various buying stages. While marketers feel the need to invest in digital and social technologies to engage with the buyers, there is minimal integration of customer information across channels and limited understanding of how these strategies work (Moorman 2016).

Against this backdrop, the purpose of this research is to examine the changes in the buying cycle and effectiveness of the three customer engagement channels, namely personal selling, digital marketing, and social media, in facilitating engagement across the B2B customer journey. Specifically, I seek to address the following three research questions: 1) How many and what specific stages comprise the new buying process, 2) Which communication channel is most effective in customer engagement at the different buying stages?, and 3) Is the importance of a communication channel different, as seen by buyers versus sellers?

The rest of the essay is as follows. I begin by surveying past literature and the theory underlining the conceptual framework. Next, I present an exploratory study, followed by the hypotheses about the effects of communication channel attributes on the likelihood of channel selection. I follow up by describing the empirical strategy, data and results. I then discuss the empirical results with an emphasis on theoretical and managerial implications of this research. I conclude with the limitations of the study and directions for further research.

BACKGROUND LITERATURE

Researchers in B2C domain have examined the increasing influence of social media outlets on firm performance, sales, brand evaluations and word-of-mouth (WOM) publicity (e.g., see Godes and Mayzlin 2004, Chevalier and Mayzlin 2006, Onishi and Manchanda 2011, Stephen and Galak 2012, Naylor, Lamberton and West 2012). In sharp contrast, a recent review of the past 15 years of digital, social media and mobile marketing research makes no mention of research in the B2B domain (Lamberton and Stephen 2016).

Channel attribution has gained momentum as a subject of interest over the past decade. A number of studies in the B2C domain have studied channel attribution to examine the role of online ads (Kireyev, Pauwels, and Gupta 2016; Abhishek, Fader, and Hosanagar 2012), and sponsored or paid search (Agarwal, Hosnagar, and Smith 2011; Ghose and Yang 2009; Rutz and Bucklin 2011; Rutz, Bucklin, and Sonnier 2012; Yang and Ghose 2010; Yao and Mela 2011). While most of these studies have applied sophisticated estimation techniques (such as hierarchical Bayesian) for analysis, almost all of these studies have examined the influence of online channels in B2C context, without considering the cross-channel effects of direct selling. Jap and Gilbride (2016) attempt to bridge that gap by examining channel cross-effects between own and franchised retail stores, indirect retailers and electronic channels (such as telesales and online sales) for a mobile phone service operator. However, their study does not account for social media channels and focuses only on B2C markets, leaving a wide gap in our understanding of the B2B customer engagement (see Table 1 for a literature review).

Thus, to the best of my knowledge, no academic research has examined the influence of digital and social media on firm level outcomes in B2B environment. This is despite the fact that industry surveys and similar research continuously report a growth in use of such non-traditional platforms by B2B buyers in making buying decisions, suggesting a major shift in buyer behavior and a need for systematic research to understand the emerging trends. These changes have defining implications for the buying process and how marketers view it. Industry reports indicate that prospective customers now prefer limited engagement with sales representatives in the early stages of the buying process. Instead, they conduct preliminary research through online networks, blogs and digital marketing tools. The point of contact with sales has been pushed much later in the customer journey, which has grown more complex with the evolution of multiple marketing channels.

According to a study published in Forbes Insights, nearly 40% of North American marketing executives surveyed quoted website data, digital transactions and social as the most common data for predictive marketing (eMarketer 2015). This can help marketers focus on correct engagement platforms to match the pattern adopted by the prospect at various stages and achieve a better conversion rate. Digital marketing, social media and personal selling – the three engagement strategies have their respective strengths and can be useful at different stages across the buying cycle. While SEO is a better platform for the seller to engage with the buyer, undertaking internet searches, social media blogs and chats are effective when the buyer refers to online communities (Mantrala and Albers 2012). For example, according to Forrester research, digital and social media platforms offer the advantages of current and visually rich information, presented in easily understandable fragments, matching the information processing needs of digital natives (Shea et al. 2017). Nearly three-fourth of millennials surveyed in a study by Merit report being involved in purchase decisions at their companies, with a third being the sole decision-maker for their department (Vasquez and Walinger 2016). However, older buyers are also adopting these habits of millennial researchers in B2B buying (Almquist, Cleghorn, and Sherer 2018). Additionally, digital and social media channels offer multiple elements of value to B2C and B2B customers in terms of reduced costs, time savings, integrated information sources, and access to hard-to-find data and expertise (Almquist, Senior, and Bloch 2016). Thus, the seller needs to identify the patterns of consumption of information through various channels by the buyer throughout the process and deploy matching combinations to engage with the buyer at various stages.

KEY CHANNELS OF COMMUNICATION

I define personal selling, digital marketing, and social media channels as follows:

Personal selling. This channel involves a supplier's sales representatives, contacting potential and existing customers, utilizing face-to-face or video meetings, conversing with them over the phone, or interacting with them through personal email, to generate sales.

Digital marketing. This channel comprises a firm's own web-based platforms, includes marketing through website, utilizing search engine marketing, email campaigns, mobile apps, etc.

Social media. This channel is a collection of online platforms that bring people together for the exchange of information. I further identify the various categories of social media channel as: 1) social and media sharing networks, 2) interest-based communities and discussion forums, 3) online markets, review and comparison networks, and 4) blogs and publishing networks.

STUDY 1: THE EXPLORATORY STUDY

I conducted in-depth interviews with six marketing and sales managers to gain a better theoretical understanding of the customer journey in the emergence of digital marketing and social media channels. I had multiple objectives for this study. First, I seek to understand whether, similar to B2C markets, digital marketing and social media channels have actually disrupted the purchase process or the traditional channel of personal selling is still the preferred choice for customers. It is important to ascertain this because, despite increasing debate in practitioner literature about how digital and social media are disrupting the B2B buying decision-making, academic research on this subject is mute. Second, I wanted to understand whether the stages in the buying journey have changed, making the overall buying process shorter or longer. In addition, I wanted to gain a better theoretical understanding of managers' preferences with respect to using the three channels at various buying stages. Third, I wanted to learn about the underlying communication objectives and attributes of a communication channel that make the channel more or less conducive to effective communication and engagement. This was particularly important from a standpoint of understanding whether the required outcomes of an effective engagement are uniform or different across the different buying stages.

I identified the interviewees through personal contacts and used snowballing technique to recruit more interviewees. The interviews lasted 45-60 minutes. I selected the participants from different industries. I conducted all interviews, which were recorded and then transcribed verbatim. All interviewees possessed at least 10 years of industry experience. Table 3.2 summarizes the positions held by the interviewees, their experience, and industries they worked in.

Communication channels: The changing B2B marketing landscape

A summary of interviewee responses shows that despite a vacuum in academic research about use of digital marketing and social media channels in B2B industries, use of these channels is prevalent in industry. An increasing number of B2B customers are relying heavily on digital marketing and social media channels to conduct their research before meeting marketers and salespeople. For example, the president of market operation of a banking company noted,

> "The selling process has changed, and it has changed due to I would say not just social media, but (as) you also mentioned the digital [marketing] environment. Our customers and potential customers are definitely more informed on the

> marketplace, on various services that banks can provide. I would say they are more up to date, have more current information than they did say even seven, eight years ago."

Other interviewees offered parallel ideas, highlighting how customers are adopting digital marketing and social media channels and it forces the marketers to follow the customers on these channels:

> "I would say we first adopted those [digital marketing and social media] elements probably, I'd say six or seven years ago when they really started to change. Certainly in the digital space when we started seeing the way the consumer behavior was changing for us, and that's where we started to make the necessary changes to our platforms to incorporate those elements in a digital space. Moving away from, not moving away, but certainly expanding upon the traditional elements [personal selling] that we relied on previously." (CEO, information technology services firm).

On one hand, it can be viewed as adding pressure on marketers due to less knowledge asymmetry between customers and marketers (customers are more aware of alternative solutions and market trends now compared to a few years ago). On the other hand, it also helps marketers accumulate more knowledge about their customers and adapt accordingly.

> "I would say a lot of going into meetings now – and this goes both ways – I know more about who I'm meeting with before I sit down in front of them, and my clients they know more about me before I'm in front of them. Where historically it was more word of mouth, where you know this person, you know their background, you don't know them so okay I'm more blind before I'm going to sit down in front of them vs. now, between LinkedIn, between Facebook searches can sometimes depending on their Twitter profile, you know see what are they

> tweeting about. We're able to have a good grasp of them before we go out there and they of us."

To summarize, both the practitioner literature and the interviewed managers suggest that the influence of digital marketing and social media channels is not limited to B2C environment alone. B2B industries are also witnessing a continuous change in customer behavior and are trying to follow their customers at these new channels.

Buying stages

Talking to the managers, I observed that while the Buygrid framework is still a relevant model of buying stages that comprise customer journey, there is a good overlap in some stages. Practitioners group these together in fewer themes to facilitate a better understanding of customers' position in the journey and differentiate between customers based on the broader stage they are at – a signal of customer preparedness.

> "…so they [buyers] have identified the problem. Once they have identified the problem and they go through the research analysis, and they now understand the type of solution they're looking for, they assess a number of proposals, they pilot, and after piloting they would make the decision to purchase. So in between there are a couple of other steps, but those are the main steps." (SVP–sales & marketing, supply chain management).

In support of previous research, interviewees appear to define the progression of a customer in three primary stages (for example see Abhishek, Fader, and Hosnagar 2012; Court et al. 2009; Jansen and Schuster 2011; Smith, Gopalakrishna, and Chatterjee 2006). First, an internal or external driver triggers a need and the customer tries to describe that need in detail. This is followed by the next stage, where the customer actively conducts research about alternative solutions and their suppliers. At this stage, the customer reviews available information across different channels and solicits proposals. The third stage is purchase where the customer actively engages with the supplier to fine-tune contractual details, pricing and other support. These primary themes reflect in the following view:

> “So they may be doing things in a live classroom but they've got a new boss or something, or restricted budget and say "Hey, you can't keep flying people in and putting them up in hotels". You've got to be able to figure out how to deliver this information at a lower cost. And so there's some external trigger that's forcing them to go find a more cost effective solution. So there's some external trigger or driver that makes them have this "Oh shit" moment of "I can't do what I was doing before because it's not going to work for this upcoming problem. And so now I'm going to try and find a solution. So that's when they go from, they go into the solution mode. And they then start asking around, or looking up online. So it goes from some kind of a problem or trigger, to a search for a solution, to reviews or, they look for some information… so they try and use this kind of data to narrow down their list before they engage with the prospect of the solution. That is followed by the actual purchase stage.” (VP–product & marketing, cloud-based learning management solution provider).

Another manager echoes this classification by comparing (and mapping) the buying stages to a sales funnel:

> “I would say first is awareness. That is the very top of the funnel. The second I'd say broadly is consideration. The positioning, the value proposition to even engaging with a potential client. Then consideration moves all the way down into the purchase decision. Perhaps there's gradients within that that you can identify. I think very broadly that's where I would say; at least as far as robotics is concerned.”

Although the complete buying process may be broken down into many micro stages (for example there are eight buying stages in the Buygrid framework), it is evident from the findings of these interviews that managers combine these overlapping stages into three broad categories of high strategic importance. Additionally, most managers did not see review of a solution or a supplier as an independent post-purchase activity. Instead, they believe that review is an ongoing process and that the purchase stage factors in the implications of a review. Based on these findings, I propose that the customer journey comprises the following three strategically important stages:

Requirements specification – At this stage, the buyer is identifying their requirements and deliberating possible ways to address those requirements. The buyer's objective at this stage is to explore and learn more about all of the alternative solutions that can address the requirements and to progress further toward identifying, selecting and buying the best possible solution.

Solution identification and vendor shortlisting – This stage entails solution specification, supplier search and proposal solicitation on part of the buyer. At this stage, the buyer collects and evaluates information about the various solutions, researched in the previous stage, to select the best alternatives.

