Essays on Business-to-Business (B2B) Marketing Network and Firm Value

By

Guiyang Xiong

Doctor of Philosophy

Business

Sundar Bharadwaj, Ph.D.

Professor of Marketing, Emory University

Advisor

Rajendra Srivastava, Ph.D.

Professor of Marketing, Emory University

Committee Member

Ryan Hamilton, Ph.D.

Assistant Professor of Marketing, Emory University

Committee Member

Accepted:

Lisa A. Tedesco, Ph.D.

Dean of the James T. Laney School of Graduate Studies

Date

Essays on Business-to-Business (B2B) Marketing Network and Firm Value

By

Guiyang Xiong

B.B.A., Fudan University, 2006

Advisor: Sundar Bharadwaj, Ph.D.

An abstract of

A dissertation submitted to the Faculty of the

James T. Laney School of Graduate Studies of Emory University

in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

in Business

2010

Abstract

Essays on Business-to-Business (B2B) Marketing Network and Firm Value

By Guiyang Xiong

The objective of this dissertation research is to empirically investigate the impact of Business-to-Business (B2B) relationship network on firm value.

Essay 1 links three types of B2B networks with startups' Initial Public Offering (IPO) value, and identifies three matching types of absorptive capacity that transforms B2B social capital into IPO value. For the transformation to occur, I find that young firms need not only the opportunity to access the resources provided by B2B relationships, but also the ability to leverage them through absorptive capacity. This study based on a sample of 177 IPOs provides empirical evidence of B2B social capital's financial value, as well as the contingency factors that are manageable through marketing activities. The results are robust to alternative measures and modeling approaches. As one of the first studies in marketing-finance interface that focus on young firms, this essay's findings provide novel insights to entrepreneurs, managers, and investors, including the deleterious financial consequence of having marketing and R&D alliance relationships without the relevant absorptive capacity.

Essay 2 demonstrates that B2B network can add financial value to the firm by influencing the evolution pattern of Customer-to-Customer (C2C) Word-of-Mouth (WoM) in new product introductions. Based on marketing strategy, consumer behavior, and sociology literature, I develop and test a set of hypotheses to systematically examine the linkages among B2B network, C2C WoM evolution, and new product success. Using functional data analysis method, the study reveals significant heterogeneity in the pattern of pre-release C2C WoM evolution across products. Results show that B2B network characteristics influence not only the WoM evolution pattern, but also the impact of WoM evolution pattern (volume and velocity) on sales and firm value upon new product release. Moreover, the influence of B2B network characteristics varies over time across the pre-release period. The study provides unique insights as of how B2B and C2C network influences new product performance, and meaningful implications in WoM and new product management.

Essays on Business-to-Business (B2B) Marketing Network and Firm Value

By

Guiyang Xiong

B.B.A., Fudan University, 2006

Advisor: Sundar Bharadwaj, Ph.D.

A dissertation submitted to the Faculty of the
James T. Laney School of Graduate Studies of Emory University
in partial fulfillment of the requirements for the degree of
Doctor of Philosophy
in Business
2010

TABLE OF CONTENTS

TABLES

FIGURES

OVERVIEW

The persistent need to justify marketing's financial accountability has motivated a growing body of research on the marketing-finance interface. Marketing scholars have linked various marketing activities and metrics with a set of stock-market outcomes (e.g., Tuli and Bharadwaj 2009). Such studies reveal the significant influence of marketing strategy on firm valuation, and provide meaningful implications for CMOs and other marketing managers to communicate marketing's accountability to top management and other functional departments (e.g., Srinivasan and Hanssens 2009). Meanwhile, there has been a growing recognition that Business-to-Business (B2B) relationships can constitute valuable market-based intangible assets and thus influence firms' cash flows (e.g., Srivastava, Shervani, and Fahey 1998). However, few marketing-finance interface studies have empirically explored the linkage between B2B network and shareholder value. A systematic understanding of this linkage can not only provide meaningful insights for B2B relationship management, but also novel implications for investors to identify superior investment opportunities.

Against this backdrop, this dissertation empirically investigates the impact of B2B networks on firm value. Social network research argues that actual or potential resources stemming from B2B relationship networks can constitute social capital that might be transformed into financial value (e.g., Van den Bulte and Wuyts 2007). In Essay 1, I identify the conditions under which B2B social capital can be realized into financial value. The study is conducted in the Initial Public Offering (IPO) context, and shows that, to financially benefit from B2B social capital in horizontal alliance networks and customer relationship networks, young technology firms need relevant types of absorptive capacity.

A valuable resource that B2B networks provide is the customer bases brought together by multiple business partners (e.g., Srivastava et al 1998). The impact of B2B network on firm performance can thus come from the dynamics in the potential customer base fostered by this B2B network. Therefore, in Essay 2, I link B2B network and Customer-to-Customer (C2C) network and demonstrate that B2B network can add value to the firm by influencing the evolution pattern of C2C Word-of-Mouth (WoM) in new product introductions.

ESSAY 1: Realizing B2B Relationships into Financial Value in IPOs: The Role of Absorptive Capacity

INTRODUCTION

The persistent need to justify marketing's financial accountability has motivated a growing body of research on the marketing-finance interface. Scholars have linked various marketing activities and assets with a set of stock market outcomes, and revealed a significant impact of marketing on firm valuation (e.g., Luo 2007; Srinivasan and Hanssens 2009). However, extant marketing-finance interface research has almost exclusively focused on large established firms and has for the most part ignored startup firms. I posit that it is equally important to examine these issues in the context of startups. Startup firms[1] are a critical component of the US economy serving as sources of job creation, with higher productivity and productivity gains than established firms (Kauffman Foundation Report 2008). There are significant differences in the management and valuation of young firms compared to mature firms (e.g., Sheth and Sisodia 2001). Thus the implications generated from research on mature firms may not apply to startups, whose valuation and management are important not only to entrepreneurs and managers but also to venture capitalists and other private investors.

Startups are an interesting context to study the value of market based assets such as business-to-business (B2B) relationships. The conceptual literature has recognized that both horizontal and vertical B2B relationships are valuable market-based intangible assets, since they constitute social capital that might be transformed into financial value

[1] I use the terms startups and young firms interchangeably. While this might be debatable in some circumstance, it seems appropriate for this study since the average of the firms in the sample is 7.7 years on the day of the Initial Public Offering (IPO).

(e.g., Srivastava, Shervani, and Fahey 1998; Van den Bulte and Wuyts 2007). B2B relationships can be of particular importance to young technology firms and their firm value for several reasons. First, such firms typically do not have the internal resources and capabilities of an established firm and thus rely on external B2B relationships for access to critical resources and knowledge (e.g., Lin 1999, Stuart 1998, Uzzi 1999). Second, investors are likely to seek indirect signals to assess young firms since these firms have short observable histories and limited performance records (e.g., Stuart, Hoang, and Hybels 1999). Previous literature has acknowledged that B2B relationships can not only signal the legitimacy of new ventures but also help develop corporate reputations (e.g., Florin, Lubatkin and Schulze 2003). Finally, investors' uncertainty about future prospect is especially high for startups in high technology industries (e.g., Aldrich and Fiol 1994). B2B relationships can help young technology firms track fast environmental changes and boost innovation speed, product adoption, and firm growth (e.g., Rindfleisch and Moorman 2001), thus lower investors' uncertainty in evaluating the firms' value potential.

The prior empirical literature, however, provides conflicting evidence on the role of B2B relationships. Some studies argue that these external relationships are valuable sources of information and thus enhance survival and performance of young firms (Brudere and Priesendorfer 1998; Hager, Galaskiewicz and Larson 2004). On the other hand, others find that such ties do not always translate into better performance (Gulati and Higgins 2003; Guo, Lev and Zhou 2005). These mixed findings appear to suggest that it might not be the mere presence or absence of such B2B relationships that are critical, but that the phenomenon is more complex calling for further study.

Against this backdrop, I explore the conditions where B2B relationships increase startups' shareholder value. This study is conducted in a unique financial context, the Initial Public Offering (IPO) market, in which a firm seeks public equity investment for the first time. According to Ernst & Young Global IPO Trend reports, in the year 2006 alone, US-based companies generated 187 IPOs, raising $34.1 billion. IPO is a crucial event in a firm's life and probably the most important corporate financing and strategic development decision for a young firm. IPO research has proliferated in finance and management. However, marketing scholars have not paid much attention to this area, though marketing strategies can play an important role in a young firm's performance (Luo 2008, DeKinder and Kohli 2008). Moreover, IPO value provides a systematic forward-looking evaluation of young firms' future performance, which is ideal for this research context. This is because startup firm value highly depends on the expected future performance and growth opportunities, while historical financial performance measures, such as sales or profitability, are often zero or negative for young firms.

This essay's findings suggest that mere access to social capital in certain B2B networks does not necessarily benefit a young firm's IPO market capitalization. However, for young firms with strong absorptive capacity, social capital from each type of B2B networks can significantly enhance the IPO value because of the firms' ability to leverage these relationships. This study thus helps startup managers better understand *why* certain B2B relationships may or may not pay off, as well as the *how* to manage each type of relationships so as to maximize their value potential. In addition, I provide evidence that marketing efforts do not only build up social capital but also help realize its financial value, hence helping senior marketing managers (such as CMOs) better communicate marketing's value and accountability. The results can also help institutional and individual investors better value young firms and identify IPO investment opportunities that can yield superior financial returns.

In the rest of the essay, I briefly review two streams of relevant literature and highlight the theoretical contributions. I then develop the conceptual framework and specify hypotheses. In developing my hypotheses, I rely on established theory and five in-depth interviews with domain experts who have extensive investment banking experience. Data, methods, and empirical results will then be presented, followed by a general discussion of the results, and implications for research and practice.

PRIOR RESEARCH

B2B Relationships: Previous research provides mixed results about the influence of B2B relationships on firm performance. With regard to strategic alliance relationships, some studies show that forming alliances increases alliance participants' stock performances (e.g., Chan et al 1997, Das et al 1998). In contrast, other studies imply that alliances have a value-reducing effect (Guo, Lev, and Zhou 2005), or no significant impact on firm value (Gulati and Higgins 2003). Among the studies focusing on customer relationships, some find that relational constructs such as relationship quality and satisfaction positively influence the seller's sales, profit, and share of wallet (e.g., Doney and Cannon 1997, Siguaw et al 1998), while other researchers show no significant impact (e.g., Crosby, Evans, and Cowles 1990, Gruen, Summers, and Acito 2000). Palmatier and colleagues (2006) conclude in their review that the mixed findings imply that the effect of B2B relationships on firm performance may be contingent on other non-modeled factors.

Absorptive Capacity: Cohen and Levinthal (1990) introduced the concept of absorptive capacity to describe a firm's ability to identify, assimilate, and exploit external knowledge. Research on absorptive capacity has grown since then, as the construct provides a unique viewpoint and can be applied to many research areas (Lane, Koka, and Pathak 2006). Absorptive capacity has been associated with both intra and inter-organizational learning, and is recognized as playing a key role in B2B relationship performance (e.g., Lane and Lubatkin 1998). Scholars have unveiled the importance of absorbing implicit or tacit knowledge, i.e., "know-how", in addition to the simple "know-what" (e.g., Simonin 1999, Narasimhan et al 2006). However, extant studies have almost exclusively focused on research and development or R&D (Lane et al 2006) and largely ignored the learning and knowledge absorption that commonly exist in other contexts.

In this study, I incorporate these two streams of literature along with marketing strategy, finance, and social network research to investigate the financial impact of "social capital" from different types of B2B relationships – as well as the moderating role of absorptive capacity – in the context of young firms at IPO. This essay departs from and extends existing research in at least four ways. First, it enriches the B2B literature by demonstrating the contingent value of various types of B2B relationships, thus resolving the conflict in the literature's findings about B2B relationships' impact on firm performance. Second, previous absorptive capacity research merely considers R&D or technological know-how. I also identify and measure marketing know-how and customer know-how absorptive capacities to match specific types of B2B relationships. Third, sociology studies argue that social capital can contribute to financial capital, but only limited empirical testing of this expectation has been attempted. This study provides realworld evidence for B2B network capital's financial value. More importantly, I demonstrate that while B2B relationships provide access to resources (i.e., opportunity), firms require absorptive capacity (i.e., ability to leverage the resources) to deliver financial value, and thus contribute to the marketing-finance interface literature. Finally, my focus on startups also adds unique insights to the entrepreneurship literature.

CONCEPTUAL FRAMEWORK

Social capital is "the aggregate of the actual or potential resources linked to possession of a durable network of more or less institutionalized relationships" (Bourdieu 1985, p. 248). It consists of: (1) the relationship itself that provides access to resources possessed by their associates; (2) the nature and amount of those resources (Portes 1998). In this study, I capture the *nature* of the resources by classifying startups' B2B relationships into three types: R&D alliance relationships, marketing alliance relationships, and key customer relationships. In the social network literature, a node with higher centrality has access to more resources from other nodes (Tsai and Ghoshal 1998). I thus employ the local (ego) centrality, i.e., the number of ties a firm has in each type of its B2B networks, to capture the *amount* of resources (e.g., Scott 2000).

To determine the financial outcome, IPO value, I follow the logic of Srivastava et al (1998) by analyzing the *level* (both inflows and outflows), *timing*, and *volatility* of a young technology firm's future cash flows. Table 1 summarizes of the potential impact of the three types of B2B relationships. Figure 1 is an overview of the conceptual framework.

The Positive Impact of R&D Alliance Relationships

R&D alliances involve R&D (research and development) and innovating activities. Innovations, especially technology-based, have become increasingly complex and require sizable resources (e.g., Mowery and Rosenberg 1998). Social capital from R&D alliance relationships (RAR) is a critical source of these resources for a young technology firm's innovation activities, which in turn influence their cash flows. First, RARs help reduce cash outflows. For instance, due to high operational risks, young firms often need to bear high financing costs, such as high interest on debt (e.g., Uzzi 1999). RARs often bring access to financial resources and lower young firms' financing costs. For example, an internet startup *INKTOMI CORP* obtained $2 million funding from *INTEL* under their alliance agreement.

Second, RAR social capital help reduce the volatility of cash flows. Innovation is widely recognized as highly risky (e.g., Sorescu and Spanjol 2008). Pooled technological and financial resources in RARs put young firms in a better position – in a jointly-developed and well-funded laboratory with many experienced scientists – to lower the risks inherent in innovation processes (Hill and Jones 1995, Deeds and Hill 1999).

Third, RAR social capital accelerates cash flows. Rich information and resources brought by RARs enable firms to quickly identify and respond to critical information, such as technical advancements and opportunities (Lane & Lubatkin 1998). RARs bring about rapid prototyping, which shortens new product development (NPD) cycle and speeds up cash flows (Thomke 1998).

As a young firm's number of RARs (or RAR network centrality) increases, it is exposed to more R&D resources (e.g., Tsai and Ghoshal 1998). Richer resources enhance all three effects – reduction in cash outflows and cash flow volatilities, and acceleration of cash flows – and thus further increase the NPV of cash flows and finally the IPO value. In addition, the investment bankers interviewed suggested that while RARs are expected for established firms, for young firms they are critical as they serve as a stamp of approval. As one articulated, (the presence of RARs) "*shows that you are a company that can operate at that level….and lowers business risk, which should enhance the multiple an investor would pay for the business*." Recent literature in marketing also points to the importance of signal value for startups (Dekinder and Kohli 2008).

The Negative Impact of R&D Alliance Relationships

However, joining RARs may also decrease startups' financial value. First, financially constrained firms, such as startups, have lower negotiating power and tend to give up too much of their ownership when entering an alliance. This has been called the "risk of equity relinquishment" (Aghion and Tirole 1994, Guo et al 2005). RAR partners may make use of their resource advantage to behave opportunistically at the expense of the young firms. Young firms thus may not obtain fair gains from the value created in the alliance. This view was echoed by the investment bankers interviewed. As one pointed out, "*… If the partner can extract all the value out of the relationship… partnerships can be a detractor of value*."

RARs also run the risk of leakage of strategically important knowledge to competitors, especially if opportunistic partners have or build ties with the startup's competitors (Dutta and Weiss 1997). Such partners may also play-off one partner against the other (i.e., the *divide et impera* principle) to appropriate gains from the relationship (Van den Bulte and Wuyts 2007).

To sum up, since joining RARs can have both positive and negative influence on IPO value, the overall effect is unclear.

The Moderating Role of R&D Know-how Absorptive Capacity

To transform social capital into financial value, a firm needs to actively deploy the B2B resources and convert them to a desired end. The resource based view contends that the ability to identify and utilize external knowledge is critical in this process (e.g., Bharadwaj, Varadarajan, and Fahy 1993). Past research has referred to this ability as *absorptive capacity* (Cohen and Levinthal 1990). Following Narasimhan et al. (2006), I conceptualize absorptive capacity as *the efficiency of a firm to absorb external know-how, relative to the maximal amount of know-how absorbable given the relevant resources it accesses*. Consistent with the input-output framework in economics (e.g., Silberberg 1990), this definition captures the ability of know-how absorption by comparing the amount of know-how a firm actually absorbs (output) with the amount of know-how it could have absorbed conditional on the resources accessible (input). I label the efficiency of absorbing technological and R&D know-how as *R&D know-how absorptive capacity*. Notably, R&D know-how absorptive capacity coincides with the traditional conceptualization of absorptive capacity, which takes an R&D focus.

RAR social capital pools up external R&D resources that can influence the level, volatility, and speed of cash flows. For young firms with strong R&D know-how absorptive capacity, these effects can be reinforced. For example, better leverage of R&D resources enabled by strong absorptive capacity increases the economies of scale and synergies (e.g., Gomes-Casseres 1997), thus enhancing R&D cost efficiency and reducing the risk of R&D failure. This further reduces expected cash outflows and increases the predictability of the future cash flows. Reduction in failures or iterations in developing products also shortens the NPD cycle and accelerates cash flows.

R&D know-how absorptive capacity can also enhance the generation of both short-run and long-run cash inflows from RAR social capital. The pooled R&D resource base is more valuable when the participating firms can recognize and synthesize external resources (e.g., Gomes-Casseres 1997), in order to materialize the ideas and resources into new products that generate future cash inflows. This process becomes more efficient as a young firm's R&D know-how absorptive capacity grows. More importantly, R&D know-how absorptive capacity can benefit a young firm in the long-run. In B2B networks, knowledge is embedded in a social context, making it more unique and less imitable, and thus more likely to create strategic value (Spender 1996). With strong absorptive capacity, a firm can absorb such tacit knowledge and build up its unique R&D capabilities, which are rare, imperfectly tradable, and costly to replicate. They therefore form the basis of competitive advantages (e.g., Bharadwaj et al 1993), predicting superior future R&D performance (Spender 1996; Lane and Lubatkin 1998), and thus high long-term cash inflows. In contrast, if a firm lacks absorptive capacity, even if it has many RAR resources, it cannot efficiently leverage the social capital to build up or improve its capabilities, and may not be able to generate superior long-term cash inflows.

As investors tend to seek indirect signals to assess startups, a firm with strong absorptive capacity can potentially convey a positive signal to investors regarding their ability to benefit from RARs and alleviate their concerns about the potential equity relinquishment. In sum,

H1: *The greater a young technology firm's R&D know-how absorptive capacity, the stronger the positive effect of R&D alliance relationship centrality on the IPO value.*

The Positive Impact of Marketing Alliance Relationships

Marketing alliances involve activities such as co-branding, joint-marketing, and sharing of distribution channels. Marketing alliance relationship (MAR) social capital can decrease cash outflows and cash flow volatility, and accelerate cash flows. First, MAR partners' established marketing and sales forces can reduce startups' marketing spending, and lower the chance of failures in product introductions and promotions (Comanor 1965). For example, young biotech firms often partner with large pharmaceutical companies, who not only have rich experience with the FDA approval process, but also have an experienced sales force to detail drugs to physicians.

Second, MAR social capital can decrease the volatility of cash flows. Joining MARs may entail an access to the partners' existing relationships with customers. For instance, *Kana Communications* was allowed access to the user base of its partner *NISUS*; similarly, *BottomLine Technologies* gained access to *PeopleSoft*'s customers upon their alliance formation. Access to loyal customer bases is valuable since cash flows from such customers are less susceptible to competition (Tuli, Bharadwaj, and Kohli 2010). In addition, MAR partners' established supply chains enhance coordination through the channel and promotes stability in operations (Bharadwaj, Bharadwaj, and Bendoly 2007), thus lowering variability of cash flows. MAR partners' brand equity also helps stabilize cash flows (Srivastava et al 1998).

Third, MAR partners' established distribution channels and sales forces facilitate new product adoption (Mitchell 1989) and thus enhance the speed of a young firm's cash flows. An investment banker I interviewed pointed out that a key driver of *Monster Beverage*'s value is its distribution partnership with *Anheuser-Busch*. In a global market context, MARs help quicker penetration of a bigger portion of the world markets simultaneously and thus accelerate cash flows. For instance, an alliance with *AskNet* expands the software startup *InterVideo*'s European market presence. This is valuable since few firms are capable of quickly penetrating all markets around the world (Robertson 1993).

The Negative Impact of Marketing Alliance Relationships

Despite the three above-mentioned benefits, MARs also expose young firms to high risks of equity relinquishment and lower their IPO value. Most MAR partners are established firms and are very likely to seek ownership of the products. Due to financial constraints, young firms may give up too much of the ownership when joining MARs (Aghion and Tirole 1994, Pfeffer and Salancik 1978). Here, much of the value created is appropriated by the established MAR partners rather than the young firms themselves, therefore negatively influencing young firms' financial value. As MAR centrality increases, the probability of such risks grows.

In sum, MAR centrality can have a mixed impact on startups' IPO value.

The Moderating Role of Marketing Know-how Absorptive Capacity

Previous literature discusses absorptive capacity almost exclusively in terms of absorbing R&D or technological know-how. I conceptualize the efficiency with which a firm absorbs *marketing* know-how, compared with the maximal amount of marketing know-how it could absorb given its marketing resources, as *marketing know-how absorptive capacity*. Marketing know-how absorptive capacity enhances the economy of scale by more efficiently combining and synthesizing resources form MARs to fit the young firm's own needs. This reinforces the positive impact of MAR social capital.

A young firm weak in marketing know-how absorptive capacity may over-rely on its partners' marketing support and fail to develop its own marketing capabilities, placing constraints on its further growth. In other words, they are subject to the "danger of dependence" (Miles, Preece, and Baetz 1999). This viewpoint was echoed by one of the investment bankers who pointed out that, "*Development of a unique marketing capability obviously has more value for a company than if it is dependent on someone else to market their offerings alone*." Strong absorptive capacity enables a young firm to grow marketing knowledge and build its own marketing capabilities. For example, if the software startup *BottomLine* could efficiently absorb marketing know-how from the consulting experience of its alliance partner *Arthur Andersen*, it can better understand the market trends, more effectively convey and deliver the consumer value. As an investment banker concluded," *Having your own marketing capability typically means you can capture more economics of a transaction*." It should be noted that capabilities built on tacit knowledge are unique and less imitable. They lead to competitive advantages and promote future marketing success, predicting high long-run cash inflows.

In sum, absorptive capacity alleviates the danger of dependence, and the enhanced positive impact of MAR social capital compensates for equity relinquishment risk. Formally,

H2*: The greater a young technology firm's marketing know-how absorptive capacity, the stronger the positive effect of marketing alliance relationship centrality on IPO value.*

The Positive Impact of Key Customer Relationships

Key customers are the business customers that contribute a significant portion of a young firm's sales. Social capital from key customer relationships (KCR) helps decrease cash outflows, as the growing mutual understanding, trust, and commitment continuously reduce transaction costs (e.g., Ganesan 1994). Firms with more KCRs are also likely to have more effective inventory and distribution management than firms with high customer turnover (e.g., Kalwani and Narayandas 1995). This lead to reduction in inventory costs and thus cash outflows.

Young firms' cash flow volatilities can also be lowered when they possess KCRs, which provide more stable cash flows as a result of smoother revenue streams (e.g., Tuli et al 2010) and less variant inventory and production costs. Customer loyalty constitutes a significant entry barrier to potential competitors and makes the firm's revenues less vulnerable (Srivastava et al 1998). As a young firm gets familiar with key customer's demand patterns, it can anticipate and make appropriate adjustments to its production cycle (Kalwani and Narayandas 1995). This can reduce the chances of high customer order demand coinciding with low firm inventory levels and vice-versa (Bharadwaj et al 2007). Hence, a firm with committed customers is likely to have less variable inventory costs. KCR social capital can also lower the variance of production costs. As a firm gains experience working with a customer, its better understanding of customer needs reduces the risks of being rejected for unsuitable offerings (Anderson, Fornell, and Lehmann 1994). In line with the logic of KCRs' reducing variance of cash flows, an interviewed investment banker opined that if a startup has an established relationship with a customer, "*you should apply a lower discount rate to these cash flows given that there is more certainty*".

KCR social capital also helps accelerate cash flows. Firms with KCRs can quickly detect and react to the changes in customer needs, thus reducing the NPD cycle. In addition, KCRs increase the likelihood and speed of customer adoption, reducing the market penetration cycle (Robertson 1993). Both effects accelerate cash flows (Srivastava et al 1998).

The Negative Impact of Key Customer Relationships

However, developing KCRs often requires substantial relationship-specific investments that may have little or no value outside the relationship (Heide and John 1990). This can limit the supplier firm's resources available to service other customers or explore other markets, thus placing constraint on the firm's sales growth or cash inflows. For example, Miles and Snow (1992) suggest that the focus on servicing a small number of customers could make a supplier less competitive in other markets. Similarly, others find that a tight coupling with customers can restrict a firm's vision and hurt its competitiveness in the long-run (Day 1999; Danneels 2003).

KCRs may also reduce the speed of converting sales revenue into cash flows, as young firms may not want to risk their relationships with key customers by imposing severe late-payment penalties (e.g., Summers and Wilson 2003).

Since key customers contribute a significant proportion of a firm's sales, the risks of credit concentration might raise investors' concerns of the firm's ability to collect future cash inflows (e.g., Pike and Cheng, 2001). Also, the significant customers can pose threat to a startup's survival and stability of cash flows if they ever switch. As one of the interviewed investment bankers stated, "*Relationship with customers are important, particularly if you have any customer concentration, which can act as a red flag to the investors that you are susceptible to losing a big chunk of your business or that they have negotiating power over you when it is time to renegotiate price, etc*."

In sum, the impact of KCR centrality on IPO value turns out inconclusive, with both the positive effects and negative effects considered.

The Moderating Role of Customer Know-how Absorptive Capacity

Customer know-how absorptive capacity refers to the efficiency of a firm in absorbing know-how about its key customers. Due to the learning effects that enhance relation-specific economies of scale, a firm with committed customer relationships can have increasing transaction volumes and lower costs over time (Johnson and Selnes 2004; Danneels 2003). If a firm can efficiently absorb customer know-how, it will further benefit from such learning effects and raise the level of cash flows. Knowledge about the key customers' specific needs enables a firm to develop products that provide a better fit than its competitors (Hoch and Deighton 1989). This helps develop the young firm's competitive advantages, and increases customers' dependence on the firm, resulting in a broader relationship scope and higher sales (O'Neal and Bertrand 1991).

As customers' dependence on the supplier firm increases, they have a higher motivation in maintaining the on-going relationships, and this could mitigate the potential credit risks and volatility of cash flows. In addition, suppler firms with high absorptive capacity can make more effective production adjustments that lead to even lower variance of production and inventory costs. Better and deeper customer knowledge also enhances innovation speed and customer adoption rate, and thus further shortens the NPD cycle and market penetration cycle, facilitating the speed of cash flows. In sum, customer know-how absorptive capacity reinforces the positive effects of KCR social capital on the level, speed, and volatility of cash flows. Consequently,

H3*: The greater a young technology firm's customer know-how absorptive capacity, the stronger the positive effect of key customer relationship centrality on the IPO value.*

DATA

I combine several secondary data sources in this study. I obtained a list of first-time-IPO firms in the computer industry (SIC 357) and the software industry (SIC 7371 and 7372) from 1996 through 2006 from Thomson Financial Global New Issue Database – excluding those whose IPO prospectuses cannot be located. Then I looked for and confirmed pre-IPO information about alliance type, alliance partners, and key customers for each company from SDC Platinum, IPO prospectus, Securities and Exchange Commission (SEC) 10-K filings, and FACTIVIA. I utilize the databases of National Bureau of Economic Research (NBER) and United States Patent and Trademark Office (USPTO) for patent, patent citations, and trademarks data. I collected IPO value, venture capital involvement, shares held by insiders, upper echelon information, as well as accounting data, from multiple sources: IPO prospectus, SDC, Thomson Financial, CRSP, COMPUSTAT, and SEC 10-K filings. I found the number of employees in R&D and Selling and Marketing from the "Employees" sections in IPO prospectuses and SEC 10-K filings. I obtained a final sample of 177 IPO firms, including 70 firms in the computer industry and 107 firms in the software industry, with an average age-at-IPO of 7.7 years. In addition to these IPO firms, I obtained information from Standard & Poor's NetAdvantage on 116 private companies in the computer and software sector that were founded in the same period as the sample firms but did not offer an IPO.