Purchase – This is the last stage in buyer journey and includes selecting a final supplier, specifying solution details, and completing the purchase process. In this stage, the buyer selects a supplier based on the attractiveness of its solution and proposal elements.

Communication channels: Engagement by stage

The next objective of the exploratory study was to identify whether any particular channel offered stronger customer engagement than others and if yes then at what stage. It appears from the interviews that while all three communication channels have strategic importance for marketers across all three buying stages, their respective benefit may vary by stage, i.e., personal selling, digital marketing, and social media vary in their ability to offer successful customer engagement across buying stages. In the words of a general manager of a logistics solutions company,

> “I would say digital marketing [is] more [used] than the social media. Social media is being used most definitely. It’s [social media] part of it… YouTube is probably one of the ones that is more utilized maybe…There’s a lot of content that’s being generated through videos. Exactly. Google Ad Words, digital marketing, banners, those are the things on websites that are probably more driving lead generation, rather than the social media. That [social media] space is growing, but it is still extremely small.”

Another manager offers parallel ideas:

> “So a lot of it [lead generation] is through pay per click, but a lot of it is also through organic traffic that we get based on Google. So we put out a lot of articles and content, and those rank highly on Google's organic search results.”

I observe through these interviews that marketers were trying to follow the customers by establishing a presence on the channels that customers are most likely to use at different stages. From conducting a google search to find alternative solutions (and suppliers) for a requirement, to reading through reviews about different solutions and suppliers on third-party social media platforms – customers are using different channels to find answers to their queries, based upon what stage they are at in the buying process. It is hard to establish a concrete pattern of customers’ channel usage along different buying stages only by using the interviews. However, the likelihood of customers’ use of a particular channel at a given stage can be inferred from the extent of marketers’ participation in that channel to obtain higher customer engagement.

THE B2B MODEL OF CUSTOMER ENGAGEMENT

Building on extant B2B and B2C literature, and in line with the results from Study 1, I propose a model of B2B customer engagement for new buy tasks (Figure 3.1). This model depicts the relationship between the three communication channels and customer engagement variables. I propose that while utilizing all three channels – personal selling, digital marketing and social media – is critical for achieving customer engagement at all stages, and that marketers need to deploy a combination of the three channels, instead of using them in isolation, the respective utility of each channel is different at different buying stages. In other words, the importance of personal selling, digital marketing and social media as a communication channel varies by the buying stage of the customer.

In this study, I adapt the existing measure of customer engagement (Pansari and Kumar 2017) to suit the requirements of B2B markets. Pansari and Kumar (2017) define the customer engagement construct as the direct (customer purchases) and indirect (customer referrals, customer influence, and customer knowledge) ways through which a customer contributes to the firm. I conceptualize customer engagement value as comprising three measures – purchase likelihood, direct engagement, and knowledge sharing. This conceptualization is particularly important for B2B markets for a number of reasons. First, while customer purchases directly contribute to firm value (Gupta, Lehmann, and Stuart 2004), it is hard to evaluate a purchase unless the customer has traversed all stages prior to purchase in the buying cycle. Hence, a customer's likelihood to buy indicates the probability of conversion of an intention into actual purchase at early stages. Second, customers utilize digital marketing and social media channels to search for information to make informed decisions regarding suitable solutions and suppliers. This makes it essential for the marketers to have a direct engagement with customers and third-party channel participants through effective communication to attract leads and capitalize on third-party influence at various buying stages. Third, I propose that, unlike purchase likelihood and direct engagement, knowledge sharing is somewhat restricted to later buying stages, specially the purchase stage. Customers can help suppliers better understand customer preferences by participating in knowledge development (Joshi and Sharma 2004). This deep knowledge can be useful in further improving the solutions (Kumar and Bhagwat 2010) and customizing them to exact customer preferences. However, such knowledge exchange between the customer and the supplier is more likely to take place when the customer has shortlisted a supplier and starts to work with that supplier – purchase stage.

Additionally, my focus in this essay is to examine the relative effectiveness of the three communication channels in generating customer engagement. At any given stage, customers prefer one communication channel to another because of the underlying attributes of that communication channel. For example, when searching for available solutions to its requirements, a customer may prefer to conduct a Google search instead of talking to a salesperson. The reason may be that a Google search offers more perceived control and unbiased information as compared to talking to a salesperson. However, once the same customer has shortlisted a supplier, they may prefer talking to a sales person instead of using social media channel to negotiate the terms of purchase because personal selling channel offers more privacy and direct communication. Thus, I propose that in order to identify the suitability of a channel for customer engagement at any stage, it is imperative to identify the attributes underlying a communication channel. In the next section, I identify the main attributes of a communication channel that render that channel suitable or unsuitable for customer engagement and propose my hypotheses.

Communication channel attributes

In order to design the optimal mix of communication channels and manage the relationships between different channels in that mix, it is critical for marketers to understand how customers process communication directed toward them and how does it influences their decision-making (Batra and Keller 2016; Naik 2007; Keller 2016). Scholars examine B2C contexts have explored key communication objectives, such as creating awareness, building trust, etc., underlying the communication between firms and consumers (e.g. Batra and Keller 2016; Keller 2016). Communication objectives for B2B marketers are similar to those of B2C marketers. Marketers should consider all communication options, which help them achieve communication objectives at each buying stage and move the customers along in their journey with highest efficiency. Keller (2016) summarizes some characteristics of major communication platforms and calls for further research to examine the defining characteristics in more detail. I define communication channel attributes as the characteristics of a communication channel that alter its effectiveness in achieving desired communication objectives by delivering certain kind of information and make the channel more or less engaging. Adapting primary characteristics of major communication platforms outlined by Keller (2016) to a B2B context and answering his call for further research, I propose ten important attributes that marketers need to consider in selecting a communication channel to generate higher customer engagement (Figure 3.2).

Information Timeliness. This attribute refers to how up-to-date and timely is the channel in providing current information. Information timeliness is associated with the relevance of the information (Miller 1996), and has been shown to provide an edge to investors in predicting stock and futures returns (Östermark and Hernesniemi, 1995). While it is important for buyers to obtain timely and up-to-date information when researching for solutions and seeking answers to their queries, it is also critical for marketers to retrieve up-to-date information on potential leads to generate higher engagement. Additionally, while it is important to obtain timely information across the buying process, it may be more critical at earlier stages. A delay in response to the buyer's queries may be perceived as a sign of dis-interest or a laid-back culture at supplier firm, making the buyer quickly turn-away to another alternative.

Content Richness. This refers to whether the channel enables use of multi-media formats, such as images, graphical presentation, audio, video, virtual reality, etc. to make the communication highly informative and engaging. Content richness of a channel can help marketers differentiate their offerings from their competitors and subsequently generate higher customer engagement through vivid and easy to digest information delivery. Content richness can be more important particularly at early buying stages, when multiple suppliers compete for buyers' attention to get in the consideration set. Buyers seeking more information on the solution may also find it easier to learn with the content is presented in a rich manner.

Customization. This refers to whether the channel offers information that caters to, and is directly relevant to, the buyer's specific requirements and queries. The level of information customization sought by the buyer should also vary by their stage in the journey. This is so because a buyer may be more interested in seeking information on general trends and technological updates at an early stage, whereas the requirements become more defined and specific as the buyer moves further along the journey. Accordingly, the buyer may use communication channels that provide less customized information at early than later stages. For example, a buyer may search through the web and interest-based online communities to learn about the upcoming technologies. However, the buyer is more likely to subscribe to channels, say digital marketing and personal selling, which offer more customization based on the buyer's queries and need for specific information.

Empathy. This refers to whether the channel enables its participants to pay attention, listen patiently, and understand problems from each other's point of view. Buyers may prefer a communication channel to others when the requirements are not well defined and need counselling. Further, channels that are high on empathy may offer marketers an advantage to differentiate from their competitors by building a relationship with the buyers.

Reach. This refers to whether you can contact and communicate with few or many buyers through the channel. Reach is an important attribute for marketers as they try to broadcast their message to multiple leads. From a buyer's perspective, it relates to whether the channel is easily accessible and available to conduct research. For example, the salesperson of a supplier firm may not be available for a visit or there may not be enough information available through social media on a particular solution.

Cost Efficiency. Cost is a major concern for marketers in selection of a channel to engage with prospective and current customers. Sales people are limited in their capacity and available time to service all leads, and hiring more sales people is expensive. Similarly, it costs financial resources to develop content for and advertise through digital marketing and social media channels. While, marketers' cost of developing and deploying a channel to attract leads is not of prime concern to buyers, they also incur costs in terms of time and effort. For example, buyers are limited in terms of how much time and effort they can spend on social media, posting queries and searching for answers. Similarly, attending webcasts or trade-shows, reading white papers, meeting salespeople to search for solutions and evaluate offerings requires significant investment of time and effort. Thus, I propose that marketers and buyers seek to maximize their returns on investments (including time and effort) while selecting a channel to obtain information, such that, everything else being constant, they will select the least expensive channel to obtain information. For a marketer, *cost efficiency* refers to how inexpensive is the channel in helping the marketer engage with the buyers. From a buyer's point of view, it relates to the efficiency of the channel in terms of time and effort required to learn about various offerings, evaluate the offerings, and make a purchase decision.

Vulnerability. Martin, Borah, and Palmatier (2017) present a taxonomy of customer data vulnerability in a B2C context. In a discussion of the negative effects of firms' data management practices on customers' feelings of vulnerability, they suggest that a customer's perception of being harmed by personal data breach is a critical construct that captures privacy concerns. In a similar vein in B2B context, I define vulnerability *as the susceptibility of a channel to security breach and loss of proprietary data or intellectual property loss*. Unlike B2C customers, who have concerns about their personal data, B2B customers are also liable for their firms' intellectual property and other trade related data. However, because B2B purchases are more complex, buyers are often required to work closely with suppliers, sharing trade details, to attain higher solution customization. Thus, a channel's vulnerability to data loss is a prime driver in selection of a channel by buyers to communicate and conduct research at any stage.

Communication Control. This attribute refers to whether the channel is seen as intrusive in nature, such that the communication is uninvited and unwelcome by the buyer. If the buyer can manage the flow of information, they perceive greater control (Emler 1994). Lack of control is seen as a driver of vulnerability in consumer research (Baker, Gentry, and Rittenburg 2005). If the buyer has low control on transmission of communication, they may perceive marketing communication as intrusive, negatively affecting supplier's image. This is often evident in case of cold calling by marketers, unsolicited e-mails, behavioral targeting digital advertising and sales visits.

Transparent Interaction. This attribute refers to whether the buyer perceives the channel as transparent in their interactions with the supplier and obtaining unbiased information. Transparency has been linked with positive peer relationships (Myers et al. 1995), trust (Korsgaard, Sapienza, and Schweiger 2002), better leader-follower relationships and higher follower motivation (Kay and Christophel 1995). Transparency has also been shown to reduce the negative effects of vulnerability (e.g. Martin, Borah, and Palmatier 2017). If the buyer perceives that the supplier is not transparent in their interactions and the information disclosed is biased to make the supplier appear more attractive, it may breed distrust and discontentment in the relationship.

Credibility. Credibility of a channel pertains to the channel's reputation in delivering trustworthy information. For example, a communication channel that can establish and authenticate the source of information can be relied upon more than one that cannot. While information obtained through social media channels about a supplier may be less biased than that obtained from a digital marketing channel of the same supplier, buyers may be more skeptical of information shared through social media if the source of that information cannot be established.

STUDY 2. COMMUNICATION CHANNEL ATTRIBUTES FOR EFFECTIVE CUSTOMER ENGAGEMENT

In this study, my main objective is to empirically test the key attributes of a communication channel that I identified in the earlier section. These attributes are the leading characteristics of a communication channel that make the interaction between channel participants dynamic and engaging.