MEASURES

Dependent Variable – IPO Value (IPOV): I employ four alternate measures for IPOV. First, following Guo et al (2005), I calculated the *initial offer value* by multiplying the initial offer price (midpoint of the expected offer price range established by the underwriters filed with SEC) with the expected number of shares outstanding after IPO. Second, I obtained from the front page of IPO prospectus the *total price to public*, i.e. the product of price per share and number of shares to be offered. Third, since the finance literature points to the common phenomena of under-pricing in IPO, I also employ the firms' *market value at the end of the first trading day* and *at the end of the 90th day after IPO* in the robustness tests. These two values are calculated by multiplying the closing price with the number of shares outstanding on the relevant day.

R&D Alliance Relationship Centrality (RAR_Centrality): is a count of a young firm's partners in all the R&D alliances it participates in prior to IPO, i.e., I use the absolute local centrality (the number of links incident upon an actor), the same as the ego degree centrality in an ego network of RARs with the young firm as the ego (e.g., Everett and Borgatti 2005, Freeman 1982).

Marketing Alliance Relationship Centrality (MAR_Centrality): is a count of a firm's unique partners in all the alliances involving marketing activities (including co-branding alliances, joint-marketing alliances, channel-sharing alliances, etc.) the firm has participated prior to its IPO.

Key Customer Relationship Centrality (KCR_Centrality): is a count of significant customers[2], from which a firm has generated revenues for three consecutive years or longer and which were *not* reported as terminated in the IPO prospectus.

[2] Companies report "major customers" or "customer concentration" (e.g., individual customers that contribute to 10% or higher of the firm's annual revenues in the past years) in their IPO prospectus and statements of income. Companies also report the termination of major selling contracts or customer relationships in their SEC filings. I also searched the companies around their IPO dates in FACTIVIA to check news about termination of customer relations.

<u>*Absorptive Capacity*</u>: Absorptive capacity is the efficiency of absorbing know-how, given the amount of resources available. I now illustrate how to capture this efficiency with Figure 2. Based on the production frontier model in economics (e.g., Silberberg 1990), the maximal amount of know-how absorbable for firm *i* can be written as a function of the resources (Narasimhan et al 2006) the firm accesses:

(M-1) $y_{Mi} = f(X_i\text{: Resources}_i, \alpha)$
, where y_M is the maximal amount of know-how absorbable, X is a vector of resource inputs, and α is a vector of parameters for the resources.

For instance, in Figure 2-1, given the resource x_1, the maximal amount of know-how the firm could absorb is y_{M1}. The curve thus describes the frontier of the maximal know-how absorbable as the amount of resource changes.

However, firms often cannot reach the maximal level in the frontier. In other words, the actual amount of know-how absorbed is usually lower, say y_{A1}, due to random shocks out of a firm's control, such as luck or macroeconomic conditions. If the random shock is unfavorable to the firm, it can lower the amount of know-how the firm could absorb to the level of y_{O1}. Now, the difference between y_{O1} and y_{A1} can be considered the *inefficiency* of firm 1 in absorbing know-how. Putting it formally, the amount of R&D know-how a young firm actually absorbs is:

(M-2) $y_{Ai} = f(X_i\text{: Resources}_i, \alpha) \times \exp(\varepsilon_i) \times \exp(-\eta_i)$, where
y_A is the actual amount of know-how absorbed
ε is the random shock
η captures the inefficiency of absorbing know-how, $\eta \geq 0$.

Figure 2-2 illustrates the situation when random shock is favorable to a firm.

Since absorptive capacity is the *efficiency* of absorbing know-how, I can derive absorptive capacity measures based on the estimation of the inefficiency term η_i.

<u>*R&D Know-how Absorptive Capacity (RD_AC)*</u>: Assuming that both η and $\boldsymbol{\varepsilon}$ are stochastic, i.e., each is a random variable from a specific distribution function that is common across all firms, I now follow Narasimhan et al. (2006) and utilize stochastic frontier method to estimate RD_AC. Taking natural logarithm on both sides of (M-2), for firm *i* in each year *t* (t= 1, …, T_i) during the past T_i fiscal years before IPO,

(M-3) $ln(\text{RDKA}_{it}) = \alpha_0 + \alpha_1\, ln(\text{XRD}_{it}) + \alpha_2\, ln(\text{INV\_S}_{it}) + \alpha_3\, \text{MC}_{it} + \alpha_4\, \text{RAREX}_{it} + \varepsilon_{it} - \eta_{it}$

where,

RDKA = R&D Know-how Absorbed (following Narasimhan et al 2006, RDKA is measured as the number of patent classes drawn by a firm that do not overlap with the firm's original domain of expertise, i.e., the collection of total classes of patents it owns);
XRD = R&D expenditure;
INV_S = innovation stock (citation-weighted patent count);
MC = market conditions (dummy variables based on the four-digit SIC codes); and
RAREX = RAR experience (number of years since the firm formed its first RAR).

The factor η thus captures the inefficiency of know-how absorption. Assuming that $\varepsilon_i \sim N(0, \sigma_\varepsilon^2)$, $\eta_i \sim N(\mu, \sigma_\eta^2)$ with $\mu>0$, $E[\varepsilon_{it}\, \eta_{it}] = 0$, and that the error components are independently distributed of the predictors in Equation (M-3), I follow Battese and Coelli (1992) to obtain the maximum likelihood estimates of the parameters in M-3. The log-likelihood is

(M-4) $ln\mathbf{L} = -0.5\, (\sum^{N}_{i=1} T_i)\, [\ln(2\pi) + ln(\sigma^2_S)] - 0.5 \sum^{N}_{i=1}(T_i-1)\, ln(1-\gamma) - 0.5 \sum^{N}_{i=1} ln(1 + T_i\, \gamma) - N\, ln\{1- \Phi[-\mu / (\gamma\, \sigma^2_S)^{0.5}]\} - 0.5\, N\, \mu^2 / (\gamma\, \sigma^2_S) + \sum^{N}_{i=1} ln[1 - \Phi(-w_i^*)] + 0.5 \sum^{N}_{i=1} (w_i^*)^2 - 0.5 \sum^{N}_{i=1} \sum^{Ti}_{t=1} \{\xi_{it}^2 / [(1-\gamma)\, \sigma^2_S]\}$,

where

$\sigma^2_S = \sigma_\varepsilon^2 + \sigma_\eta^2$, $\gamma = \sigma_\eta^2/\sigma^2_S$,

$\xi_{it}=ln(\text{RDKA}_{it})-[\alpha_0+\alpha_1 ln(\text{XRD}_{it})+\alpha_2 ln(\text{INV\_S}_{it})+\alpha_3\text{MC}_{it} +\alpha_4\text{RAREX}_{it}]$,

$w_i^* = [\mu/(1-\gamma)- \gamma\sum^{Ti}_{t=1} \xi_{it}] / \{\gamma(1-\gamma)\sigma^2_S[1+ T_i\, \gamma]\}^{0.5}$, Φ is the C.D.F of normal distribution.

The parameters μ, σ_ε, and σ_η (mean of η_i, standard variance of ε_i and η_i) can then be estimated by maximizing the log likelihood above. Consistent estimates for η_i can be obtained from the mean of the conditional distribution $f(\eta|\xi)$, i.e.,

(M-5) $E(\eta_i|\xi_{it}) = M_i + D_i\{[\varphi(-M_i/D_i)] / [1-\Phi(-M_i/D_i)]\}$,

where $M_i = (\mu\sigma_\varepsilon^2 - \sum^{Ti}_{t=1}\xi_{it}\sigma_\eta^2) / (\sigma_\varepsilon^2 + \sum^{Ti}_{t=1}\sigma_\eta^2)$, and $D_i = (\sigma_\varepsilon^2\, \sigma_\eta^2) / (\sigma_\varepsilon^2 + \sum^{Ti}_{t=1}\sigma_\eta^2)$.

Finally, I rescale the estimation of η_i to be between 0 and 100 and measure R&D know-how absorptive capacity as RD_AC$_i$ = 100 - η_i* (the higher the inefficiency, the lower the absorptive capacity).

<u>Marketing Know-how Absorptive Capacity (MK_AC)</u>: While R&D activities create value by converting resources into innovations, marketing efforts help appropriate value from the marketplace by generating revenue (e.g., Mizik and Jacobson 2003). Accordingly, I use revenue to proxy the amount of marketing know-how absorbed by a startup. The shortfall between the actual revenue achieved and the optimal revenue the firm should have generated given the resources deployed reflects the firm's inefficiency in absorbing marketing know-how. The higher the MK_AC, the more efficient the firm is in deploying available inputs – including marketing expenditures, stock of marketing assets (e.g., brands and trademarks), and MAR experience – to achieve the desired outputs (e.g., Silberberg 1990). The rationale thus is to model the efficiency of a young technology firm's realization of its revenue potential, given the available marketing resources deployed. For firm *i* in year *t*,

(M-6) $ln(\mathrm{REV}_{it}) = \alpha_0 + \alpha_1 ln(\mathrm{REV}_{it-1}) + \alpha_2 ln(\mathrm{XSM}_{it}) + \alpha_3 ln(\mathrm{NTM}_{it}) + \alpha_4 ln(\mathrm{MC}_{it}) + \alpha_5 \mathrm{MAREX}_{it} + \varepsilon_{it} - \eta_{it}$

where, REV = sales revenue,
XSM = selling and marketing expenditure,
NTM = the number of trademarks,
MC = market conditions (the industry growth rate), and
MAREX = MAR experience (number of years since the firm formed its first MAR).

Then η_i* is estimated and rescaled following the same approach as above and marketing know-how absorptive capacity can be derived as: MK_AC$_i$ =100-η_i*.

<u>Customer Know-how Absorptive Capacity (C_AC)</u>: Similar to the measure of MK_AC, I assume that customer know-how absorbed is reflected in the sales revenue generated from the key customers. For firm *i* in year *t* with K_i key customers *k* (k = 1, 2, …, K_i;),

(M-7) $ln[(\sum^{Ki}_{k=1} REV_{i,k,t})/K_i] = \alpha_0 + \alpha_1 ln[(\sum^{Ki}_{k=1} REV_{i,k,t-1})/K_i] + \alpha_2 ln[(\sum^{Ki}_{k=1} AGE_{i,k,t}) /K_i] + \alpha_3 ln(PAT\_S_{it}) + \alpha_4 ln(SMEMP_{it}) + \alpha_5 ln([(\sum^{Ki}_{k=1} REC_{i,k,t-1})/K_i] + \varepsilon_{it} - \eta_{it}$
where,

$REV_{i,k,t}$ = firm *i*'s sales revenue generated from customer *k* in year *t* and $REV_{i,k,t-1}$ is firm *i*'s sales revenue generated from customer *k* in year *t*-1;
$AGE_{i,k,t}$ = the age of firm *i*'s relationship with customer k;
$SMEMP_{it}$ = firm *i*'s number of selling and marketing employees;
PAT_S_{it} = patent stock (count of the patents owned) to represent technological advantage; and
$REC_{i,k,t}$ = firm *i*'s account receivables to customer *k* in year *t* (receivables are interest-free loans to customers and can be considered as a firm's investment in the customer relationship).

Then η_{it}* is estimated and rescaled in the same way as above and customer know-how absorptive capacity is measured as $C\_AC_{it} = 100 - \eta_{it}$*.

Control Variables (Q): I include a set of control variables in the model. A comprehensive review by Certo, Holcomb, and Holmes (2009) categorized extant research on the topic of IPO performance into four themes: relationships with stakeholders, corporate governance, upper echelon, and innovation. This essay focuses on one type of stakeholder relationships, B2B relationship. I control for the impact of two other important stakeholders, venture capital (VC) and underwriter, both of which can signal issue quality and lead to favorable valuation of a firm (e.g., Ritter and Welch 2002, Fitza, Matusik,& Mosakowski 2009). Following the literature, I employ two alternative approaches to control for VC involvement: (1) VC backing dummy (VC_i = 1 if a firm has venture capital backing; 0 otherwise); (2) VC ownership (percentage of firm stock owned by VC) in robustness check. I adopted the Carter-Manaster ranking to control for underwriter reputation (e.g., Carter and Manaster 1990).

Second, I control for corporate governance structure with management stock incentives (the percentage of shares held by insiders after IPO) (e.g., Sanders and Boivie 2004). Third, I control for the experience of upper echelons, i.e., top managers and directors (e.g., Cohen and Dean 2005; Chen, Hambrick, and Pollock 2008; Kor and

Misangyi 2008). I measure upper echelon experience by the average managerial and board positions a firm's upper echelons had prior to joining the current firm. Fourth, I include R&D expenditures to control for firms' innovation spending (e.g., Aboody and Lev 2000). I also control for other accounting information, including cash flows from operations, ROA, and selling & marketing expenditures of the last fiscal year before IPO. Finally, IPO markets fluctuate with macroeconomic cycles. I include IPO year dummies to control for the financial market conditions at the time a firm goes IPO. I also use a dummy to control for the industry effect (0 to computer and 1 to software).

MODEL & ESTIMATION PROCEDURE

The basic regression equations explaining the IPO Value of firm *i* are:

(1) $ln(\text{IPOV}_i) = \beta_0 + \beta_1 \times ln(\text{RAR\_Centrality}_i) + \beta_2 \times ln(\text{MAR\_Centrality}_i) + \beta_3 \times ln(\text{KCR\_Centrality}_i) + \beta_4 \times \text{RD\_AC}_i + \beta_5 \times \text{MK\_AC}_i + \beta_6 \times \text{C\_AC}_i + \beta'_Q \times Q_i + e_i$

(2) $ln(\text{IPOV}_i) = \beta_0 + \beta_1 \times ln(\text{RAR\_Centrality}_i) + \beta_2 \times ln(\text{MAR\_Centrality}_i) + \beta_3 \times ln(\text{KCR\_Centrality}_i) + \beta_4 \times \text{RD\_AC}_i + \beta_5 \times \text{MK\_AC}_i + \beta_6 \times \text{C\_AC}_i + \beta_7 \times ln(\text{RAR\_Centrality}_i) \times \text{RD\_AC}_i + \beta_8 \times ln(\text{MAR\_Centrality}_i) \times \text{MK\_AC}_i + \beta_9 \times ln(\text{KCR\_Centrality}_i) \times \text{C\_AC}_i + \beta'_Q \times Q_i + e_i$

However, firms self-select whether to go public or stay private (e.g., Pagano et al 1998), and IPO value is only observable for firms that do go public. Following Shaver (1998), I control for the self-selection bias with the two-stage estimation approach suggested by Heckman (1979). A firm's choice to go public (i.e., IPO value is observed, or $\text{IPO}_i=1$) can be explained as a function of firm attributes and industry conditions, i.e.,

(3) $\text{IPO}_i^* = \gamma' W_i + u_i$, and $\text{IPO}_i=1$ if $\text{IPO}_i^* > 0$

Following Ritter and Welch (2002), Pagano et al (1998), and Gulati and Higgins (2003), I include the number of employees (to reflect firm size), revenue, geographical location, industry, and year of foundation in the W_i vector to explain the likelihood of going IPO.

Assuming u~N(0,1), e~N(0,σ), and corr(u,e)=ρ, and using X to denote the vector of all independent variables and control variables in Equation (1) or (2), one can get

(4) $E[ln(IPO_i)|\ \gamma'W_i + u_i > 0] = \beta'X_i + E[e_i|\ u_i > -\gamma'W_i] = \beta'X_i + \rho\sigma[\varphi(\gamma'W_i)/\Phi(\gamma'W_i)]$
, where φ and Φ are, respectively, the probability density function (PDF) and cumulative density function (CDF) of normal distribution.

Notably, the estimates of β will not have desirable statistical properties and conclusions can be misleading unless ρ=0 or the last term in Equation (4) is controlled for in the estimation (e.g., Shaver 1998). It is not likely that ρ=0 in this case because (1) firms do not randomly go public or stay private and (2) although I include many control variables, I can hardly include all determinants of IPO value to make e_i a random effect and uncorrelated to u_i. Consequently, I add one term, the inverse Mills Ratio $\lambda = \varphi(\gamma'W_i)/\Phi(\gamma'W_i)$ derived from the probit specification[3] in Equation (3), into Equation (1) and (2) to control for the selection bias, i.e.,

(5) $ln(IPOV_i) = \beta_0 + \beta_1 \times ln(RAR\_Centrality_i) + \beta_2 \times ln(MAR\_Centrality_i) + \beta_3 \times ln(KCR\_Centrality_i) + \beta_4 \times RD\_AC_i + \beta_5 \times MK\_AC_i + \beta_6 \times C\_AC_i + \beta'_Q \times Q_i + \beta_\lambda \lambda + e_i$,

(6) $ln(IPOV_i)=\beta_0 + \beta_1 \times ln(RAR\_Centrality_i) + \beta_2 \times ln(MAR\_Centrality_i) + \beta_3 \times ln(KCR\_Centrality_i)+\beta_4\times RD\_AC_i+\beta_5\times MK\_AC_i+\beta_6\times C\_AC_i+\beta_7\times ln(RAR\_Centrality_i)\times RD\_AC_i + \beta_8\times ln(MAR\_Centrality_i)\times MK\_AC_i + \beta_9\times ln(KCR\_Centrality_i)\times C\_AC_i + \beta'_Q\times Q_i + \beta_\lambda \lambda + e_i$.

Note that β_7, β_8, and β_9 are the major parameters of interest that test H1, H2 and H3, respectively, and β_1, β_2, and β_3 describe the main effects of the three types of B2B social capital.

RESULTS

Table 2 provides the descriptive statistics and correlation matrix of the variables in the main model. Although the difference between the initial offer value and total price to public indicates that original shareholders typically retain a large proportion of shares

[3] I employed robust variance estimator in Probit regression to correct for heteroscedasticity.

outs upon IPO (e.g., Busaba, Benveniste, and Guo 2001), these two measures are highly correlated (0.81). In line with the convention of IPO studies (Guo et al 2005), I scale the values by total assets to address skewness and control for heteroscedasticity, since other possible deflators such as sales, book value of equity, or earnings often take negative or zero values for young firms. R&D know-how absorptive capacity, marketing know-how absorptive capacity, and customer know-how absorptive capacity are derived from stochastic frontier estimations as specified.

Table 3 provides the results of the Heckman two-stage model. In the main-effect model (Model 1), the estimated coefficients for young firms' R&D alliance relationship (RAR) centrality and marketing alliance relationship (MAR) centrality are not significant. This suggests that social capital from horizontal alliance networks do not lead to high IPO value. However, the coefficient of key customer relationship (KCR) centrality is positive and significant ($\beta_3 = 0.20$, $p<0.10$ when IPO value is measured by the initial offer value; $\beta_3 = 0.31$, $p<0.05$ when IPO value is measured by the total price to public). Hence, despite the potential dark side, key customer relationships can be very beneficial to young firms.

Model 2 includes the moderating effects of absorptive capacity hypothesized in H1, H2, and H3. The model fit is significantly enhanced after adding the three interaction factors (in the initial offer value models: R^2 increases from 41.28% to 46.24%, F-test of the change in R^2: $F[3,147] = 4.52$, $p<0.01$; in the total price to public models: R^2 increases from 62.68% to 67.57%, F-test of the change in R^2: $F[3,147] = 7.39$, $p<0.01$). The estimated interaction effect between RAR centrality and R&D know-how absorptive capacity (RD_AC) is positive, but is only significant when IPO value is measured by the total price to public ($\beta_4 = 0.04$, $p<0.05$). The moderating effect of marketing know-how absorptive capacity (MK_AC) on MAR centrality is positive and significant in both cases ($\beta_5 = 0.07$, $p<0.05$ in initial offer value model; $\beta_5 = 0.06$, $p<0.01$ in total price to public model), supporting H2. This indicates that young firms need strong marketing know-how absorptive capacity to transform the social capital from MARs into IPO value. Similarly, as predicted in H3, customer know-how absorptive capacity (C_AC) significantly enhance the positive relationship between KCR centrality and IPO value ($\beta_6 = 0.31$, $p<0.01$ in initial offer value model; $\beta_6 = 0.19$, $p<0.01$ in total price to public model), suggesting that the benefits of KCRs are further enhanced for those firms that can more efficiently leverage their customer relationship resources and absorb customer know-how.

Consistent with the literature, I find a positive impact of VC involvement, underwriter ranking, and management stock incentives. The coefficient of the inverse Mills Ratio λ is not significant. The positive association between the year1999 and year 2000 dummies and IPO value might be attributable to the Dot-com bubble peaking around 1999 to 2000.

Robustness Check

I employed both alternative measures and alternative modeling approaches to confirm the robustness of the results.

Alternative Measures: First, I reran the model with market value at the end of 1^{st} trading day and the 90^{th} day after IPO, respectively, as the dependent variable. The signs and significances of the estimated coefficients (the first two columns of Table 4-1) remain the same as in the previous estimations, except that the coefficient for the interaction term MAR Centrality x MK_AC becomes insignificant in the model with 90-day value (possibly due to the new "news" released during the 90 day period post IPO). Second, I replaced the absolute degree centrality with weighted centrality to address the potential concern that partners of different sizes may contribute asymmetric amount of social capital. I weighted RAR Centrality by the R&D expenditures of RAR partners[4], MAR Centrality by the selling and marketing expenditures of MAR partners[5], and KCR Centrality by the shares of sales generated from key customers[6]. The results (the third column in Table 4-1) are consistent with Table 3. Third, I counted the number of significant customers from which the IPO firms have generated revenues consecutively for at least two years (instead of three years as I did before) and recalculated the KCR centrality. All the coefficients of interest remain consistent. Fourth, since joining alliances may influence the maximal amount of relevant know-how a firm could absorb, I added $\text{RAR\_Centrality}_{i,t}$ and $\text{MAR\_Centrality}_{i,t}$ to the right hand side of Equations (M-3) and (M-6), respectively, and re-estimated R&D know-how absorptive capacity and marketing know-how absorptive capacity. As reported in the fifth column of Table 4-1, the results using the new estimates of R&D and marketing know-how absorptive capacity remain consistent. Finally, I use VC ownership percentage to replace VC backing dummy

---

[4] $\text{Weighted-RAR-Centrality}_{i=1} = (\sum^{Ji}_{j=1} \text{XRD}_{i,j}) / \{[\sum^{I}_{i=1} (\sum^{Ji}_{j=1} \text{XRD}_{i,j})]/(\sum^{I}_{i=1}\text{J}_i)\}$, where; $i = 1, 2, \ldots, I$, and $I = 177$ is the number of sample firms; $j = 1, 2, \ldots, J_i$, and J_i is the number of firm i's RAR partners; $\text{XRD}_{i,j}$ is the R&D expenditure of firm i's Value-Creation Alliance partner j.

[5] $\text{Weighted-MAR-Centrality}_{i=1} = (\sum^{Ji}_{j=1} \text{XSM}_{i,j}) / \{[\sum^{I}_{i=1} (\sum^{Ji}_{j=1} \text{XSM}_{i,j})]/(\sum^{I}_{i=1}\text{J}_i)\}$, where $i = 1, 2, \ldots, I$, and $I = 177$ is the number of sample firms; $j = 1, 2, \ldots, J_i$, and J_i is the number of firm i's MAR partners; $\text{XSM}_{i,j}$ is the selling and marketing expenditure of firm i's Value-Appropriation Alliance partner j.

[6] $\text{Weighted-KCR-Centrality}_{i=1} = (\sum^{Ji}_{j=1} \text{SHARE}_{i,j}) / \{[\sum^{I}_{i=1} (\sum^{Ji}_{j=1} \text{SHARE}_{i,j})]/(\sum^{I}_{i=1}\text{J}_i)\}$, where $i = 1, \ldots, I$, and $I = 177$ is the number of sample firms; $j = 1, \ldots, J_i$, and J_i is the number of firm i's key customers; $\text{SHARE}_{i,j}$ is the percentage of firm i's sale to its key customer j per the firm's total sale.

as a control variable, and obtained consistent results. Overall, the results are robust across different measures of the key constructs.

Alternative Modeling Approaches: Firms may self-select to form B2B relationships, and better firms can be more likely to attract relationship partners. To control for this potential self-selection bias, I conducted a probit regression[7] to explain the likelihood for sample firms to form B2B relationships. I then added the inverse Mills ratio derived from this selection model in Equation (2) and reran the analysis (the lambda derived from the IPO-selection equation was no longer included since the error terms of the two selection equations can be correlated). The results are reported in the first column of Table 4-2, and are consistent with those in Table 3.

I also employed three Hierarchical Bayes Model (HBM) specifications to re-estimate the coefficients. HBM effectively estimates a different distribution of random effects for each group (e.g., industry) and separates the variance due to group-level differences from within-group variance (e.g., Raudenbush and Bryk 2002). In the first two HBMs, I either hold the coefficients of the relationship centrality variables constant or allow them to vary randomly. The results are reported in the second and third columns in Table 4-2. The signs and significances of the coefficients remain unchanged and consistent with the Heckman two-stage estimations.

To explore whether the impact of B2B relationships would vary under different market conditions, I incorporated the industry concentration ratio (IC, measured by the

---

[7] Following Stuart (1998) and Villalonga & McGahan (2005), I included sale (to control for firm size), R&D expenditures (R&D resources), selling & marketing expenditures (marketing resources), number of patents (technological base), number of trademarks (stock of marketing assets), ROA (current general accounting performance), and industry dummy to predict the likelihood of forming B2B relationships. The dependent variable in the probit regression equals one if the firm has formed at least one pre-IPO B2B relationship. I employed robust variance estimator to correct for heteroscedasticity. Inverse Mills ratio is calculated in the same way as in the approach to control for IPO-decision self-selection bias.

sum of market shares of the largest four companies) in explaining the industry-level variation. Specifically, I model $\beta_i = \gamma_{i0} + \gamma_{i1}(\mathrm{IC}) + \varsigma_i$, i = 1,2,3, in the level 2 of HBM. The results (reported in the fourth and fifth columns in Table 4-2) remain consistent. In addition, I find that industry concentration is positively associated with the coefficient of key customer relationship centrality ($\gamma_{31} = 0.21$, $p<0.05$). This indicates that KCR social capital can be more valuable in highly concentrated markets, where startups face strong competition from major incumbent firms. The coefficients γ_{11} and γ_{21} that explain the betas of RAR and MAR centrality are insignificant.

Finally, I use HBM to control for the potential firm age effects. Specifically, I classify the sample firms into three groups based on their tenure at IPO, i.e., firms of 1) two to five years old, 2) six to ten years old, and 3) eleven to fifteen years old. Treating age groups as the second level, I derived the HBM estimations by holding the coefficients of the B2B relationship variables constant or allowing them to vary randomly. This approach provides consistent results, as reported in the last two columns in Table 4-2.

DISCUSSION

Theoretical Contribution

A systematic review of prior literature indicates that B2B relationships can both benefit firm performance and pose potential risks, and the overall effect might be contingent. I examine the financial value of three types of B2B social capital, conditional on the relevant type of absorptive capacity, in the context of young IPO firms.

This study makes distinctive contributions to the marketing-finance interface literature and provides unique evidence to justify marketing’s financial accountability. First, I show that marketing efforts do pay off since they *both* (1) help build up valuable

B2B social capital (e.g., the significant main effect of KCRs), *and* (2) enhance the financial benefits of such social capital (e.g., the significant moderating effects of absorptive capacity). Second, this study is among the first to investigate the financial impact of marketing resources and capabilities in the *IPO market*. This unique perspective provides insights to marketing strategy and financial performance of startup companies, which have rarely been studied in the extant marketing-finance literature.