Measures

In the earlier section, based on the extant literature and managerial interviews, I identified ten important attributes, underlying a communication channel, after a careful consideration of the communication needs of both, the customers and the marketers. I designed an initial pool of items from the in-depth interviews and extant research, followed by a refinement of items based upon inputs from academic and professional experts. I then pretested the scales using a small sample comprising marketing managers and MBA/MMR students, who possess past industry experience ($N = 15$). These respondents did not participate in the main study. The pretest helped identify some minor comprehension issues with wording of the items, which were further refined based on inputs from the pretest.

I asked respondents from both buying and sales group to rate each of the three channels on its respective performance on the ten attributes: *information timeliness* (1 = very ineffective, 5 = very effective), *content richness* (1 = very poor, 5 = very rich), *customization* (1 = very standardized, 5 = very customized), *empathy* (1 = very indifferent, 5 = very empathetic), *reach* (1 = very low, 5 = very high), *cost efficiency* (1 = very inefficient, 5 = very efficient), *vulnerability* (1 = very safe, 5 = very vulnerable), *communication control* (1 = not at all intrusive, 5 = extremely intrusive), *transparent interaction* (1 = not at all transparent, 5 = completely transparent), and *credibility* (1 = not at all credible, 5 = extremely credible) in a communication channel that they will consider to use. Please see appendix 1 for survey details.

Sample and Procedure

I utilized a Qualtrics panel for the purpose of this study. The Qualtrics panel utilizes online recruitment of respondents only by-invitation, avoiding self-selection and professional survey taking. This ensures a better cross-section representation and generalization. In order to participate in the study, the respondents had to fulfill two criteria. First, the respondent should belong to an organization of size $ 1 million – $1 billion. Second, the respondent should hold a position at the managerial or above rank. After screening out respondents who did not fulfill the above two criteria, a total of 166 managers with a functional background of sales or marketing and 171 managers with a functional background of organizational buying roles participated in the study. Further, after removing incomplete responses, respondents who failed attention check, respondents who failed speed check, and respondents who showed strong acquiescence bias, I reached at a final sample of 102 responses (response rate of 30%), equally divided between the two groups. Almost all managers were of age 35 or older, and 45% were female. The vast majority (81%) of respondents held an undergraduate degree or higher and 65% of managers had an industry experience of 6 years or more. The respondents in the sample represented a wide variety of industries, such as educational services, finance and banking, information technology, retail and wholesale trade, manufacturing, etc. I did not find any statistically significant differences between those included in the sample and those who were not, eliminating the potential for nonresponse bias (Armstrong and Overton 1977).

Model free evidence

In order to determine the effectiveness of each channel with respect to the 10 attributes identified in the previous section, I asked managers from the buying as well as the sales group to rate the channels on those attributes.

Figure 3.3 (a) and 3.3 (b) provide some model free evidence of the relative performance of each of the three channels on these attributes, as seen by the respondents in the two groups, respectively. While personal selling is generally rated higher on interpersonal attributes, such as *transparent interaction* (M_{buyer} = 3.8; M_{seller} = 3.8), *credibility* (M_{buyer} = 3.8; M_{seller} = 3.8), and empathy (M_{buyer} = 4.2; M_{seller} = 4.6), digital marketing is rated higher on attributes of interactional efficiency, such as i*nformation timeliness* (M_{buyer} = 4.3; M_{seller} = 4.2), *reach* (M_{buyer} = 4.2; M_{seller} = 4.4), content richness (M_{buyer} = 4.1; M_{seller} = 4.2), and cost efficiency (M_{buyer} = 4.1; M_{seller} = 4.2). Social media, in a similar vein, is also rated higher on attributes of interactional efficiency, such as *content richness* (M_{buyer} = 3.7; M_{seller} = 4.0). Figure 3.3 (a) and 3.3 (b) summarize the ratings of the three communication channels on these attributes for the buying and marketing groups, respectively.

Based on these preliminary insights, I propose that personal selling, digital marketing and social media channels offer different levels of engagement as the levels of these attributes vary for each channel. For example, for a customer seeking fast response to a basic search query, digital marketing or social media may be the preferred communication channels over personal selling due to their capacity to offer higher speed of obtaining information. However, when a customer query is of complex nature and requires higher level of understanding, personal selling may outperform the other two channels as it can offer higher empathetic exchange of information. Based on these insights, I offer the following propositions:

P1: Digital marketing and social media, in comparison to personal selling, are more effective channels of communication when the communication requires attributes, which support interactional efficiency, such as information timeliness, content richness, cost efficiency, and reach.

Conversely, I propose that digital marketing and social media channels lack emotional and interpersonal elements.

P2: Digital marketing and social media, in comparison to personal selling, are less effective channels of communication when the communication requires attributes, which support interpersonal support, such as empathy, customization, transparent interactions, communication control, and less vulnerability.

In the next section, I empirically analyze the relative strengths and weaknesses of digital marketing and social media channels in comparison to those of personal selling.

Analytical Strategy

I divide my analytical strategy in two sections. In the first section, I classify the ten attributes into two scales – rational richness and emotional richness – to measure the overall effectiveness of a communication channel based on these two dimensions.

First, I conduct a principal component analysis to examine whether the 10 attributes load on two dimensions or multiple factors. The results of exploratory factor analysis show that 9 out of the 10 communication attributes load on two factors, whereas control loads on a third factor by itself. The Bartlett test of sphericity is significant (chi2 = 301.9, p = .000) and the Kaiser-Meyer-Olkin measure of sampling adequacy suggests that the sample is large enough (KMO = .76). Cronbach's Alpha is .77 & .71 respectively. The correlation coefficients and factor loadings are summarized in Table 3.3 (a) and 3.2 (b), respectively. Next, I performed a confirmatory factor analysis. The model indicated a satisfactory fit (comparative fit index [CFI] = .825; Tucker-Lewis index [TLI] = .758; Root Mean Square Error of Approximation [RMSEA] = .126). The structural equation model with item loadings and coefficients is reported in Figure 3.4.

Next, I perform a multinomial regression to determine the effect of rational richness and emotional richness on the likelihood of selection of digital marketing channel or social media channel over personal selling as the base outcome. Table 3.4 summarizes the regression coefficients. Model 1 reports the main effects of rational richness and emotional richness in the likelihood of selection of digital marketing and social media over personal selling. As can be seen, rational richness has a positive and significant effect on selection of digital marketing (β = 1.96, $p <.001$) and social media (β = 1.41, $p <.001$) over personal selling. Whereas, emotional richness has a negative effect on selection of digital marketing (β = -2.31, $p <.001$) and social media (β = -2.56, $p <.001$) over personal selling. In model 2, I include the group dummy to account for variation by group. However, the direction and magnitude of the main effects of rational richness and emotional richness remain similar. Model 3 reports the effects of interactions between group dummy and the two richness scales, in addition to the main effects. For digital marketing, the effects of rational (β = 1.92, $p <.05$) and emotional richness (β = -2.22, $p <.01$) remain similar. Effect of emotional richness for social media remains similar (β = -2.48, $p <.01$). However, the effect of rational richness for social media is no more significant.

In this study, I showed that the selection of a communication channel is guided by the underlying attributes, which restrict or propel effective engagement. However, it would be naïve to assume that buyers consume information from one channel at a time and overlook the possibility of cross-channel influence. Not only are buyers more likely to simultaneously engage with multiple suppliers and information sources through multiple channels, but also they are highly likely to use these channels at varying rates at different stages of the buying decision process. For example, a buyer may use social media or digital marketing channels heavily, together with sparse use of personal selling, at early buying stages. The same buyer may assign lower utilities to these channels at later buying stages, although they may continue to use them to supplement personal selling channel. I undertake *Study 3* to examine above-mentioned scenarios.

STUDY 3. CONJOINT ANALYSIS

The objective of this study is twofold: to conduct a conjoint study with buying and selling professional to identify the channel preferences as a function of channel attributes, and to examine the group specific differences in selection of channels. While *Study 2* shows that attributes underlying a communication channel have a strong influence in selection of that channel, it also reveals that buying and sales groups may view these channels differently.

Procedures and sample

I utilized a Qualtrics B2B panel of buying and sales professionals for the conjoint study for the merits that I have discussed in the earlier section. The criteria for participation in this study was the same as the previous study. The respondents should belong to an organization from the middle market ($1 million – $1 billion in annual revenues), and should a position at the managerial or above rank. After screening out respondents based on these two criteria, a total of 146 managers with a functional background of sales or marketing and 141 managers with a functional background of organizational buying roles participated in the study. Further, after filtering data for incompletes, failed attention check, failed speed check, and acquiescence bias, I reached at a final sample of 100 responses (response rate of 34.8%), equally divided between the two groups. Almost all managers were of age 25 or older, and 41% were female. The vast majority (75%) of respondents held an associate degree or higher and 77% of managers had an industry experience of 6 years or more. The respondents in the sample represent a wide variety of industries and there are no significant differences between those, who are included in the sample and those who are not, eliminating the potential for nonresponse bias (Armstrong and Overton 1977).

Method

I conduct a choice-based conjoint to reveal the channel preference of a respondent based on their selection. The main difference between choice-based conjoint and other forms of conjoint analysis techniques is that the respondent expresses preferences by choosing concepts from various sets of concepts, instead of rating or ranking them. The conjoint is a 2^3 full factorial design of a total eight profiles with two levels (high/low or available/unavailable) of three attributes (personal selling, digital marketing and social media channel) each. The respondent exhibits their preference by selecting one of the two profiles from each set. The study is divided in multiple sections. First section reviews information on the three stages of the buying process and the three communication channels. In the second section, the respondent from a purchasing (sales) background is shown a main scenario of a typical buying (selling) situation in a B2B context. All respondents are shown the first two sections of the study. Next, the respondents are randomly assigned to one of the four conditions: between subjects – stage 1/2/3, or within subject (all 3 stages). Each respondent is then shown a set of two profiles and is asked to answer three questions – one each pertaining to direct engagement, purchase likelihood and knowledge sharing – by selecting one of the two profiles – once for each question. The respondents in between-subjects condition are shown a total of eight sets, whereas those in within condition are shown four sets to reduce their cognitive load. Figure 3.5 summarizes the conjoint design in terms of respondent assignment.

After completing the conjoint section of the study, each respondent is taken to the attributes section, where the respondent rates each of the three channels on each of the ten attributes. On average, respondents take under ten minutes to complete all sections of the study.

Measures

I measured *customer engagement* by recording responses to three questions – one each for *direct engagement, buyer progression,* and *purchase likelihood*. The respondents are asked to exhibit their answer to each question by selecting the best alternative from a choice-set. The questions were adapted to match the stage in the buying process and the responding group (buying versus sales). However, the three constructs of customer engagement underlying the questions remain consistent across stages and groups. Information about the questions is available in Appendix 1.

Analytical Strategy

In order to analyze the choice data from the conjoint study, I adopt a conditional logistic regression approach. A conditional logistic regression is helpful in investigating the relationship between an outcome of being selected or not, when each matched set consists of one event and one non-event. This is suitable in the case of a choice-based conjoint, where the observations are not independent but are grouped.

Results

The results of the conditional logistic regression are summarized in Table 3.5 (a) through (e). Table 3.5 (a) reports the results of the main effects regression only for customer engagement as the united dependent variable. Model 1a reports the results from the combined responses of the buying and the sales group. The coefficients for personal selling (β = 2.98, p <.001), digital marketing (β = .51, p <.001) and social media (β = .54, p <.001) are all significant. Model 1b and 1c report the main effects coefficients for the buying and sales group separately. All three channels are significant for the sales group (β_{PS} = 2.86, p <.001; β_{DM} = .42, p <.05; β_{SM} = .75, p <.001), whereas only personal selling is significant for the buying group (β = 3.14, p <.001). Next, I perform the analysis by breaking up the united *customer engagement* variable into its three components – direct engagement, buyer progression, and purchase likelihood. Table 3.5 (b) summarizes the results by each construct for all respondents (Model 2a–2c), buying group (Model 3a–3c), and sales group (Model 4a–4c). As can be seen from the table, coefficients for all three channels are significant for buyer progression and purchase likelihood constructs for the sales group and combined response group.