I also add to the prior literature that has attempted to explain the relationship between young firms' interfirm networks and financial performance. Uzzi (1999) investigates the impact of relationship embeddedness on startup borrowing (interest rates on loans). In comparison, I focus on another significant financing event, i.e., the IPO, and examine the factors that help increase the value potential of B2B relationships. This essay also resolves a conundrum that prior research in management has faced. Specifically, Gulati and Higgins (2003) find that, in spite of significant investments, the total number of strategic alliances does not have significant impact on biotech companies' IPO success. In contrast, I classify three types of B2B social capital and find that, though the main effects vary, their contingent relationships with relevant absorptive capacity have a positive impact on IPO value. The essay thus provides empirical evidence to the sociology theories about the financial potential of social capital. More importantly, I reveal the conditions under which such potential can be best realized.

The study enriches the marketing strategy literature by demonstrating the role of relevant absorptive capacity in B2B relationship management. In the process, it is one of the first studies to link absorptive capacity with B2B social capital and firm value. In contrast to previous absorptive capacity research that focuses primarily on R&D know-how, I expand this concept and unveil its importance in marketing alliance relationships and customer relationships.

Though extant research has recognized that customer relationships may pose mixed effects on firm performance (e.g., Danneels 2003), few studies have explicitly investigated the financial value of customers. On the other hand, the IPO literature has largely ignored customer relationships. I fill in the research gaps by demonstrating the impact of key customers on IPO value. I also contribute to the customer relationship management literature by highlighting the role of customer know-how absorptive capacity in realizing KCRs' financial potential.

Managerial Implications

The findings in this essay supplement the extant finance and management studies in IPO and provide meaningful guidelines for entrepreneurs, managers and investors.

First, although startup managers and investors have widely recognized the importance of B2B relationships, they know little about how much value these relationships. As an investment banker (I interviewed) said, "*In general, everyone understands there is a value to these relationships but what it is worth is a different matter*." In this study, I empirically demonstrated the financial value of three types of B2B relationships. The results reveal that R&D and marketing alliance relationships do not have significant main effects on IPO value, while key customer relationships do. Thus it pays off for young firms to invest in key customer relationships to enhance firm value. However, one should note that, the results do not necessarily indicate that key customer relationships are more important than other types of B2B relationships. The insignificant main effect coefficients of R&D alliance relationships and marketing alliance relationships might be due to the high uncertainty in R&D and marketing activities. In other words, it is difficult for investors to forecast the outcomes of forming R&D and marketing alliance relationships and estimate their influence on firm value. In comparison, it is relatively easier to assign values to key customer relationships, as the outcomes (e.g., sales revenue generated from key customers) are directly observable.

A critical observation for managers is that, getting into R&D and marketing alliance relationships without the absorptive capacity to leverage from them can harm a startup. Employing the Johnson-Neyman technique (see Hayes & Matthes 2009), I plotted the three interaction effects in Figure 3. The technique allows us to identify the statistical significance of the impact of each type of B2B relationships on IPO value at a given level of absorptive capacity. As shown in Figure3-1, R&D alliance relationships do not significantly impact IPO value for firms with high levels of absorptive capacity. In contrast, if firms have low absorptive capacity, the impact is negative and significant. This means that R&D alliance relationships can potentially harm firm value if firms lack absorptive capacity. I provided the rationale of this negative impact, as well as how absorptive capacity moderates this impact, in Table 1.

Figure 3-2 shows that, for young firms with relatively low (high) marketing know-how absorptive capacity, the negative (positive) impact of marketing alliance relationships on IPO value is statistically significant. Firms that have even moderate levels of marketing know-how absorptive capacity can better understand, evaluate, and assimilate the relevant marketing resources and capabilities of their partners. By complementing and supplementing their existing capabilities, such young firms are likely to design superior value propositions for their market.

The study is among the first to demonstrate the impact of key customer relationships on IPO value. This finding is especially important since accounting standards (FASB Statements 14 and 131) require the reporting of customers who contribute 10% or more of a firm's revenues, since it makes the firm vulnerable to customer switching. This study not only reinforces the importance of such reporting, but also points out that young firms with adequate levels of absorptive capacity can in fact benefit significantly from such customers (Figure 3-3). Young firms with adequate levels of customer related absorptive capacity are not only more sensitive to business opportunities in the customer firm, but are perhaps more proactive in exploiting them.

If firms do have the ability to leverage B2B relationships, it is important for them to signal these to the investors in order to capture a better IPO value. In fact, one of the investment managers who I interviewed suggested that firms must trumpet this ability along with the relationships during the road shows prior to IPO. He argued that this could better inform investors and "*one or two things may happen … (1) investors will qualitatively be more excited about the company's prospects which leads to bigger book (more demand for the stock) being built which will lead to the offering being priced at the high point of the range or (2) investors assess a lower discount rate to future projections which pumps up value*." This recommendation is also consistent with recent calls for including more marketing related information in external communication to the investment community.

My findings help CMOs and other marketing managers of startup firms better justify and communicate marketing's financial accountability to CEOs and other functional departments such as finance and accounting. This is especially meaningful in economic downturns when most firms face tight budgetary constraints. To obtain sufficient financial support to build and leverage B2B relationships, marketing managers have to demonstrate the value of the proposed marketing spending. Based on this study, they can link marketing investment with cash flow outcomes and prove that their efforts do not only build up valuable B2B social capital, but also help realize the social capital's financial value.

This study also helps institutional and individual investors better evaluate startups, and identify IPO investment opportunities that yield superior financial returns. For example, despite the concern about the risk of credit concentration, startups with more key customers generally have higher IPO value. Moreover, firms that can learn better are more valuable, and this essay's approach can help identify firms with higher absorptive capacity.

Limitations and Directions for Future Research

Although I employ multiple methods to enhance the robustness and rigorousness of the empirical analyses, I can only test association, instead of causation. However, the IPO value measure is forward-looking, while the exogenous variables in the model are contemporaneous or lagged. Thus the reverse direction of causation is less likely under this context. The systematic theory construction strongly supports the direction of the relationships hypothesized and tested.

I reveal the significant role of different types of absorptive capacity in B2B relationship management and financial market capitalization. It is thus important for future research to investigate the antecedents of the three types of absorptive capacity (or the η in each SFE) so as to provide more insights on how to develop the three types of absorptive capacity. In addition, future research could examine firms' effectiveness in applying and further enhancing its previously-developed absorptive capacity in newly-formed B2B relationships.

Mizik and Jacobson (2007) show that changes in marketing spending influence stock market returns following seasonal equity offering (SEO). It is reasonable to expect that marketing capabilities and B2B relationships can also impact SEO performance. Under this context, future research could explore the dynamics in the valuation process, i.e., how the value of startups changes when they acquire new resources and capabilities. Future studies can also develop richer measures of B2B social capital. For example, one could expand the scope of the network beyond local or ego network. In addition to network structures, strength of ties can be examined. Based on the results, firms not only need the opportunity to access social capital, but also the ability to leverage its social capital. Therefore, it is even more important to understand how to manage social capital and realize its value potential, than merely look at the nature of B2B network resources. A comparison between the firm value drivers for startups and those for established firms would also be meaningful.

ESSAY 2: Linking B2B Network with C2C Word-of-Mouth Evolution to Explain New Product Success: A Functional Analysis

INTRODUCTION

Recently, customer-generated media and conversations in Customer-to-Customer (C2C) networks, especially online Word-of-Mouth (WoM), have attracted significant attention among both marketing scholars and practitioners. Illustrative of this interest is the conference on user-generated content (UGC) recently hosted by the Marketing Science Institute in conjunction with the Wharton School. A growing body of academic research illustrates the usefulness of online WoM data and shows that C2C WoM can have significant impact on product sales (e.g., Godes and Mayzlin 2004, Chevalier and Mayzlin 2006). This stream of research focuses on either volume or valence of post launch WoM. Although some studies have explored the role of pre-release WoM in the new product context, they have limited their attention to accumulated or average WoM (e.g., Liu 2006, Elberse and Eliashberg 2003). In contrast, this study examines the pattern of WoM evolution during the pre-release period. In addition to WoM volume, I also examine the impact of velocity, i.e., the rate of growth in WoM. Dynamics and evolution patterns of pre-release C2C WoM can significantly influence consumer information processing, and thus alter purchase decisions (e.g., Chiodo et al 2004).

The marketing literature has demonstrated the key role of Business-to-Business (B2B) relationships and B2B network on new product success (e.g., Rindfleisch and Moorman 2001, Rothaermel and Deeds 2004). B2B networks have also been recognized as an important market-based asset (e.g., Srivastava, Shervani, and Fahey 1998). An important reason is that B2B partners bring together their own installed bases and foster a larger potential customer base. Therefore, it can be expected that B2B network can influence new product success partially because of the C2C network dynamics in the broader customer base. However, despite extensive research in each of the two streams of literature on C2C and B2B networks, few studies have linked the two networks together in the new product context. The linkage is important since, as will be shown in this essay, it can provide unique and deeper insights as to why and how each type of network influences new product performance. Against this backdrop, a key objective of this study is to investigate the effect of B2B network characteristics on C2C WoM.

Drawing on consumer behavior and sociology theories, I develop hypotheses on (1) the influence of B2B networks on C2C WoM evolution pattern, and (2) the impact of C2C WoM evolution pattern on new product sales and firm value created upon the product introduction. I utilize a data set from the video game industry to empirically test the hypotheses with the functional data analysis methodology. The method allows to not only to recover the underlying WoM evolution, but also to examine the antecedents and consequences of the WoM level and velocity across the pre-release period. I focus on video game industry for the following three reasons. First, video games are products of intangible or experiential nature. Thus it is difficult to judge the game quality before actually playing it. Consequently, voice and opinions from peers can be very influential. Moreover, for such goods, C2C buzz is considered more trustworthy and informative than advertising (e.g., Liu 2006). Second, new product introductions in the video game industry frequently involve cooperation between publishers and developers, providing an ideal context to investigate B2B network. Third, video gamers are extremely active in online communities, and make a significant proportion of their communications online. The abundant online WOM information enables a close look at the C2C buzz evolution.

THEORETICAL BACKGROUND

B2B network and new product performance

The marketing strategy literature has widely acknowledged the importance of Business-to-Business (B2B) relationships in new product success (e.g., Sivadas and Dwyer 2000). Vertical relationships with both buyers and suppliers can influence new product development, introduction, and diffusion (e.g., Wilson 1995, Ragatz, Handfield, and Scannell 1997). Similarly, a number of studies have also demonstrated the role of horizontal relationships such as alliances on product innovation and market performance (e.g., Rindfleisch and Moorman 2001, Rothaermel and Deeds 2004).

Scholars have also examined the impact of B2B relationships from a network perspective. For example, Sorenson and Waguespack (2006) demonstrate the effect of B2B network structure by showing that deep inter-firm ties (large number of previous direct ties) can lead to over-allocating resources to certain parties and may not increase new product sales. The theoretical rationale of these existing studies is typically based on sharing of knowledge, complementary capabilities, economy of scale and scope, as well as resource allocations in B2B relationships and their effects on new product success.

The concept of strength-of-ties has attracted major attention since repeated partnership is a widely common phenomenon in B2B relationships (e.g., Uzzi 1996; Tuli, Bharadwaj and Kohli 2010). Literature has shown that repeated partnership can significantly influence product and firm performance (e.g., Rowley, Behrens, and

Krackhardt 2000; Wuyts, Dutta, and Stremersch 2004). However, the impact of strength-of-ties is complex and the debate on embedded exchange still exists. For example, while strong ties may reduce transaction costs and opportunistic behavior (Granovetter 1985), they may also lead to misallocation of scarce resources (Halpern 1997). As a result, it appears meaningful to further explore other mechanisms under which strength-of-ties influences performance outcomes. This study contributes to this stream of research by providing unique insights into effects of the strength of B2B ties.

B2B relationships can also constitute valuable market-based assets (Srivastava, Shervani, and Fahey 1998). One important reason is that multiple business partners can bring together a broader customer base (Bucklin and Sengupta 1993). Therefore, the B2B network's impact on new product performance can come from the effects of the customer base fostered by this B2B network. However, the linkage between B2B network characteristics and C2C network dynamics has rarely been studied.

C2C WoM and new product performance

Online C2C word-of-mouth (WOM) has recently attracted growing attention among marketing practitioners and scholars. The literature shows that WoM can have a significant impact on product sales (for both mature products and newly introduced products). For instance, according to a McKinsey & Company report, sixty-seven percent of consumer goods purchases are made based on WOM (Taylor 2003). Godes and Mayzlin (2004) find that WoM can play an important role in determining product success, and online conversations provide an effective way to study WoM. Chevalier and Mayzlin (2006) demonstrate the effect of book reviews on consumer purchase behavior and find that relative sales ranks across two online retailers can be explained by differences in WoM. Another study with book reviews data shows that the growing volume of online WoM may lead the ratings to decrease in ordinality (Godes and Silva 2006). Godes and Mayzlin (2008) conducted field studies and laboratory experiments to investigate when WoM influences sales and who are the most effective WoM creators, with a focus on the factors within the C2C network. Although it has been recommended that firms get involved in WoM management (Dwyer 2009) and practitioners appear to have the intention to build and influence C2C WoM (King 2003), little is known about the impact of firm-level characteristics and efforts on WoM.

Many studies investigating the impact of online WoM on *new* product performance are conducted in the context of entertainment goods. Using movie data, Liu (2006) shows that online reviews add power in explaining box office revenue. Moreover, he finds that WOM volume, rather than WOM valence (or sentiments), contributes to most of the explanatory power increase. Dellarocas, Zhang and Awad (2008) find that adding movie review information increases sales forecasting accuracy. However, the utilization of accumulated or average WoM measures in these studies cannot capture the dynamics of patterns of C2C WoM evolution, which can significantly alter consumers' information updating processes and purchase decisions (e.g., Chiodo et al 2004).

Although little evidence has been provided about the impact of C2C buzz on financial value, Luo (2007) suggests that investors do pay attention to customers' voices due to the existence of various media.

HYPOTHESIS DEVELOPMENT

One important benefit of B2B relationships to new product performance is that business partners in collaboration bring together their own customer bases (e.g., Srivastava, Shervani, and Fahey 1998). In other words, new product projects involving a larger number of participating partners (e.g., developers for video games, actors and directors for movies) can have a larger potential customer base. The larger the number of potential customers, the higher volume of C2C conversations can be generated. Hence,

H1: There is a positive association between the size of B2B network and the volume of pre-release C2C WoM.