The next set of tables summarize the results for regressions with main and interaction effects for the three channels. Table 3.5 (c) reports the coefficients for *customer engagement* variable for combined response group (Model 5a), buying group (Model 5b), and sales group (Model 5c).the interaction between personal selling and digital marketing channels is negative and significant for the buying group (β = -.58, p <.05), whereas it is positive and significant for the sales group (β = .54, p <.05), highlighting the difference in group preferences. Table 3.5 (d) further break down the analysis into each of the three engagement constructs by respondent groups. The interaction between personal selling and social media is negative and significant for the buying group for purchase likelihood (β = -2.35, p <.05) and positive and significant for the sales group for buyer progression (β = 1.30, p <.001). Similarly, interaction between digital marketing and social media is negative and significant for the buying group (β = -2.35, p <.05), but positive and significant for the sales group (β = 1.63, p <.01). Finally, to account for stage level variation, I perform additional analysis with interactions between the channels and the three stages. Table 3.5 (e) summarizes the regression results for the combined response group by the united *customer engagement* variables and by each individual construct. As can be seen, the influence of personal selling is higher during the second stage for *direct engagement* ($\beta = 1.71$, $p < .05$) and *buyer progression* ($\beta = 2.14$, $p < .05$). Also, the influence of personal selling is higher during the third stage for *customer engagement* ($\beta = 2.21$, $p < .05$), *buyer progression* ($\beta = 2.54$, $p < .01$), and *purchase likelihood* ($\beta = 2.398$, $p < .05$).

Supplementary Analyses

In the previous section, I performed a conditional logistic regression to model the effects of levels of the three channels and buying stages on respondent preferences for channel selection. However, it should be noted that a channel is (not) selected due to the underlying attributes that make the channel suitable (unsuitable) candidate for communication. In other words, a channels can be seen as a bundle of different levels of underlying attributes. Thus, a respondent may select a channel over another based on the need for a given level of a particular attribute. To examine the effects of attributes on respondent choices, I adopt a Hierarchical Bayesian (HB) estimation strategy. HB estimation is a suitable approach in my context for a number of reasons. Choice-based conjoint data contains limited information on respondent preferences as compared with traditional conjoint. While we know the chosen alternative, we do not know how much more desirable the selected alternative is over those not selected. In this regard, HB estimation offers higher accuracy in predicting individual as well as shared estimations (Orme 2000). Additionally, HB allows use of individual level covariates to predict preferences of respondents. This is particularly useful in Bayesian shrinkage of individual part-worth estimates to reflect their relative location in the population distribution to a large density of respondents with similar covariate values (Howell 2009). Moreover, Bayesian methods do not require optimization of any function and offer consistency and efficiency under more relaxed conditions. This is particularly helpful in case of random effects model, where optimization of the likelihood function can be difficult.

To conduct HB estimation, I use the Bayesian choice procedure in SAS with estimation of the nonzero mean of the random effects as a function of the channel attributes. The Bayesian discrete choice model helps determines individual level utilities. When respondents are asked to make a choice among given choice sets in the conjoint study, they select an option based on the level of utility of each alternative offer.

In a choice-based conjoint, the utility derived by individual *i* from alternative *j* in choice set *t* (t = 1,…,*T*) can be given as:

$$u_{ijt} = X'_{ijt}\beta + z'_{ijt}\gamma_i + \varepsilon_{ijt}$$

$$y_{ijt} = \begin{cases} 1 \; if u_{ijt} > max(u_{i1t,} u_{i2t}, \ldots u_{iJt}) \\ 0 \qquad\qquad otherwise \end{cases}$$

Where:

y_{ijt} is the observed choice for individual *i* and alternative *j* in choice situation *t*

X'_{ijt} is the fixed design vector for individual *i* and alternative *j* in choice set *t*

β is the vector of fixed effects coefficients

z_{ijt} is the random design vector for individual *i* and alternative *j* in choice set *t*, and

γ_i is the vector of random coefficients for individual *i* corresponding to z_{ijt}.

Also, in the random-effects model, I assume that each γ_i is drawn from a superpopulation, distributed normal, γ_i ~ iid N(0, Ω_γ) with a stage added to specify the prior for Ω_γ:

$$\pi(\gamma_i) = N(0, \Omega_\gamma)$$

$\pi(\Omega_\gamma)$ = inverse wishart(v_0, V_0)

where the covariance matix $\Omega_\gamma$characterizes heterogeneity among respondents.

However, unlike individual level covariates (such as age, household income, family size, etc.), covariates (channel attributes) in my model are specific to channels and not respondents. For example, rating of *personal selling* on the attribute *empathy* should only influence the effect of *personal selling* on *channel selection* and not that of *digital marketing*. Thus, to avoid one channel's attribute rating from cross-influencing another channel's effect on selection, I need to restrict the influence of covariates. As the procedure doesn't allow such restriction, I adopt a two-phase estimation procedure. In the first phase, I regress the channel selection on the three channels and estimate the respondent-level random-effects coefficients. In the next phase, I regress the respondent-level random-effects coefficients, obtained from the first stage, upon the channels and channel attributes. As the sample size for this study is small, analyzing response data disaggregated by stage and by question severely reduces the power of the model. So, I conduct the two-phase estimation again for response data aggregated at the question level.

Results

I report the empirical results of this analysis in Table 3.6 (a) and Table 3.6 (b). Stage 1, 2 and 3 in Table 3.6 (a) summarize regression results of conjoint analysis from each of the three buying scenarios (three stages in the buying journey). The coefficients are obtained from a by-stage by-question regression, where I performed a separate regression for analyzing the response of each question at each stage. Personal selling is the base outcome. As we can see, the main effects of digital marketing and social media channels are mostly negative and significant, suggesting that personal selling is a preferred channel of engagement. However, one interesting difference between group choice is revealed by the main effects of the group variable (buying group=0, sales group=1) and interactions between channels and the group dummy. It appears that respondent utilities for personal selling as compared to the other two channels is lower for sales group than the buying group. Also, sales group has a stronger positive utilities when social media channel is present than when it is not. The coefficients for rational and emotional richness are generally not significant.

However, one should be careful with the interpretation of these coefficients due to the limited power of the model in predicting relationships (N=39) due to disaggregation of data at the lowest level. For this reason, I conduct both phases of the analysis again by aggregating response data across the three stages at question level. First, I generate the random effect means of respondents at question level. Then I regress the respondent means obtained from the first phase on channels and the two scales. The results are summarized in Table 3.6 (b). The coefficients for digital marketing as well as social media are negative and significant for *direct engagement* ($\beta_{DM} = -1.34$, $p < .01$; $\beta_{SM} = -2.36$, $p < .001$), *progression* ($\beta_{DM} = -2.47$, $p < .001$; $\beta_{SM} = -3.28$, $p < .001$), and *purchase likelihood* ($\beta_{DM} = -2.74$, $p < .001$; $\beta_{SM} = -3.35$, $p < .001$). Further, sales group shows lower utilities associated with personal selling compared with buying group. Also, the interaction between group and channels is positive and significant for *progression* ($\beta_{GxDM} = 1.25$, $p < .05$; $\beta_{GxSM} = 2.24$, $p < .001$), and *purchase likelihood* ($\beta_{GxDM} = 1.39$, $p < .01$; $\beta_{GxSM} = 3.04$, $p < .001$). Additionally, emotional richness is positive and significant for *progression* ($\beta = .32$, $p < .05$), and *purchase likelihood* ($\beta = .53$, $p < .001$).

DISCUSSION

Building upon a combination of exploratory and confirmatory research, this study helps improve our understanding of the effect of alternative communication channels, such as digital marketing and social media, on customer engagement in a B2B context. The study reveals that similar to B2C markets, customer engagement in B2B markets is also experiencing significant alteration in customer grounded theory behavior.

The exploratory study suggests that not only digital marketing and social media are redefining the purchase process, but also the customer journey is different from what has been suggested by the Buygrid framework. Additionally, I identify the underlying attributes of a communication channel that render the channel suitable or unsuitable for customer engagement, given the stage of the customer.

The results of empirical studies indicate that some communication channel attributes have a considerable influence in selection of a channel. However, the preferences are different for buying group as compared to the sales group. In *Study 2*, I find that various communication attributes that make a channel more or less effective in engagement, have a considerable impact on channel choice. I conduct an exploratory and a confirmatory factor analysis to identify two dimension of a communication channel – rational richness and emotional richness. Through a multinomial logistic regression, I find that while digital marketing and social media channels are preferred choices for attributes that add to the rational richness in communication, personal selling offers more emotional richness and hence is preferred over the two channels.

In *Study 3*, I conduct a choice-based conjoint analysis for buying and sales groups to uncover their respective utilities associated with the use of a channel. Using a Bayesian discrete choice estimation, I find that the utilities for buying group and sales group are different for different channel usage. While sales people prefer to use digital marketing and social media channel to personal selling, buyers prefer personal selling over the other two channels.

Overall, the findings of this study contribute to the understanding of how modern channels of communication are altering customer behavior and changing the landscape of B2B marketing. Moreover. These findings contribute to managerial understanding significantly by examining underlying attributes, which are of importance to customers for effective communication. By identifying these attributes and examining the performance of different communication channels on each attribute, marketers can make informed choices about which channel to invest in to obtain highest customer engagement, given the stage of the customer in the buying process.

LIMITATIONS AND FUTURE RESEARCH

The study has a limitation in terms of its sample size, which restricts the estimation and prediction power. The data analyzed in *Study 3* is part of a larger data collection effort, which is underway at the time of analyses and writing of this essay. Another limitation of this study is its focus on new buy tasks. Due to the limitations of the conjoint technique and to avoid cognitive load on respondents, I do not analyze purchase tasks that are of modified or repeat nature.

In future research, I plan to analyze a larger dataset to answer these questions and examine the effects of buyer and seller demographics to identify the differences in channel preferences of the two groups.

REFERENCES

Abhishek, V., Fader, P., & Hosanagar, K. (2012). Media exposure through the funnel: A model of multi-stage attribution.

Agarwal, A., Hosanagar, K., & Smith, M. D. (2011). Location, location, location: An analysis of profitability of position in online advertising markets. Journal of marketing research, 48(6), 1057-1073.

Almquist Eric, Jamie Cleghorn, and Lori Schere (2018), "The B2B Elements of Value", Harvard Business Review, March-April issue, available at - https://hbr.org/2018/03/the-b2b-elements-of-value.

Almquist, Eric, John Senior, and Nicolas Bloch (2016), "The Elements of Value", Harvard Business Review, September issue, available at - https://hbr.org/2016/09/the-elements-of-value.

Armstrong, J. S., & Overton, T. S. (1977). Estimating nonresponse bias in mail surveys. Journal of marketing research, 396-402.

Baker, S. M., Gentry, J. W., & Rittenburg, T. L. (2005). Building understanding of the domain of consumer vulnerability. Journal of Macromarketing, 25(2), 128-139.

Batra, R., & Keller, K. L. (2016). Integrating Marketing Communications: New findings, new lessons, and new ideas. Journal of Marketing, 80(6), 122-145.

Chevalier, J. A., & Mayzlin, D. (2006), "The Effect of Word of Mouth on Sales: Online Book Reviews," Journal of Marketing Research, 43(3): 345-354.

eMarketer, "Does your marketing influence B2B decision-makers?", August 2015.

Emler, N. (1994). Gossip, reputation, and social adaptation.