However, if the business partners involved in this new product have strong ties among each other (e.g., they have a high level of repeated partnering in previous new product projects), their customer bases are likely to have a significant level of overlap, and thus can reduce the positive impact of B2B network size on C2C WoM volume.

H2: The strength of ties among B2B partners mitigates the positive association between the size of B2B network and the volume of pre-release C2C WoM.

Given a fixed amount of WoM (e.g., blog postings), the more customers read the blogs, the stronger the impact of WoM on customer purchases. Stronger B2B ties are likely to predict higher C2C network density, which can augment the impact of WoM. For example, Figure 1 compares the situations of weak B2B ties versus strong B2B ties. Both business partners have their own established customer bases, constituting the potential customer base for an upcoming new product introduced by the two firms.

When B2B ties are weak, as in Figure 4a, only a small proportion of their associated customer bases overlap. In this case, customers A, C, and D belong to firm 1's customer base; customers B, D, and E are in customer base 2; and customer D is a potential customer of both firms. While customer C reads A's blog often, E subscribes to B's blog. In the overlapped area, customer D is a subscriber to blogs of both A and B, since s/he likes the brands of both firm 1 and 2.

Given the same number of customers, the density of the C2C network can be increased when B2B ties become strong. In Figure 4b, as the overlapping customer base is enlarged, new C2C ties (AE and BC) are created and the blog postings are exposed to more customers more quickly[8]. Therefore, when B2B strength-of-tie grows, the impact of WOM becomes stronger.

H3: The strength of ties among B2B partners enhances the impact of pre-release C2C WoM on sales.

The B2B partners bring up a portfolio of different customer bases. Variations across these customer bases (e.g., differences in demographic factors and preferences) can predict diversified customer opinions about a same product or product feature. High variance in the valence of C2C WoM can reduce the impact of WoM volume on sales, since the effects of positive and negative sentiments wash each other out. Therefore,

H4: The size of B2B network mitigates the impact of pre-release C2C WoM on sales.

---

[8] Let n_{12} be the number of potential customers in the overlapped area, n_1 (n_2) be the number of potential customers in the non-overlapped area in customer base 1 (2). Keep the total number of potential customers $n = n_1 + n_2 + n_{12}$ as a fixed number. Let P denote the proportion of potential customers that publish blog postings, and R denote the proportion of potential customers that read blog postings. For simplicity in illustration, assume $n_1 = n_2 = (n - n_{12})/2$. Hence, the number of C2C ties connected to blog posters in the overlapped area is $(n_{12}P)\times(nR)$, and the number of C2C ties connected to blog posters in the non-overlapped area is $(n_1P)\times(n_1R + n_{12}R) + (n_2P)\times(n_2R + n_{12}R)$. Let $n_{12} = \theta n$, the total number of C2C ties is thus $(n_{12}P)\times(nR) + (n_1P)\times(n_1R + n_{12}R) + (n_2P)\times(n_2R + n_{12}R) = n^2PR[1 - (1 - \theta)^2/2]$. Therefore, given the total number of potential customers fixed, as the proportion of overlap θ increases, the total number of C2C ties increases.

C2C WoM builds awareness among potential consumers, which can lead to high sales (e.g., Liu 2006). In addition to this awareness effect, I expect that C2C WoM volume can influence sales performance through an organizational learning process. If the producers or distributors hear a sufficient amount of C2C WoM in the earlier stage of the pre-release period, they can have sufficient time to incorporate the insight from C2C WoM into the product design and promotion plans, thus leading to high quality of the new product and thus high level of overall sales (Vincent and Bharadwaj 2009; Dwyer 2009). In addition, early C2C WoM can have a significant impact on sales due to the novelty effect. For example, the first blogs posted about a new product can be more influential than later postings containing similar information. In comparison, C2C WoM closer to the release day might have strong influence on sales due to recency effects, since purchase decisions can be made shortly after being exposed to relevant WoM. However, close-to-release WoM may only be relevant to the opening sales because of the large amount of customer attention, but less likely to influence quality and long-term sales since there is little time for a firm to modify the product offering based on these customer voices right before release.

H5: The level of C2C WoM earlier in the pre-release period is positively associated with the quality of the new product.

H6: The level of C2C WoM earlier in the pre-release period is positively associated with overall sales of the new product.

H7: The level of C2C WoM later in the pre-release period is positively associated with opening sales of the new product.

Classic economic models assume that consumers make purchase decisions based on expected utility. In the simplest case, suppose a video game purchase only leads to two possible outcomes for a potential customer: a fun game with utility U_1 and a boring game with utility U_2. If the corresponding possibility of each outcome is p_1 and p_2 respectively, the expected utility for this potential customer is $EU = p_1U_1 + p_2U_2$. As time goes by during the pre-release period, the customer keep updating her information set as new information becomes available. As a result, p_1 and p_2 keep changing to be consistent with the updated information set. The customer will purchase the game if EU>0 at a point of time after the release of the new game.

However, psychologists have suggested that, individuals sometimes neglect available information, i.e., they do not always update their information set (e.g., Chiodo 2004). Therefore, when a potential customer sees new blog postings about an upcoming new game, his/her expected probabilities (p_1 and p_2) of possible outcomes may not be updated, and thus his purchase decisions may not be influenced by these blog postings. However, if the customer is frequently exposed to blog postings about this new product, the odds that she considers such C2C WoM in updating her information set will increase. And once the customer updates her information set with C2C WoM for the first time, she is more likely to update her information set again when exposed to such buzz the next time. This, according to the psychological literature, is called the *rehearsal effect* (Mullainathan 2002). Rehearsal effect predicts that, a steady growth in the C2C WoM volume will enhance the chance of a potential customer to update her information set based on C2C WoM. Compared to a sudden takeoff closer to release day, C2C WoM with a steadily growing evolution pattern can have a higher impact on customer purchase decision. In this sense, positive velocity throughout the pre-release period should enhance new product performance.

H8: The velocity of C2C WoM is positively associated with overall sales of the new product.

Sorescu, Shankar, and Kushwaha (2007) find that pre-release information on forthcoming new products could significantly influence shareholder value of technology firms. In the video game industry, game developers are usually called upon by publishers to develop new products, and the publishers make periodical payments across the product development phases to the developers based on their progress. Accordingly, to investigate the firm value implications, I will focus on the stock market performance for the publishers, who assume most of the risks and gain most of the profits.

According to the efficient market hypothesis, the stock market should reflect all publicly available information. If the information is perfectly symmetric, a firm's stock price should already reflect all the information about the new product before the release date. In this case, there should not be significant abnormal stock returns (gains or losses) on the day of new product release for a firm. The less is known about the new product in the pre-release period, the more significant the abnormal stock returns could be on the release day. The higher the level of C2C WoM is, the more publicly available information or the lower level of information asymmetry there is before release. Thus high level of pre-release C2C WoM can be associated with low level of abnormal stock gains or stock losses on the release day.

H9: The level of pre-release C2C WoM is negatively associated with the level of change in firm value on the release day.

METHODOLOGY

Functional Data Analysis

The data consist of a sequence of online C2C WoM volume on a daily basis over time for each new product. Due to random influences and recording errors, it is often difficult to observe how WoM evolves by directly plotting the daily records over time. It is reasonable to assume that the daily values reflect a smooth variation in WoM, due to the continuous development in the potential customer base and the continuous diffusion of new information about the upcoming product. In other words, I have a WoM evolution function for each new product. By analyzing curves rather than points (Ramsay and Silverman 1997), functional data analysis (FDA) method effectively incorporates WoM records across the whole pre-release period and recovers the underlying pattern of pre-release WoM evolution. FDA does not merely incorporate more information than other time-series models which includes only a limited number of lagged observations, but also makes it possible to conveniently examine the derivatives of the functions, e.g., the velocity (first order derivative) and acceleration (second order derivative) (e.g., Reddy and Dass 2006). This allows me to study the rate of growth in WoM, whose impact is highlighted in the hypotheses.

As will be seen in the later part of the essay, the smooth splines show that, for each product, WoM dynamics change significantly across the per-release period. However, WoM growth differs from product to product in terms of both timing and intensity. Treating C2C WoM evolution curves as functional variables, functional regression analysis is ideal to explain such heterogeneity, since it can provide insights as of the impact of predictor variables on WoM across various stages during the pre-release period. It can also use the heterogeneity in WoM evolution curves to explain differences in new product performance, by demonstrating the asymmetric impact of WoM at time 1 (say early) versus time 2 (say late) on new product outcomes. I then employ functional regression analysis treating to test the hypotheses and examine how C2C WoM is affected by B2B network characteristics at various stages across the pre-release period, as well as how the dynamics of C2C WoM at different pre-release stages influence new product and firm performance. In addition to using the functional nature of the WoM evolution curves, the functional modeling approach, as a non-parametric method, assumes only smoothness but not the parameter distribution specifications. This permits as much flexibility as required by the data in the estimation process. In comparison, parametric models are typically restricted by a fixed and small number of parameters that follow "textbook density functions", while possibly none of these specifications can capture how the data actually behaves (Ramsay and Silverman 2005). The major weakness of non-parametric models is the high variability in the estimates accompanied with the enhanced flexibility. In this study, however, the problem is mitigated by using a large number (over 300) curves that add strength to the regression (e.g., Sood, James, and Tellis, 2008).

To employ FDA, I first use a flexible smoothing *spline* technique to recover the underlying pre-release C2C WoM evolution curve for each new product. I then use covariates of B2B network characteristics to explain the heterogeneity in these pre-release C2C WoM evolution paths. Finally, I use the C2C WoM paths to explain the new product performance metrics (i.e., sales and firms' abnormal stock returns).

Recovering C2C WoM evolution Curves

The data record WoM volume for each new product in the 120 days prior to its release. The 120-day window is reasonable to represent the pre-release period, since the average length of time between new product (video game) announcement and product release is around four months in the sample. Let t_i be the ith day in the pre-release period, $i = 1, 2, \ldots, n$ (n=120), $z^{(j)}_i$ denote the volume of C2C WoM at time t_i for product j ($j = 1, \ldots, N$), and $z^{(j)} = (z^{(j)}_1, z^{(j)}_2, \ldots, z^{(j)}_n)$ representing the vector of WoM series for each new product j. I now utilize penalized smoothing splines (Ramsay and Silverman 1997) to recover the underlying C2C WoM evolution curves. Smoothing splines do not only provide overall smoothness, but also readily yield different derivatives of the evolution curve. The goal is to identify a function $f^{(j)}$ to minimize the penalized residual sum of squares (e.g., Reddy and Dass 2007)

$$\mathrm{PENSS}^{(j)}_{\lambda,m} = \sum\nolimits^{n}_{i=1}(z^{(j)}_i - f^{(j)}(t_i))^2 + \lambda\int[D^m f(t)]^2\,dt, \tag{1}$$

where the smoothing parameter λ provides the tradeoff between fit $[(z^{(j)}_i - f^{(j)}(t_i))^2]$ and variability of the function (roughness) as measured by $\int[D^m f(t)]^2\,dt$,[9] and $D^m f$, $m = 1, 2, 3, \ldots$, is the mth derivative of the function f.

I then estimate a smoothing spline $f_j(t)$ for each new product j. The derivatives of the C2C WoM evolution curves derived from these smoothing splines provide a detailed look at the underlying dynamics, such as velocity [first derivative $f_j'(t)$] and acceleration [second derivative $f_j''(t)$].

---

[9] The smoothing parameter λ is chosen by cross-validation. I then use the values of λ and p that generate the smallest root mean squared error to recover the buzz curves. For details about the cross-validation procedure, refer to Ramsay and Silverman (2005).

Functional Regression

Finally, I conduct two functional regression analyses to test the hypotheses. First, I use B2B network characteristics (scalar covariates) to explain the heterogeneity in the C2C WoM paths (functional responses). In this process, I control for the effects of game platform versions, publisher experience, online advertising expenditure, other advertising expenditures, and whether the game is based on a movie or belong to a sequel. Details of these variables can be found in the "Variables and Measures" section.

Second, the functional variables of C2C buzz evolution are used as independent variables (functional covariate) to explain the variations in new product sales and changes in firm value (scalar response). To test H3 and H4, I group the sample products based on the week of release and create a two-level data structure (individual products as level 1 and weekly groups as level 2). H3 and H4 are then tested by explaining the coefficient of WoM with the B2B strength-of-ties and B2B network size, respectively, averaged on level 2. The effects of price, total advertising expenditure, and genre are controlled for in the model. Details of these variables are in the "Variables and Measures" section.

DATA AND EMPIRICAL CONTEXT

I test the hypotheses in the entertainment goods context of the video game industry. The video game industry is especially active in new product introductions. According to gamespot.com, there are 26 new game releases in the week of July 12 alone. Since new products proliferate rapidly in this industry, stakeholders pay significant amount of attention to upcoming new products and thus information about these products matters to stock prices (e.g., Sorescu et al 2007). Moreover, as suggested by previous literature, C2C WoM can be more persuasive than traditional media for entertainment goods given their intangible and experiential nature (e.g., Godes and Mayzlin 2004). There is also evidence that B2B network can have a strong influence on C2C network buzz. For instance, the video game firm Capcom has 10,888 followers on Twitter as for July 15, 2009, while the video game firm EA has 24,743 followers. If these two firms collaborate on a new game project, these followers will form a large potential customer base and are likely to generate a significant amount of C2C conversations.

The online C2C WoM volume dynamics data are obtained from a market research company that tracks the number of blog and forum postings on the world-wide-web (www) on a daily basis for each new video game. Since the information in blog and forum postings is publicly available and accessible to potentially all web browsers, online C2C WoM could be a major influencer of actual sales and firm performance. Illustrative of blog postings is a posting on June 30, 2009 on bluehawkgamez.blogspot.com about the new Wii game Klonoa. This game was also discussed on the online forum www.crunchgear.com on July 06, 2009. The data includes a random sample of 309 new game releases in 2009. The sub-sample to test H9 includes 80 products, since only a proportion of video game publishers are publicly listed in the US stock market. The daily volume of blog postings about each game is recorded during the 120 days prior to game release day. Product details, such as rate, genre, price, release date, professional rating, publisher and developer information, are collected and confirmed across major video game websites such as VGChartz, IGN, and Gamespot. Weekly sales data of each video game product is obtained from VGChartz. Advertising expenditures are collected from

TNS Ad$pender. Stock market information including stock prices for publisher firms is obtained from the Center for Research in Security Prices (CRSP) and Yahoo Finance.