Ghose, A., & Yang, S. (2009). An empirical analysis of search engine advertising: Sponsored search in electronic markets. Management Science, 55(10), 1605-1622.

Godes, D., & Mayzlin, D. (2004), "Using Online Conversations to Study Word-of-Mouth Communication," Marketing Science, 23(4): 545-560.

Grewal, R., Lilien, G. L., Bharadwaj, S., Jindal, P., Kayande, U., Lusch, R. F., ... and Sridhar, S. (2015), "Business-to-Business Buying: Challenges and Opportunities. Customer Needs and Solutions," 1-16.

Gupta, S., Lehmann, D. R., & Stuart, J. A. (2004). Valuing customers. Journal of marketing research, 41(1), 7-18.

Howell, J. (2009), “CBC/HB for Beginners,” Sawtooth Software Research Paper Series, available at - https://www.sawtoothsoftware.com/support/technical-papers/hierarchical-bayes-estimation/cbc-hb-for-beginners-2009

Jansen, B. J., & Schuster, S. (2011). Bidding on the buying funnel for sponsored search and keyword advertising. Journal of Electronic Commerce Research, 12(1), 1.

Joshi, A. W., & Sharma, S. (2004). Customer knowledge development: antecedents and impact on new product performance. Journal of marketing, 68(4), 47-59.

Kay, B., & Christophel, D. M. (1995). The relationships among manager communication openness, nonverbal immediacy, and subordinate motivation. Communication Research Reports, 12(2), 200-205.

Keller, K. L. (2016). Unlocking the power of integrated marketing communications: How integrated is your IMC program?. Journal of Advertising, 45(3), 286-301.

Kireyev, P., Pauwels, K., & Gupta, S. (2016). Do display ads influence search? Attribution and dynamics in online advertising. International Journal of Research in Marketing, 33(3), 475-490.

Korsgaard, M. A., Sapienza, H. J., & Schweiger, D. M. (2002). Beaten before begun: The role of procedural justice in planning change. Journal of Management, 28(4), 497-516.

Kovac, Mark (2016), “Social Media Works for B2B Sales Too”, Harvard Business Review, available at - https://hbr.org/2016/01/social-media-works-for-b2b-sales-too

Kumar, V., & Bhagwat, Y. (2010). Listen to the customer. Marketing Research, 22(2), 14-19.

Lamberton, C., & Stephen, A. T. (2016). A thematic exploration of digital, social media, and mobile marketing: Research evolution from 2000 to 2015 and an agenda for future inquiry. Journal of Marketing, 80(6), 146-172.

Mantrala, M. K., & Albers, S. (2012), “Impact of The Internet on B2B Sales Force Size and Structure,” Handbook of Business-to-Business Marketing, Edward Elgar, Northhampton, 539-555.

Marketing Leadership Council, “The Digital Evolution in B2B Marketing - Driving Marketing Performance with Multi-channel Content, Communications and Analytics”, 2012.

Martin, K. D., Borah, A., & Palmatier, R. W. (2017). Data privacy: Effects on customer and firm performance. Journal of Marketing, 81(1), 36-58.

McKinsey & Co. Insights and Publications, McKinsey Quarterly, "The Consumer Decision Journey", 2009.

Millward Brown and Google Inc., "The Changing Face of B-to-B Marketing," 2014.

Moorman, Christine (2016), "CMO Survey Report: Highlights and Insights," thecmosurvey, available at - https//cmosurvey.org/results/survey-results-february-2016-2/.

Myers, S. A., Knox, R. L., Pawlowski, D. R., & Ropog, B. L. (1999). Perceived communication openness and functional communication skills among organizational peers. Communication Reports, 12(2), 71-83.

Naylor, R. W., Lamberton, C. P., & West, P. M. (2012). Beyond the "like" button: The impact of mere virtual presence on brand evaluations and purchase intentions in social media settings. Journal of Marketing, 76(6), 105-120.

Onishi, H., & Manchanda, P. (2012). Marketing activity, blogging and sales. International Journal of Research in Marketing, 29(3), 221-234.

Orme, Bryan K. (1998), "The Benefits of Accounting for Respondent Heterogeneity in Choice Modelling," Sawtooth Software Research Paper Series, available at - http://www.sawtoothsoftware.com/support/technical-papers/cbc-related-papers/the-benefits-of-accounting-for-respondent-heterogeneity-in-choice-modeling-1998

Östermark, R., & Hernesniemi, H. (1995). The impact of information timeliness on the predictability of stock and futures returns: an application of vector models. European Journal of Operational Research, 85(1), 111-131.

Pansari, A., & Kumar, V. (2017). Customer engagement: the construct, antecedents, and consequences. Journal of the Academy of Marketing Science, 45(3), 294-311.

Reiss-Davis, Zachary, "The Social Behaviors of Your B2B Customers," Forrester Report, July, 2013

Robinson, Patrick J., Charles W. Faris, and Yoram Wind (1967), Industrial buying and creative marketing. Allyn and Bacon.

Rutz, O. J., & Bucklin, R. E. (2011). From generic to branded: A model of spillover in paid search advertising. Journal of Marketing Research, 48(1), 87-102.

Rutz, O. J., Bucklin, R. E., & Sonnier, G. P. (2012). A latent instrumental variables approach to modeling keyword conversion in paid search advertising. Journal of Marketing Research, 49(3), 306-319.

Shea, Mary, Shanta Samlal-Fadelle, Caroline Robertson, and Alexander Bullock (2017), “Millenial B2B Buyers Come of Age,” Forrester Research Report, available at - https://www.forrester.com/report/Millennial+B2B+Buyers+Come+Of+Age/-/E-RES132706.

Smith, T. M., Gopalakrishna, S., & Chatterjee, R. (2006). A three-stage model of integrated marketing communications at the marketing–sales interface. Journal of Marketing Research, 43(4), 564-579.

Stephen, A. T., & Galak, J. (2012). The effects of traditional and social earned media on sales: A study of a microlending marketplace. Journal of Marketing Research, 49(5), 624-639.

Üstüner, T., and Godes, D. (2006), "Better Sales Networks," Harvard Business Review, 84 (7/8), 102-12.

Vasquez, Adam, and Heather Wadlinger (2016), “The Next Generation of B2B Buyers. How The Millenial Business Buyer is Changing B2B Sales & Marketing,” Merit Insights, available at - https://madewithmerit.com/reports/Millennial_B2B-Report-Merit.pdf

Webster Jr, F. E., & Wind, Y. (1972), “A General Model for Understanding Organizational Buying Behavior,” Journal of Marketing, 36(2): 12-19.

Xiong, G., and Bharadwaj, S. (2014), “Prerelease Buzz Evolution Patterns and New Product Performance,” Marketing Science, 33(3), 401-421.

Yang, S., & Ghose, A. (2010). Analyzing the relationship between organic and sponsored search advertising: Positive, negative, or zero interdependence?. Marketing Science, 29(4), 602-623.

Yao, S., & Mela, C. F. (2011). A dynamic model of sponsored search advertising. Marketing Science, 30(3), 447-468.

TABLES

Table 3.1
LITERATURE REVIEW

Paper	Channels studied	B2B/B2C	Method	Offline/Traditional contact
Vibhanshu, Fader, and Hosanagar (2012)	Online (Display and Search ads)	B2C	Hidden Markov Model	Not studied
Anderl, Becker, Von Wangenheim, & Schumann (2016)	Online	B2C – Online travel agency and online retail	Graph-based Markov model	Not studied
De Haan, Wiesel, & Pauwels (2016)	Online (Content-integrated vs. Content-seperated)	B2C – Online retailer	Structural vector autoregression	Included as control
Li, Kannan, Viswanathan, & Pani (2016)	Online (Paid search ads)	B2C – online jewelry retailer	Simultaneous equations modelling	Not studied
Joo, Wilbur, & Zhu (2016)	Online (Category search, keyword choice, and click behavior), and TV ads	B2C – Financial services	Conditional choice model	TV ads
Agarwal, Hosanagar, & Smith (2011)	Online (Sponsored search)	B2C – Online retailer	Hierarchical Bayesian model	Not studied
Ghose, & Todri-Adamopoulos (2016)	Online	B2C – Online retailer	Individual-level Difference-in-Differences	Not studied
Ghose & Yang (2009)	Online (Paid search)	B2C – Fortune 500 retail chain	Hierarchical Bayes and Simultaneous equations model	Not studied
Kireyev, Pauwels, & Gupta (2016)	Online (Paid search & Display Ads)	B2C – Bank	Persistence modelling	Not studied

Li & Kannan (2014)	Online (Customer- and Firm-initiated)	B2C – Hospitality franchise firm	Nested Logit	Not studied
Rutz & Bucklin (2011)	Online (Paid search ads)	B2C – Lodging chain	Dynamic linear model (Bayesian estimation)	Not studied
Rutz, Bucklin, & Sonnier (2012)	Online (Paid search ads)	B2C – Lodging chain	Binary logit	Not studied
Yang & Ghose (2010)	Online (Paid search ads and Organic search listings)	B2C – Fortune 500 retail chain	Hierarchical Bayesian model (Markov chain)	Not studied
Manchanda, Dubé, Goh, & Chintagunta (2006)	Online (Banner ads)	B2C – Online retailer (healthcare, beauty, & prescription drugs)	Constant piecewise exponential hazard model	Not studied
Yao & Mela (2011)	Online (Sponsored search)	B2C – High-tech consumer products	Dynamic structure model	Not studied
Jap & Gilbride (2016)	- Own retail stores, - Franchise stores, - Indirect (national retailers), and - Electronic (Telesales & Online sales)	B2C – Mobile phone contracts	Multinomial logit	Yes
This Study	**- Traditional and Online (outbound & inbound, including social)**	**B2B**	**Interviews + Conjoint Analysis + Hierarchical Bayes**	**Yes**

Table 3.2
SAMPLE CHARACTERISTICS

Industry	Title	Experience
IT/Software	CEO	over 15 years
Logistics/Transportation	GM	over 15 years
Supply chain - Mobile Logistic Application	SVP - Marketing & Sales	over 20 years
Business-to-Business Learning Platforms	VP - Product Development	over 10 years
Banking/Financial services	President - Market Operations	over 10 years
Robotics	VP & Chief Strategy Officer	over 15 years

Table 3.3 (a)
CORRELATION MATRIX (STUDY 2)

	Variable	1	2	3	4	5	6	7	8	9	10
1	Information Timeliness	1.000									
2	Content Richness	.348	1.000								
3	Customization	.307	.458	1.000							
4	Transparent Interaction	.215	.187	.420	1.000						
5	Empathy	.040	-.064	.321	.518	1.000					
6	Reach	.477	.453	.214	.056	-.116	1.000				
7	Cost Efficiency	.520	.386	.148	.159	.028	.557	1.000			
8	Vulnerability	-.157	-.107	.037	.276	.299	-.253	-.173	1.000		
9	Credibility	.309	.257	.393	.469	.476	.182	.306	.148	1.000	
10	Control	-.211	-.126	.010	-.036	.148	-.130	-.117	-.086	-.146	1.000

Table 3.3 (b)
FACTOR LOADINGS (STUDY 2)

Variable	Factor1	Factor2	Uniqueness
Reach	**.811**	-.070	.337
Cost Efficiency	**.761**	.085	.413
Information Timeliness	**.730**	.171	.438
Content Richness	**.690**	.160	.498
Empathy	-.143	**.804**	.333
Transparent Interaction	.122	**.798**	.349
Credibility	.315	**.707**	.401
Customization	.394	**.576**	.513
Vulnerability	-.415	**.511**	.566