VARIABLES AND MEASURES

Strength-of-ties in the B2B network: Following Sorenson and Waguespack (2006), I measure the B2B strength-of-ties with the proportion of a firm's (publisher or developer) new product (game) projects in the past ten years with the same partner firm (publisher or developer) as the current one.

Size of the B2B network: count of firms (publishers and developers) to introduce a new product.

C2C WoM: the volume of customer-generated online WoM recorded on a daily basis over the pre-release period. According to Godes and Mayzlin (2008, 2004), using online WoM is an effective way to study C2C WoM. Online WoM is especially suitable for this research since one major communication platform for video game players is online communities and blogs. As shown by Liu (2006), it is the volume rather than the valence that adds most power in explaining new product sales. I thus mainly focus on the volume of C2C WoM (the number of blog and forum postings). Another reason to focus on volume rather than valence in this study is, before product release, there is little information to judge the product or generate sentiments.

Opening sales: units of a new product sold in the first week after release.

Overall sales: units of a new product sold in the 10 weeks after release.

Quality: average score (0 to 10) of the average press/professional reviews.

<u>Change in firm value on the day of product release:</u> the absolute value of change in firm's net present value (NPV). Change in NPV is calculated as the product of firm market capitalization (21 days before new product release) and abnormal stock returns on the new product release day (Chan et al 1997). Abnormal stock return is the difference between the actual stock returns and the expected returns (i.e., stock returns that would have realized if the product had not been released on this day). Expressed in an equation: $AR_{km} = R_{km} - E[R_{km}|I_{km}]$, where AR_{km} is the abnormal return to publisher k upon the introduction of product m, R is the actual stock return, E[R|I] is the expected return given the information set I on the day before release, and E[R|I] is calculated based on the capital asset pricing model (CAPM). I use NPV change instead of abnormal returns to capture the change in firm value, since large firms' stock prices are not likely to fluctuate as much as small firms (Anand and Khanna 2000).

<u>Control variables:</u> (1) Game platform version dummy: the sample products include games for Xbox 360, Wii, PS3, PS2, PSP, and DS. I thus created five (0,1) dummy variables for Wii, PS3, PS2, PSP, and DS, respectively. (2) Publisher's experience: number of games published by a sample game's publisher ten years prior to the new game release date; (3) Online advertising expenditures: spending on internet advertising prior to new game release. (4) Other advertising expenditures: total spending in the other advertising channels than the internet (including TV, magazine, newspaper, radio, and outdoor) prior to the new game release. (6) Total advertising expenditures: total spending in advertising before and within two months after product release. (7) Movie-based dummy: variable with values of 0 or 1 indicating if the game story is based on a movie; (8) Sequel dummy: variable with values of 0 or 1 indicating if the game belongs to a sequel; (9) Price: MSRP

of each game; (10) Genre dummy: the sample products include games of the following genres: Action, Adventure, Fighter, FPS, Platform, Puzzle, Racer, RPG, Shooter, Sim, Sports, Strategy, and Other. Twelve dummy variables were created for all genres except "Other".

RESULTS

Figure 5 shows the plots of the smoothing splines of C2C WoM volume (after taken natural logarithm) and its velocity (first order derivative) for all the 309 sample products. In the X axis, day 120 is the day before new product release, and day 1 is the first day in the pre-release period. Based on the plots, there is significant heterogeneity in WoM evolution dynamics across products. The velocity plot shows that WoM volume changes the most close to the release date.

To explain the heterogeneity in WoM evolution patterns across products, I conducted a functional regression analysis with B2B network characteristics and a set of control variables as predictors. The results can be seen in Figure 6. The solid lines are the plots of the estimated coefficients across time in the pre-release period, and the dashed lines (plus or minus two standard errors) give out the confidence intervals. As shown in Figure 6a, the size of B2B network is positively associated with C2C WoM volume. The effects are not statistically significant in the first 15 days but become significant after that throughout the pre-release period. This is in support of H1. H2 hypothesizes that B2B strength-of-ties negatively moderate the association between B2B network size and C2C WoM. This hypothesis is supported by Figure 6b. As can be seen, the effects are statistically significant after around day 20. Figure 7 shows the coefficient plots of some control variables that exhibit significant impact on pre-release WoM. As can be seen, internet advertising is positively associated with C2C WoM volume. Other things being equal, PS3 games tend to have higher WoM volume than Xbox 360, while other platform versions do not.

The second functional regression model examines the impact of WoM evolution pattern on sales. The results of WoM's main effects are reported in Figure 8. Figure 8a shows the coefficient curve of WoM evolution when opening sales (sales in the first week after release) as dependent variable. The coefficient is not statistically significant throughout most of the pre-release period, other than in the very beginning. Similar results can be seen in Figure 8b when using total sales as dependent variable. Figure 8c plots the impact of WoM velocity on overall sales. The coefficient is significant for multiple time intervals in the earlier part of the pre-release period. Therefore, H8 is partially supported.

H5 and H9 hypothesize about WoM's effects on product quality and change in firm value upon release. As can be seen in Figure 9a, the impact of WoM on product quality is not statistically significant for the current sample of products. As predicted in H9, high volume of WoM reduces information asymmetry and thus firm value change on the day of new product release. Figure 9b shows that the impact is significant shortly before the new product release date, thus supporting H9.

To examine how B2B network characteristics influence the impact of WoM evolution on sales, I conducted functional regressions with the impact of WoM conditional on B2B strength-of-ties and network size. In Figure 10a, the impact of B2B strength-of-ties is not statistically significant. However, in support of H4, the impact of B2B network size is significant at both the beginning and the ending stages of the pre-release period.

DISCUSSION

Theoretical Contributions

Instead of focusing on the cumulative or averaged C2C WoM measures, this study examines the impact of C2C WoM evolution pattern. Using functional data analysis method, I not only described how WoM evolves over time prior to new product release, but also revealed the asymmetric impact of WoM dynamics at different stages during the pre-release period. For example, the results show that WoM in the earlier stage of the pre-release period may have a stronger impact on new product sales. Moreover, the study is among the first to examine the velocity in C2C WoM evolution, and demonstrated its impact on product sales. In this process, the study also contributes to the marketing strategy literature by highlighting an important predictor of new product performance, i.e., C2C WoM evolution pattern, especially velocity.

By linking B2B network characteristics and C2C WoM evolution, this study provides unique insights on (1) the antecedents of C2C WoM, and (2) how B2B network influences product performance. Employing the key constructs in the social network literature, this study demonstrated the significant impact of both B2B network size and B2B strength-of-ties on C2C WoM evolution pattern. While the literature has recognized the significant impact of B2B network on new product performance, the study provides novel findings which indicate that this impact can at least be partially attributed to the influence of B2B network on C2C dynamics in the associated customer bases.

The study also enriches the marketing-finance interface literature by demonstrating the impact of C2C WoM on firm value change upon new product release.

Managerial Implications

Though it appears that practitioners have the intention to build and influence C2C WoM (King 2003), little is known about the impact of firm-level characteristics and efforts on WoM. This study shows that firm's B2B network involvement can influence both the dynamics in C2C WoM and the impact of C2C WoM on product performance. For example, results show that while B2B network size may increase the amount of C2C WoM generated, it can at the same time reduce the effectiveness of WoM volume in impacting sales. Thus it requires caution when firms leverage its B2B network to influence C2C WoM development.

The results show that the magnitude of the impact of B2B network increases over time in the pre-release period (e.g., Figure 6). One possible reason is that firms become more involved in stimulating C2C discussions close to the new product release, rather than in the earlier stage of the pre-release period. For example, publishers and developers might update their Twitter status more intensely about the upcoming new product shortly before its release. Such efforts can enlarge the influence of B2B network size on WoM (as each B2B partner becomes more active in releasing news). On the other hand, results show that WoM in the early pre-release period can have stronger impact on sales. This raises a red flag in firm's WoM management, since firms are typically not so active in stimulating WoM in the early stage.

Another interesting finding for managers is the more significant impact of velocity (rate of growth) than the volume of C2C WoM. Thanks to the information technology, the total amount of information that people are exposed to is growing exponentially. If the amount of a product's WoM does not grow, or does not grow as fast as the total amount of new information, the chance that potential customers pay attention to the WoM becomes lower over time. This highlights the importance of focusing on velocity in WoM management.

Limitations and Directions for Future Research

The study highlights the linkage between B2B network characteristics and C2C WoM evolutions. I have specifically focused on the impact of both B2B network size and strength-of-ties. It can be meaningful for future research to examine other B2B network characteristics such as closeness, density, and the impact of indirect ties. This can be conducted with firms from industries with more complex B2B connections than in the video game industry.

The demographic and other characteristics of the customer community are not observable in the current data set. More insights can be generated to explain the C2C WoM evolution pattern, if future research can access information such as the demographics of the writers and readers of the blogs, how the content of blog postings evolve over time, what contents are more influential, etc. Such insights can also be used to predict new product outcomes. For example, *Apple*'s stock price dropped significantly upon the release of iPod Touch 3rd generation in 2009. One explanation provided was that the new product failed to meet many of the customer expectations. By comparing the difference between the expected (based on WoM) and the actual new product features, future studies can better explain the impact of new product release on firm revenue and stock market performance.

REFERENCES

Aboody, David, and Baruch Lev (2000), "Information Asymmetry, R&D, and Insider Gains", *Journal of Finance*, 55(6), 2747-2766.

Aghion, Philippe, and Jean Tirole (1994), "On the management of innovation", Quarterly *Journal of Economics*, 109, 1185–1207.

Aldrich, Howard, and Marlene Fiol (1994), "Fools rush in? The institutional context of industry creation", *Academy of Management Review*, 19 (4), 645-670.

Anand, Bharat N. and Tarun Khanna (2000), "Do firms learn to create value? The case of alliances," *Strategic Management Journal*, 21 (March), 295-315.

Anderson, Eugene, Claes Fornell and Donald Lehmann (1994), "Customer satisfaction, market share, and profitability", *Journal of Marketing*, 58(3), 53-66.

Barry, Christopher, Chris Muscarella, John Peavy, and Michael Vetsuypens (1990) "The role of venture capital in the creation of public companies", *J. of Financial Economics* 27:447–471.

Battese, G. E., and T. J. Coelli (1992), "Frontier production functions, technical efficiency and panel data", *Journal of Productivity Analysis*, 3, 153-169.

Bharadwaj, Sundar, Anandhi Bharadwaj, and Elliot Bendoly (2007), "The performance effects of complementarities between information systems, marketing, manufacturing, and supply chain processes", *Information Systems Research*, 18, 437-453.

Bharadwaj, Sundar, Rajan Varadarajan, and John Fahy (1993), "Sustainable competitive advantage in service industries", *Journal of Marketing*, 57(4), 83-99.

Brüder, J. and Preisendörfer, P. (1998) “Network support and the success of newly founded business”, *Small business economics* (10)3, 213-225

Bourdieu, Pierre (1985), “The forms of capital”, In *Handbook of Theory and Research for the Sociology of Education*, ed. JG Richardson, 241-258. New York:Greenwood

Brumback, Babette, and John Rice (1998), “Smoothing Spline Models for the Analysis of Nested and Crossed Samples of Curves”, *Journal of the American Statistical Association*, 93 (443), 961-976.

Bucklin, Louis P. and Sanjit Sengupta (1993), "Organizing Successful Co-Marketing Alliances," *Journal of Marketing*, 57 (April), 32-46.

Busaba, Walid, Lawrence Benveniste, and Ren-jin Guo (2001) “The option to withdraw IPOs during the premarket”, *Journal of Financial Economics*, 60, 73-102.

Carter, R., and S. Manaster (1990) "Initial public offerings and underwriter reputation", *Journal of Finance* 45, 1045 - 1067.

Certo, Trevis, Tim Holcomb, and Michael Holmes (2009), "IPO Research in Management and Entrepreneurship: Moving the Agenda Forward", *J. of Management*, 35(6): 1340 - 1378.

Chan, Su Han, John Kensingerc, Arthur Keown, and John Martin (1997), "Do strategic alliances create value?" *Journal of Financial Economics*, 46(2), 199–222.

Chen, Guoli, Donald Hambrick, and Timothy Pollock (2008), "Puttin' on the ritz: Pre-IPO enlistment of prestigious affiliates as deadline-induced remediation", *Academy of Management Journal*, 51(5), 954-975.

Chevalier, Judith, and Dina Mayzlin (2006), "The effect of word of mouth on sales: Online book reviews", *Journal of Marketing Research*, 43(3), 345-354.

Chiodo, Abbigail, Massimo Guidolin, Michael Owyang, and Makoto Shimoji (2004), "Subjective Probabilities: Psychological Theories and Economic Applications", *Federal Reserve Bank of St. Louis Review*, January/February 2004, 86(1), 33-47.

Cohen, Boyd, and Thomas Dean (2005) "Information asymmetry and investor valuation of IPOs: top management team legitimacy as a capital market signal", *Strategic Management Journal*, 26(7), 683-690.

Cohen, Wesley and Daniel Levinthal (1990), "Absorptive capacity", *Administrative Science Quarterly*, 35, 128-152.

Comanor, William (1965), "Market structure, product differentiation, and industrial research," *Quarterly Journal of Economics*, 81 (4), 639–57.

Crosby, Lawrence, Kenneth Evans, and Deborah Cowles (1990), "Relationship quality in services selling," *Journal of Marketing*, 54, 68–81.

Danneels, Erwin (2003), "Tight-loose coupling with customers", *Strategic Management Journal*, 24(6), 559-576

Das, Somnath, Pradyot Sen, and Sanjit Sengupta (1998), "Impact of strategic alliances on firm valuation", *Academy of Management Journal*, 41(1), 27–41.

Deeds, David, and Charle Hill (1999), "Strategic alliances and the rate of new product development", *Journal of Business Venturing*, 11, 41-55.

Dekinder, Jade, and Ajay Kohli (2008), "Flow signals: How patterns over time affect the acceptance of start-up firms", *Journal of Marketing*, 72(5), 84-97.

Dellarocas, Chrysanthos, Xiaoquan (Michael) Zhang, and Neveen Awad (2008), "Exploring the value of online product reviews in forecasting sales: The case of motion pictures". *Journal of Interactive Marketing*, 21(4), 23-45.