Table 3.4
EFFECT OF RATIONAL & EMOTIONAL RICHNESS ON CHANNEL SELECTION

	Model 1	Model 2	Model 3
Personal Selling (Base outcome)			
Digital Marketing			
Rational richness	1.957***	1.981***	1.923*
	(.48)	(.48)	(.81)
Emotional richness	-2.310***	-2.343***	-2.222**
	(.51)	(.52)	(.81)
Group		-.33	-.071
		(.59)	(3.6)
Group X Rational richness			.149
			(1.03)
Group X Emotional richness			-.202
			(1.06)
constant	.604	.824	.534
	(1.8)	(1.84)	(2.57)
Social Media			
Rational richness	1.407***	1.419**	.998
	(.43)	(.43)	(.66)
Emotional richness	-2.556***	-2.575***	-2.485**
	(.52)	(.52)	(.85)
Group		-.213	-2.746
		(.59)	(3.33)
Group X Rational richness			.764
			(.89)
Group X Emotional richness			-.096
			(1.09)
constant	3.625*	3.784*	4.999*
	(1.66)	(1.69)	(2.38)
N	117	117	117

* $p < .05$; ** $p < .01$; *** $p < .001$ (standard error in parentheses)

Table 3.5 (a)
CUSTOMER ENGAGEMENT: CHANNEL MAIN EFFECTS

Model	1a	1b	1c
Response Group	All	Buying	Sales
Dependent variable	Customer Engagement		
Personal Selling	2.986***	3.140***	2.876***
	(.40)	(.72)	(.42)
Digital Marketing	.513***	.59	.472*
	(.15)	(.34)	(.19)
Social Media	.542***	.126	.753***
	(.14)	(.32)	(.21)
N	1872	672	1200

Table 3.5 (b)
CUSTOMER ENGAGEMENT: CHANNEL MAIN EFFECTS

Model	2a	2b	2c	3a	3b	3c	4a	4b	4c
Response Group		All			Buying			Sales	
Dependent variable	Direct Engagement	Progression	Purchase Likelihood	Direct Engagement	Progression	Purchase Likelihood	Direct Engagement	Progression	Purchase Likelihood
Personal Selling	2.632***	3.023***	3.014***	2.225**	3.226***	3.555***	2.763***	2.778***	2.617***
	(.41)	(.44)	(.48)	(.76)	(.73)	(.75)	(.44)	(.44)	(.46)
Digital Marketing	.348*	.703***	.477**	.38	.820**	.639	.317	.634**	.416*
	(.18)	(.18)	(.16)	(.37)	(.25)	(.44)	(.26)	(.23)	(.19)
Social Media	.309	.481***	.831***	0	.134	.315	.509	.634**	1.020***
	(.22)	(.13)	(.15)	(.28)	(.36)	(.35)	(.33)	(.20)	(.21)
N	624	624	624	224	224	224	400	400	400

Table 3.5 (c)
CUSTOMER ENGAGEMENT: CHANNEL MAIN EFFECTS AND INTERACTIONS

Model	5a	5b	5c
Response Group	All	Buying	Sales
Dependent variable	Customer Engagement		
Personal Selling	2.802***	3.248***	2.542***
	(.44)	(.76)	(.48)
Digital Marketing	.29	.581	.15
	(.22)	(.54)	(.27)
Social Media	.349	.581	.243
	(.23)	(.38)	(.31)
PS x DM	.22	.423	.181
	(.16)	(.34)	(.22)
PS x SM	.161	-.580*	.541*
	(.25)	(.28)	(.23)
DM x SM	.234	-.358	.51
	(.33)	(.56)	(.33)
N	1872	672	1200

* *p < .05; *** *p < .01; **** p < .001* (standard error in parentheses)

Table 3.5 (d)
CUSTOMER ENGAGEMENT: CHANNEL MAIN EFFECTS AND INTERACTIONS

Model	6a	6b	6c	7a	7b	7c	8a	8b	8c
Response Group		All			Buying			Sales	
Dependent variable	Direct Engagement	Progression	Purchase Likelihood	Direct Engagement	Progression	Purchase Likelihood	Direct Engagement	Progression	Purchase Likelihood
Personal Selling	2.584***	2.230***	3.398***	2.269*	2.669***	5.430***	2.650***	1.875**	2.690***
	(.45)	(.51)	(.71)	(.88)	(.75)	(1.16)	(.53)	(.60)	(.70)
Digital Marketing	.3	-.362	.983*	.421	-.111	2.504***	.224	-.483	.673
	(.33)	(.37)	(.42)	(.62)	(.81)	(.69)	(.43)	(.46)	(.55)
Social Media	.221	-.596	1.392**	.421	-.442	2.770***	.087	-.66	1.133*
	(.38)	(.35)	(.47)	(.43)	(.73)	(.78)	(.58)	(.46)	(.56)
PS x DM	.01	.986**	-.293	.389	1	-.326	-.181	1.009*	-.218
	(.33)	(.37)	(.39)	(.34)	(.90)	(.45)	(.50)	(.47)	(.52)
PS x SM	.088	.982**	-.406	-.435	.331	-2.357*	.44	1.301***	.086
	(.30)	(.33)	(.53)	(.48)	(.36)	(1.04)	(.45)	(.37)	(.58)
DM x SM	.088	1.445**	-.669	-.436	.998	-2.356*	.4	1.634**	-.299
	(.40)	(.52)	(.57)	(.65)	(.91)	(1.18)	(.48)	(.54)	(.68)
N	624	624	624	224	224	224	400	400	400

* *p < .05;* ** *p < .01;* *** *p < .001* (standard error in parentheses)

Table 3.5 (e)
CUSTOMER ENGAGEMENT: CHANNEL X STAGES

Response Group	All			
Dependent variable	Customer Engagement	Direct Engagement	Progression	Purchase Likelihood
Personal Selling	1.867**	1.749**	1.649*	2.127**
	(.68)	(.61)	(.66)	(.82)
Digital Marketing	.539***	.273	.812***	.504**
	(.15)	(.27)	(.18)	(.17)
Social Media	.445*	.091	.456**	.804***
	(.18)	(.32)	(.14)	(.21)
Stage 2	-1.04	-1.431*	-1.052	-.472
	(.53)	(.59)	(.64)	(.50)
Stage 3	-1.03	-.659	-1.308*	-1.094
	(.63)	(.72)	(.56)	(.82)
Stage 2_Personal Selling	1.582	1.708*	2.138*	.676
	(.91)	(.84)	(.94)	(1.14)
Stage 2_Digital Marketing	0	.174	-.286	.1
	(.40)	(.53)	(.57)	(.34)
Stage 2_Social Media	.498	.979	.251	.169
	(.31)	(.52)	(.41)	(.27)
Stage 3_Personal Selling	2.207*	1.277	2.541**	2.398*
	(.98)	(1.14)	(.97)	(1.11)
Stage 3_Digital Marketing	-.023	.133	.092	-.237
	(.30)	(.35)	(.40)	(.49)
Stage 3_Social Media	-.124	-.091	-.018	.026
	(.44)	(.51)	(.30)	(.71)
N	1872	624	624	624

* $p < .05$; ** $p < .01$; *** $p < .001$ (standard error in parentheses)

Table 3.6 (a)
CONJOINT PHASE-TWO REGRESSION: BY STAGE – BY QUESTION

	Stage1			Stage 2			Stage 3		
	Direct Engagement	Progression	Purchase Likelihood	Direct Engagement	Progression	Purchase Likelihood	Direct Engagement	Progression	Purchase Likelihood
Personal Selling	Base Outcome								
Digital Marketing	-1.075	-1.278	-2.337**	-3.042**	-2.634**	-2.601**	-.462	-3.726***	-3.017***
	(.73)	(.65)	(.7)	(.91)	(.77)	(.84)	(1.68)	(-.74)	(.81)
Social Media	-1.45	-2.210**	-2.110**	-4.429***	-3.892***	-3.767***	-3.927*	-4.708***	-58.706***
	(.74)	(.65)	(.71)	(1.05)	(.89)	(.97)	(1.75)	(-.77)	(.84)
Group	.318	-1.465*	-.854	-37.048***	-36.959***	-37.859***	.951	-.605	-42.662***
	(.67)	(.59)	(.64)	(.76)	(.64)	(.7)	(1.26)	(-.55)	(.6)
Group X DM	-.223	1.897*	1.946*	.495	.455	1.488	-1.864	1.199	-.68
	(.94)	(.84)	(.9)	(1.06)	(.9)	(.99)	(1.78)	(-.79)	(.86)
Group X SM	.015	2.781**	2.981**	3.591**	2.521*	3.763**	2.58	1.903*	56.876***
	(.94)	(.84)	(.9)	(1.24)	(1.05)	(1.15)	(1.76)	(-.78)	(.85)
Rational richness	.347	.066	.082	.037	-.013	.067	-.852	.098	-.112
	(.28)	(.25)	(.27)	(.29)	(.25)	(.27)	(.58)	(-.25)	(.28)
Emotional richness	.025	.377	.546	.144	.515*	.518	.306	.086	.553
	(.31)	(.28)	(.3)	(.3)	(.25)	(.28)	(.62)	(-.27)	(.3)
constant	-.021	.71	.167	39.340***	38.119***	37.777***	5.399	4.062**	45.244***
	(1.27)	(1.12)	(1.21)	(1.69)	(1.43)	(1.56)	(2.94)	(-1.3)	(1.41)
R-sqr	.279	.391	.499	.996	.997	.997	.488	.786	.998
Deg. Freedom	31	31	31	31	31	31	31	31	31
N	39	39	39	39	39	39	39	39	39

$* p < .05; ** p < .01; *** p < .001$ (standard error in parentheses)

Table 3.6 (b)
CONJOINT PHASE-TWO REGRESSION: BY QUESTION

	Direct Engagement	Progression	Purchase Likelihood
Personal Selling (PS)	Base outcome		
Digital Marketing (DM)	-1.342**	-2.474***	-2.747***
	(.49)	(.4)	(.43)
Social Media (SM)	-2.366***	-3.283***	-3.354***
	(.5)	(.41)	(.44)
Group ID	-.039	-1.308***	-1.700***
	(.41)	(.34)	(.36)
Group X DM	-.65	1.250*	1.398**
	(.58)	(.48)	(.51)
Group X SM	1.011	2.242***	3.047***
	(.59)	(.49)	(.52)
Rational richness	-.034	-.032	-.118
	(.16)	(.13)	(.14)
Emotional richness	.102	.323*	.534***
	(.17)	(.14)	(.15)
constant	2.411**	2.571***	2.422**
	(.81)	(.67)	(.72)
R2	0.386	0.558	0.585
DF	109	109	109
N	117	117	117

* *p < .05; ** p < .01; *** p < .001* (standard error in parentheses)

FIGURES

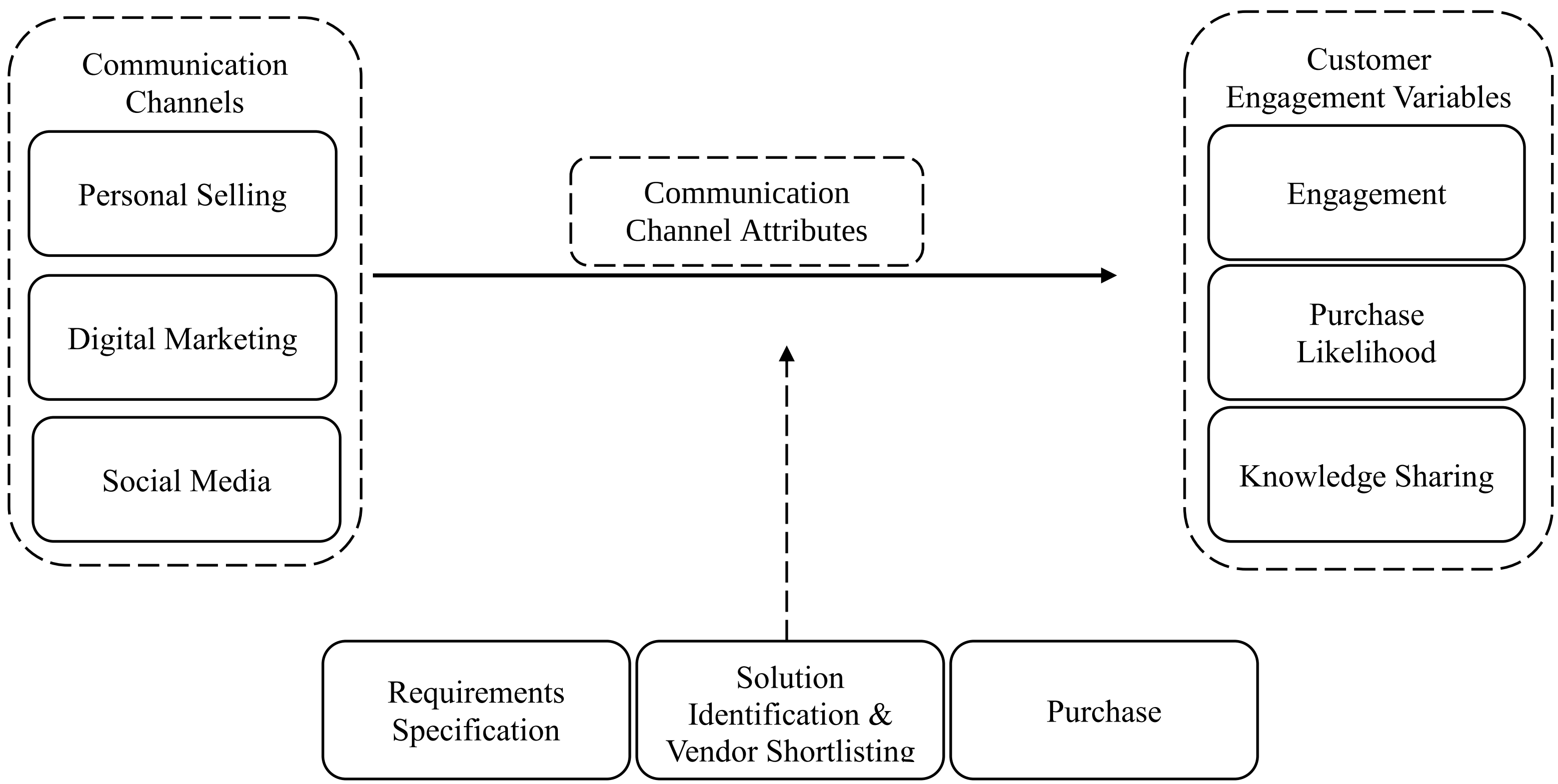

Figure 3.1. CONCEPTUAL FRAMEWORK

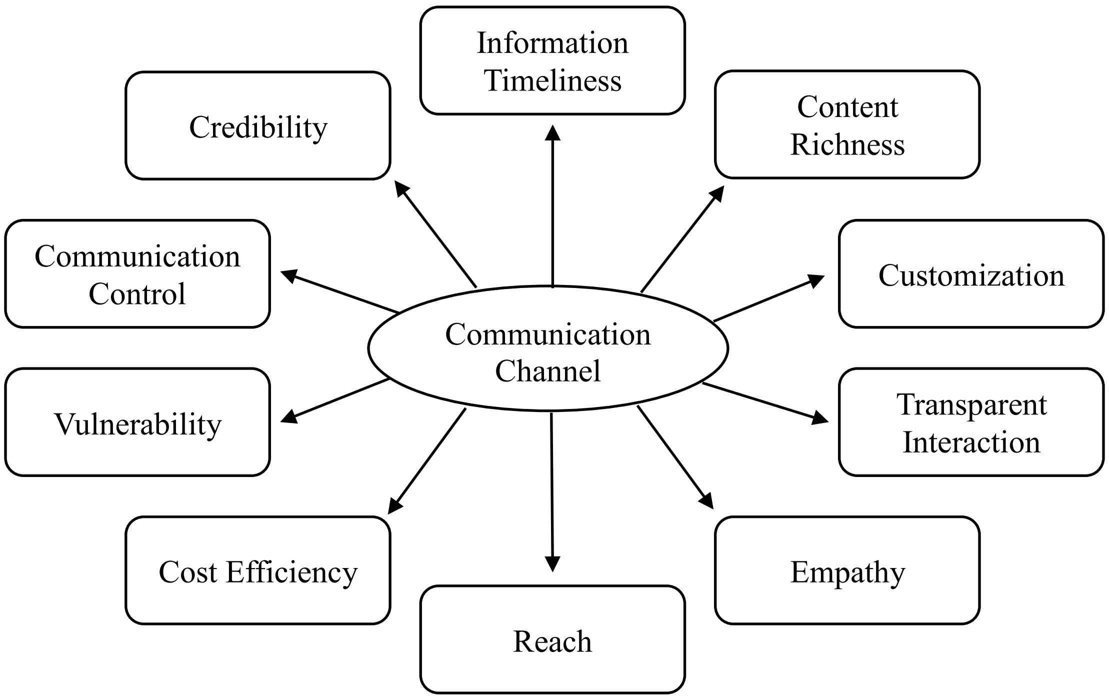

Figure 3.2 COMMUNICATION CHANNEL ATTRIBUTES

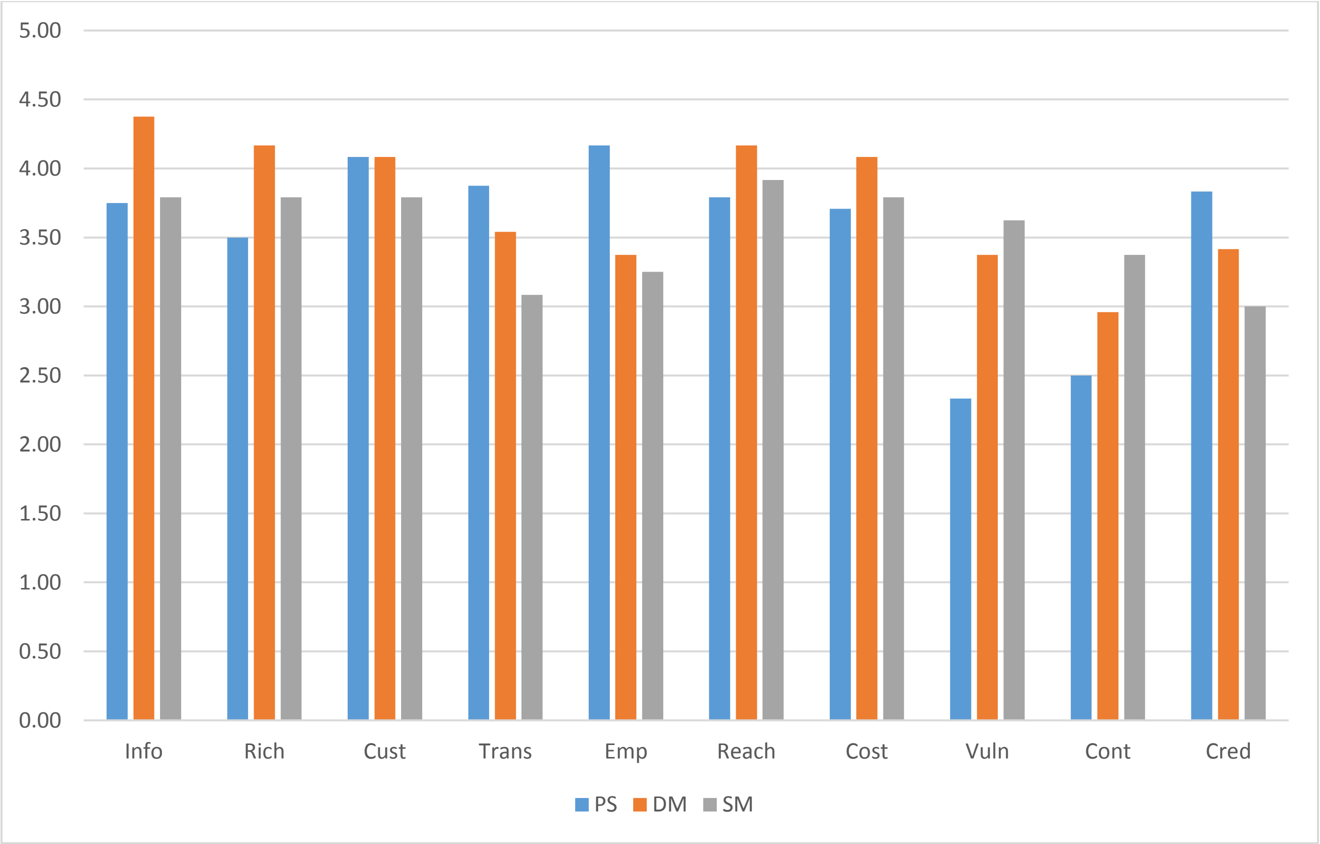

Figure 3.3 (a)

CHANNEL RATING BY ATTRIBUTE (BUYING GROUP)

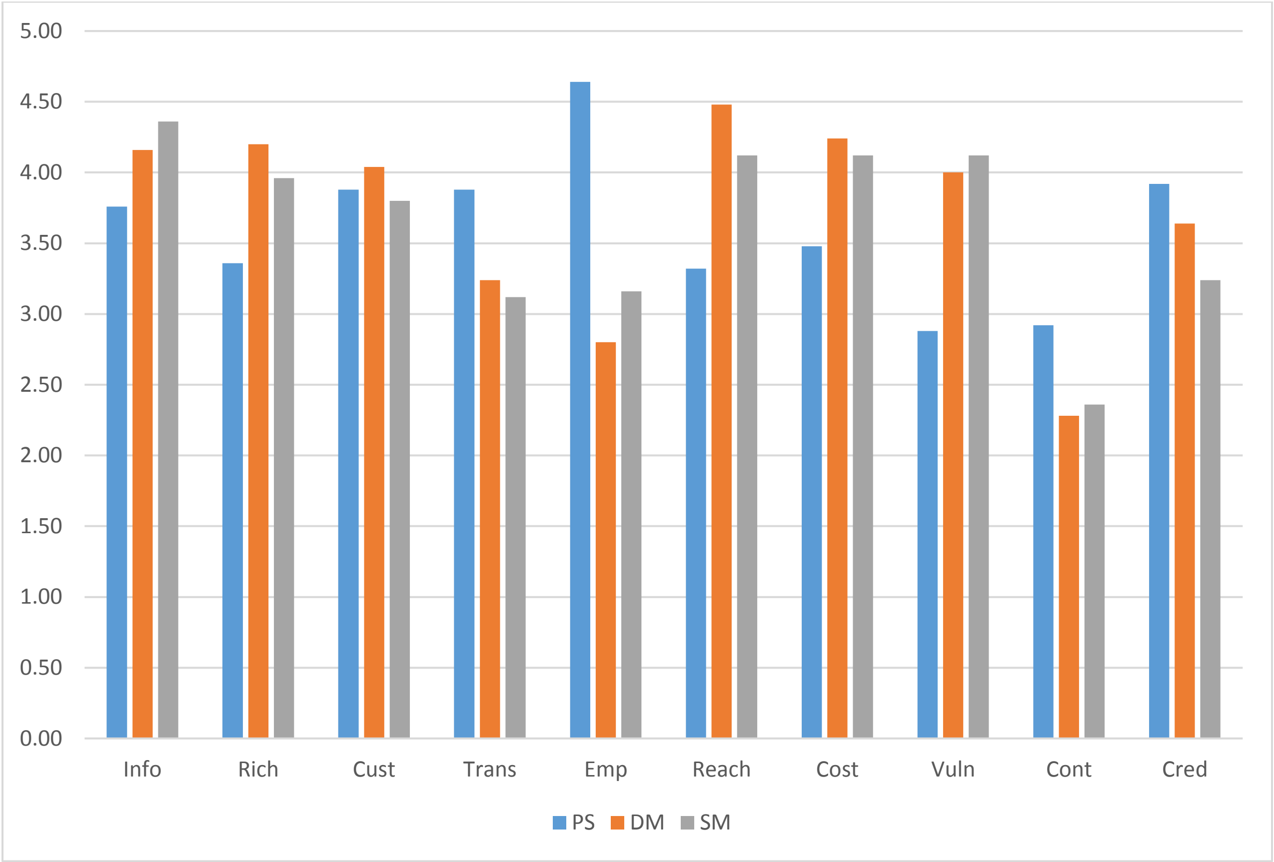

Figure 3.3 (b)

CHANNEL RATING BY ATTRIBUTE (SALES GROUP)

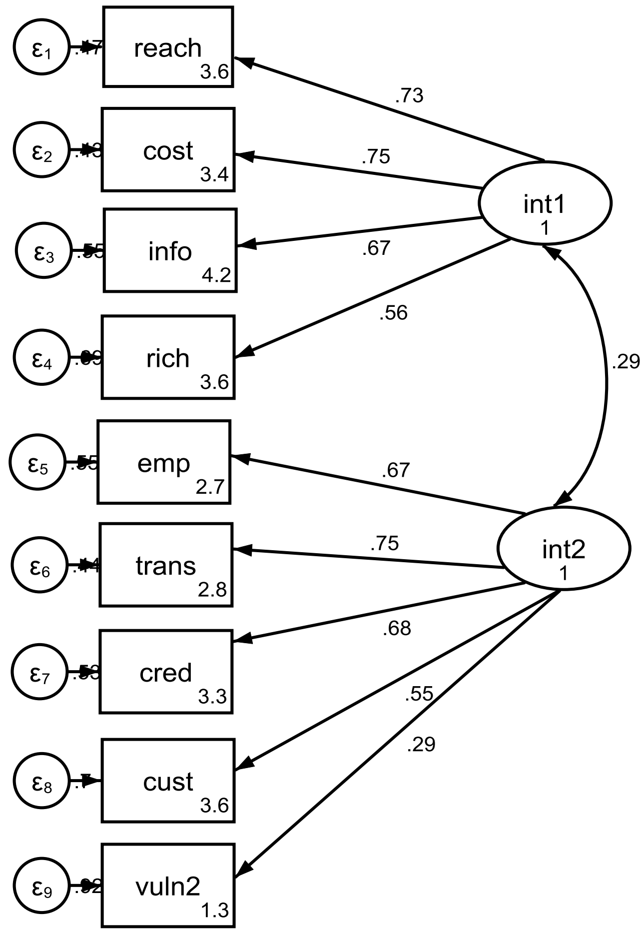

Figure 3.4

STRUCTURAL EQUATION MODEL WITH ITEM LOADINGS

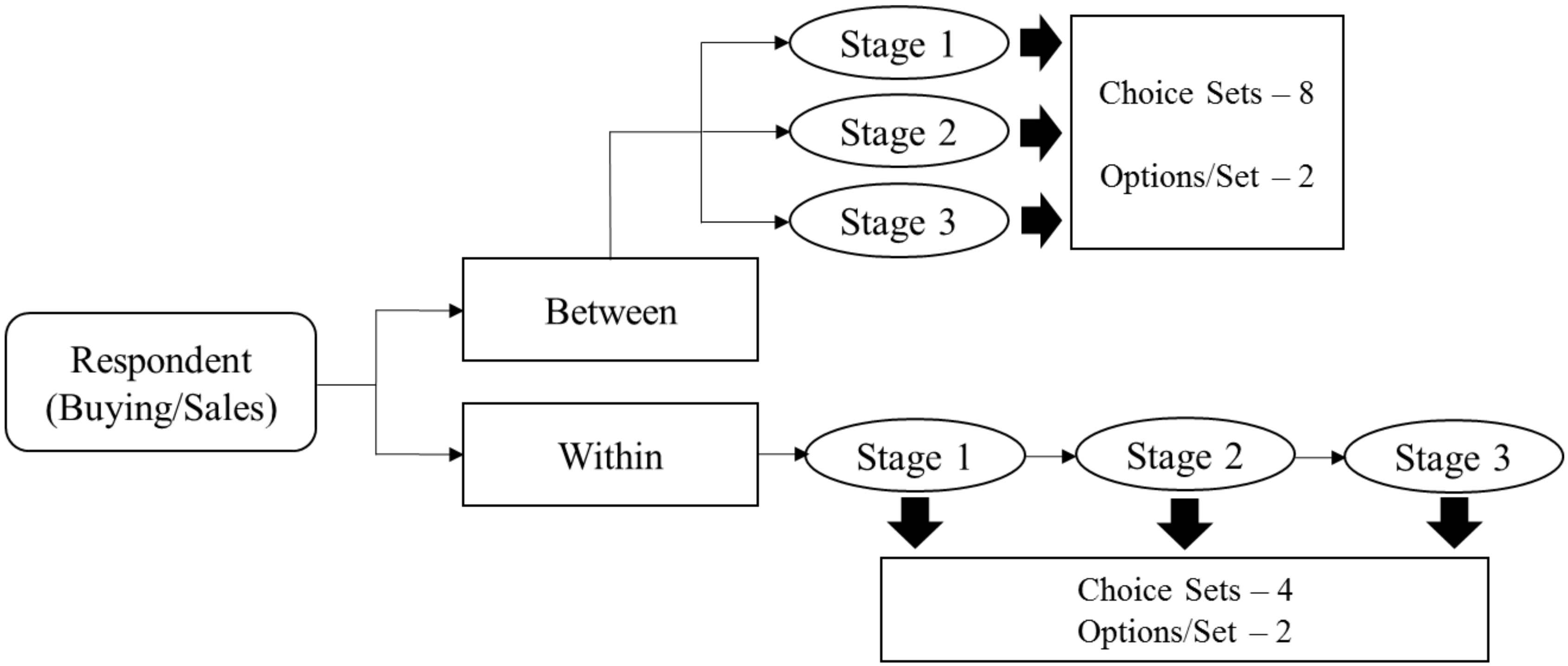

Figure 3.5

CONJOINT STUDY DESIGN

APPENDIX 1

Exhibit 3.1
CONJOINT QUESTIONS

Sales Group

Stage 1
Q1. Which option is more effective in identifying and engaging with potential leads?
Q2. Which option is more likely to move the buyer to the next buying stage?
Q3. Which option increases your likelihood to sell the solution eventually?

Stage 2
Q1. Which option is more effective in differentiating and generating greater buyer interest in your solution?
Q2. Which option is more likely to help you get into buyer's final consideration set of solutions?
Q3. Which option increases your likelihood to sell the solution eventually?

Stage 3
Q1. Which option is more effective in customizing the solution and collecting customer feedback?
Q2. Which option is more effective in upselling/cross-selling other services to this buyer?
Q3. Which option increases your likelihood to sell the solution to this customer eventually?

Buying Group

Stage 1
Q1. Which option makes it easier to learn more about alternative solutions?
Q2. Which option is more likely to help you progress to the next buying stage?
Q3. Which option increases your likelihood to buy the solution eventually?

Stage 2
Q1. Which option is more effective in generating interest in a particular solution and its supplier?
Q2. Which option is more likely to help you progress to the next buying stage?
Q3. Which option helps increases your likelihood to buy the solution eventually?

Stage 3
Q1. Which option is more effective in providing solution related feedback to the supplier and seeking any inputs?
Q2. Which option is more effective in making you consider buying additional services from this supplier?
Q3. Which option helps increase your likelihood to buy this solution from this supplier eventually?

Exhibit 3.2
SAMPLE CHOICE SET

Option 1	Option 2
Personal Selling – Available Digital Marketing – Low Social Media – High	Personal Selling – Unavailable Digital Marketing – High Social Media – High

Exhibit 3.3(a)
BUYING SCENARIO (SALES)

Buying Scenario (Sales group)

Imagine that you work with **Cloud Security Inc.** as a member of the **Sales/Marketing team**. **Cloud Security Inc.** provides security solutions for cloud computing and storage to a number of companies in different industries. While it is a relatively new offering, the market is competitive as there are other solution providers.

Your team is responsible for creating **Awareness** about your solutions, generate **Interest** in potential buyers and eventually **Sell**.

While your team wishes to maximize the utilization of all three communication channels to achieve its objectives, it may not always be possible due to cost, availability, or various other reasons.

Personal Selling – Salespeople may be **Available or Unavailable** due to their schedules.

Digital Marketing – Digital marketing may be **Low or High**, based on whether few or more of the digital marketing platforms shown earlier are made available to the buyer.

Social Media – Social media may be **Low or High**, based on whether few or more of the social media platforms shown earlier are accessible to the buyer.

Next, you will see some buying scenarios. While reading the scenario and answering questions, please continue to envision yourself as if you were actually engaging with a buyer to make a sale.

Exhibit 3.3(a)

BUYING SCENARIO (BUYING)

Buying Scenario (Buying group)

Imagine that you work with **Citrus Financial Services Inc. (CFS)** as a member of the **Buying team**. **CFS** provides financial consulting and other wealth management services to a number of Fortune 500 companies. **CFS** uses cloud computing and storage services to store and process confidential data of its business clients.

CFS experienced a data breach and is considering various options to secure its client data. Your team is responsible to search for and evaluate different solutions and their suppliers to address this need, followed by initiating and completing the purchase process with the selected solution provider. In the process, your team will go through the three buying stages and, based on your objectives, may use a combination of the three communication channels.

While your team wishes to maximize the utilization of all three communication channels to achieve its objectives, it may not always be possible due to cost, availability, or various other reasons.

Personal Selling – Salespeople may be **Available or Unavailable** due to their schedules.

Digital Marketing – Digital marketing may be **Low or High**, based on whether few or more of the digital marketing platforms shown earlier are available.

Social Media – Social media may be **Low or High**, based on whether few or more of the social media platforms shown earlier are accessible.

Next, you will see multiple buying scenarios. While reading the scenario and answering questions, please continue to envision yourself as if you were actually making a purchase.

CHAPTER 4

CONCLUSION

Overall, in this dissertation, I attempt to uncover and empirically examine a number of important gaps in B2B literature in marketing, particularly in inter-firm and customer relationships. In my first essay, I find that multiple ties between a supplier firm and its focal customers restrict the supplier firm's capacity to innovate beyond the relationship. However, the supplier firm can take some relationship-specific and firm-specific strategic decisions in order to reduce the magnitude of such negative influence. I find that engaging in loosely coupled relationships with other firms and focusing on a product-centric organization structure are some of the key strategic initiatives that can help a supplier reduce the negative effect of relationship multiplexity on its innovation. Additionally, I find the contingent effects of other environmental conditions on this relationship. This research helps academics and managers alike by enriching their understanding of B2B relationships and informing them about the potential negative consequences of multiplex relationships.

In my second essay, I augment current academic understanding of the B2B marketing and selling process. I find that B2B marketing is not immune to the influence of modern communication channels, such as digital marketing and social media. These channels are changing the process of information search and customer decision processes in B2B buying. Through a combination of exploratory and confirmatory research, I find that the model of customer engagement in B2B markets has changed significantly and the role of marketing in establishing customer engagement has increased. I also find that the selection of a communication channel is contingent upon the underlying attributes, which make a communication between customers and marketers more or less engaging. Using panel data of managers from marketing and buying backgrounds, I find that communication channel attributes, such as speed, content richness, and reach have a positive relationship with a high likelihood of selection of digital marketing and social media as the channel of communication, over personal selling. However, other attributes, such as open communication, empathy, and privacy are negatively related with the likelihood of selection of digital marketing or social media over personal selling.

In summary, this dissertation presents some novel findings regarding the underlying processes and the impact of customer relationships on firm outcomes.