Doney, Patricia, and Joseph Cannon (1997), “An examination of the nature of trust in buyer–seller relationships,” *Journal of Marketing*, 61, 35–51.

Dutta, Shantanu, and Allen Weiss (1997), “The relationship between a firm's level of technological innovativeness and its pattern of partnership agreements”, *Management Science*, 43(3), 343-356

Dwyer, Paul (2009), “Measuring interpersonal influences in Online conversations,” MSI Working Paper Series #09-108.

Elberse, Anita and Jehoshua Eliashberg (2003), “Demand and supply dynamics for sequentially released products in international markets: The case of motion pictures”, *Marketing Science*, 22(3), 329-354.

Eubank, R. L. (1988), *Spline Smoothing and Nonparametric Regression*, New York: Marcel Dekker.

Everett, Martin, and Stephen Borgatti (2005), “Ego network betweenness”, *Social Networks*, 27, 31-38.

Fitza, Markus, Sharon Matusik, and Elaine Mosakowski (2009), "Do VCs matter? The importance of owners on performance variance in start-up firms", *Strategic Management Journal*, 30, 387-404.

Florin, Juan, Michael Lubatkin, and William Schulze (2003), “A social capital model of high-growth ventures”, *Academy of Management Journal*, 40(3), 374-384.

Freeman, L.C. (1982), “Centered graphs and the construction of ego networks”, *Mathematical Social Sciences* 3, 291–304.

Ganesan, Shankar (1994), "Determinants of long-term orientation in buyer-seller relationships", *Journal of Marketing*, 58(Apr), 1-19.

Godes, David, and Dina Mayzlin (2004), "Using online conversations to study word-of-mouth communication", *Marketing Science*, 23(4), 545-560.

Godes, David, and Dina Mayzlin (2009), "Firm-created word-of-mouth communication: Evidence from a field test", *Marketing Science*, Forthcoming.

Godes, David, and Jose Silva (2006), “The Dynamics of Online Opinion”, Working paper.

Gomes- Casseres, Benjamin (1997), "Alliance strategies of small firms", *Small Business Economics*, 9(1), 33-44.

Granovetter, M. S. 1985 “Economic action and social structure: The problem of embeddedness.” *American Journal of Sociology*, 91: 481–510.

Gruen, Thomas, John Summers, and Frank Acito (2000), “Relationship marketing activities, commitment, and membership behaviors in professional associations,” *Journal of Marketing*, 64 (July), 34–49.

Gulati, Ranjay, and Monica Higgins (2003), “Which ties matter when? The contingent effects of interorganizational partnerships on IPO success”, *Strategic Management Journal*, 24, 127-144.

Guo, Re-jin, Raruch Lev, and Nan Zhou (2005), "The Valuation of Biotech IPOs", SSRN Working paper.

Hager, Mark, Joseph Galaskiewicz, and Jeff Larson (2004) “Structural embeddedness and the liability of newness among nonprofit organizations.” *Public Management Review*, 6:159-88.

Halpern, J. J. (1997), “Elements of a script for friendship in transactions.” *Journal of Conflict Resolution*, 41: 835–868.

Hayes, Andrew, and Jorg Matthes (2009), “Computational procedures for probing interactions in OLS and logistic regression”, *Behavior Research Methods*, 41, 924-936.

Heckman, James (1979) "Sample selection bias as specification error", *Econometrica*, 47, 153-161.

Heide Jan and George John (1990), "Alliances in industrial purchasing", *Journal of Marketing Research*, 27, 24-36.

Hoch, Stephen, and John Deighton (1989), “Managing what consumers learn from experience”, *Journal of Marketing*, 53(2), 1-20.

Johnson, Michael, and Fred Selnes (2004), “Customer portfolio management”, *Journal of Marketing*, 68(2), 1-17.

Kalwani, Manohar and Narakesari Narayandas (1995), "Long-term manufacturer-supplier relationships: Do they pay off for supplier firms?", *Journal of Marketing*, 59, 1-16.

Kauffman Foundation Report (2008), Young Businesses, Economic Churning and Productivity Gains. The Ewing Marion Kauffman Foundation, Kansas City:Kansas.

King, Tom (2003), “Now playing somewhere else: Studios try to build buzz by holding films back: in Muncie? Read a book”, *The Wall Street Journal*, Jan 10, W10.

Kor, Yasemin, and Vilmos Misangyi (2008), "Outside directors' industry-specific experience and firms' liability of newness", *Strategic Management Journal*, 29, 1345-1355.

Lane, Peter, Balaji Koka, and Seemantini Pathak (2006), “The reification of absorptive capacity”, *Academy of Management Review*, 31(4), 833-863.

Lane, Peter, and Michael Lubatkin (1998), “Relative absorptive capacity and interorganizational learning”, *Strategic Management Journal*, 19(5), 461-477.

Lin, Nan (1999), “Building a Network Theory of Social Capital”, *Connections*, 22, 28-51.

Liu, Yong (2006), "Word of mouth for movies: Its dynamics and impact on box office revenue", *Journal of Marketing*, 70(3), 74-89.

Luo, Xueming (2008), “When marketing strategy first meets Wall Street: Marketing spendings and firm’s Initial Public Offerings”, *Journal of Marketing*, 72, 98-109.

Luo, Xueming (2007), “Consumer negative voice and firm idiosyncratic stock returns,” *Journal of Marketing*, 71 (3), 75–88.

Miles, Raymond and Charles Snow (1992), "Causes of failure in network organizations," *California Management Review*, 34, 53-72.

Miles, Grant, Stephen Preece, and Mark Baetz, “Dangers of dependence: the impact of strategic alliance use by small technology-based firms”, *Journal of Small Business Management*, 37 (2), 20-29.

Mitchell, Will (1989), “Whether and when? Probability and timing of incumbents’ entry into emerging industrial subfields,” *Administrative Science Quarterly*, 34 ,208–230.

Mizik, Natalie, and Robert Jacobson (2003), "Trading off between value creation and value appropriation", *Journal of Marketing*, 67 (1), 63-76.

Mizik, Natalie, and Robert Jacobson (2007), “Myopic marketing management”, *Marketing Science*, 26(3), 361-379.

Mowery, David C., and Nathan Rosenberg (1998), *Paths of innovation: technological change in 20th-century America*, Cambridge University Press.

Mullainathan, Sendhil. “A Memory-Based Model of Bounded Rationality.” *Quarterly Journal of Economics*, August 2002, 117(3), 735-75.

Narasimhan, Om, Surendra Rajiv, and Shantanu Dutta (2006), “Absorptive capacity in high-technology markets: The competitive advantage of the haves”, *Marketing Science*, 25(5), 510-524.

O'Neal, Charles R, and Kate Bertrand (1991), "Developing a winning J.I.T. marketing strategy," *Small Business Reports*, 16, 68-71.

Pagano, Marco, Fabio Panetta, and Luigi Zingales (1998), "Why do companies go public? An empirical analysis", *Journal of Finance*, LIII(1), 27-64.

Palmatier, Robert, Rajiv Dant, Dhruv Grewal, and Kenneth Evans (2006),"Factors influencing the effectiveness of relationship marketing: A meta-analysis", *Journal of Marketing*, 70 (Oct), 136-153.

Pfeffer J. and G. Salancik (1978), *The external control of organizations*. Harper-Row, New York.

Pike, Richard, and Nam Sang Cheng (2001), “Credit Management”, *Journal of Business Finance & Accounting*, 28(7/8), 1013-1042.

Portes, Alejandro (1998), "Social capital: Its origins and applications in modern sociology", *Annual Review of Sociology*, 24 (1), 1-25.

Ragatz, Gary, Robert Handfield, and Thomas Scannell (2003), "Success factors for integrating suppliers into new product development", *Journal of Product Innovation Management*, 14(3), 190-202.

Ramsay, J. O. and Silverman, B. W. (1997), *Functional Data Analysis*, Springer, New York.

Ramsay, J.O. and Silverman, B.W. (2005), Functional Data Analysis, Second Edition, Springer, New York.

Raudenbush, Stephen, and Bryk, Anthony (2002), *Hierarchical linear models: Applications and data analysis methods*. Sage Publications. Thousand Oaks, CA.

Reddy, Srinivas, and Mayukh Dass (2006), "Modeling Online Art Auction Dynamics Using Functional Data Analysis", *Statistical Science*, 21(2), 179-193.

Rindfleisch, Aric and Christine Moorman (2001), "The Acquisition and Utilization of Information in New Product Alliances," *Journal of Marketing*, 65(April), 1-18.

Ritter, Jay, and Ivo Welch (2002), "A review of IPO activity, pricing, and allocations", *Journal of Finance*, 57(4), 1795-1828.

Robertson, Thomas (1993), "How to reduce market penetration cycle times," *Sloan Management Review*, 35 (Fall), 87-96.

Rothaermel, Frank, and David Deeds (2004), "Exploration and exploitation alliances in biotechnology: A system of new product development", *Strategic Management Journal*, 25(3), 201-221.

Rowley, T. J., D. Behrens, and D. Krackhardt (2000), "Redundant governance structures: An analysis of structural and relational embeddedness in the steel and semiconductor industries." *Strategic Management Journal*, 21: 369–386.

Sanders, WM. Gerard, and Steven Boivie (2004), "Sorting things out: Valuing of new firms in uncertain markets", *Strategic Management Journal*, 25, 167-186.

Scott, John (2000), *Social Network Analysis: A Handbook*, 2nd ed. London, U.K.: Sage.

Shaver, Myles (1998), "Accounting for endogeneity when assessing strategy performance: Does entry mode choice affect FDI survival?" *Management Science*, 44(4), 571-585.

Sheth, Jagdish, and Rajendra S. Sisodia (2001), “Marketing productivity: issues and analysis”, *Journal of Business Research*, 55 (5), 349-362.

Siguaw, Judy, Penny Simpson, and Thomas Baker (1998), “Effects of supplier market orientation on distributor market orientation and the channel relationship”, *Journal of Marketing*, 62 (July), 99–111.

Simonin, Bernard (1999), “Ambiguity and the process of knowledge transfer in strategic alliances,” *Strategic Management Journal*, 20: 595–623.

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

Sood, Ashish, Gareth James, and Gerard Tellis (2009), "Functional regression: A new model for predicting market penetration of new products", *Marketing Science*, 28(1), 36-51.

Sorenson, Olav, and David Waguespack (2006), “Social Structure and Exchange: Selfconfirming Dynamics in Hollywood”, *Administrative Science Quarterly*, 51: 560–589.

Sorescu, Alina, and Jelena Spanjol (2008), “Innovation's effect on firm value and risk: Insights from consumer packaged goods”, *Journal of Marketing*, 72(2), 114-132.

Sorescu, Alina, Venkatesh Shankar, and Tarun Kushwaha (2007), “New Product Preannouncements and Shareholder Value: Don’t Make Promises You Can’t Keep”, *Journal of Marketing Research*, Vol. XLIV, 468–489.

Spender, J.-C. (1996). "Competitive advantage from tacit knowledge? Unpacking the concept and its strategic implications", In B. Moingeon and A. Edmondson (eds.), *Organizational Learning and Competitive Advantage*. Sage, Newbury Park, CA.

Srinivasan, Shuba and Dominique Hanssens (2009), "Marketing and firm value, methods, metrics, findings, and future directions", *J. of Marketing Research,* Forthcoming

Srivastava, Rajendra, Tasadduq Shervani, and Liam Fahey (1998), "Market-based assets and shareholder value: A framework for analysis", *Journal of Marketing,* 62, 2-18.

Stuart, Toby (1998), "Network positions and propensities to collaborate", *Administrative Science Quarterly*, 43(3), 668-698.

Stuart, Toby, H. Huang, and R. Hybels (1999), "Interorganizational endorsements and the performance of entrepreneurial ventures", *Adm. Science Quarterly*, 44, 315-349.

Summers, Barbara, and Nicholas Wilson (2003), "Trade Credit and Customer Relationships", Managerial and Decision Economics, 24(6/7), 439-455.

Thomke, Stefan (1998), "Managing experimentation in the design of new products", *Management Science*, 44(June), 6, 743-762.

Tsai, Wenpin, and Sumantra Ghoshal (1998), "Social capital and value creation: The role of interfirm networks", *Academy of Management Journal*, 41(4), 464-476.

Tuli, Kapil, Sundar Bharadwaj, and Ajay Kohli (2010), "Ties that bind" *Journal of Marketing Research*, XLVII(February),36-50.

Uzzi, Brian (1996), "The sources and consequences of embeddedness for the economic performance of organizations: The network effect." *American Sociological Review,* 61: 674–698.

Uzzi, Brian (1999), “Embeddedness in the making of financial capital: How social relations and networks benefit firms seeking financing”, *American Sociological Review*, 64, 481-505.

Van den Bulte, Christophe, Stefan Wuyts (2007), *Social networks and marketing*. MSI.

Villalonga, Belén, and Anita M. McGahan (2005), "The choice among acquisitions, alliances, and divestitures", *Strategic Management Journal*, 26(13), 1183 - 1208.

Wilson, David (1995), "An integrated model of buyer-seller relationships", *Journal of the Academy of Marketing Science*, 23(4), 335-345.

Wuyts, Stefan, 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.

Table 1
B2B Relationships' Impact on Expected Future Cash Flows of Young Technology Firms

		R&D Alliance Relationships	*Marketing Alliance* Relationships	*Key Customer* Relationships
Impact on the *Level* of Cash Flows	**Positive** Impact (increase the level of cash flows)	- Enhance R&D cost efficiency - Reduce financing costs for R&D - Enhance R&D capabilities and long-run cash inflows for firms with high absorptive capacity	- Reduce marketing and sales costs - Enhance marketing capabilities and long-run cash inflows for firms with high absorptive capacity	- Decrease transaction costs with growing mutual understanding, trust and commitment - Reduce production and inventory costs
	Negative Impact (decrease the level of cash flows)	- Increase the likelihood of equity relinquishment, as young firms tend to give up too much ownership of the innovation - Increase the risk of leakage of strategically important knowledge to competitors	- Increase the likelihood of equity relinquishment, as most of the value created might be appropriated by the established alliance partners - Constrain future sales growth if young firms over-rely on alliance partners' marketing capabilities	- Constrain future sales growth, as substantial relationship-specific investments devoted to key customers reduce the amount of resources available to explore other markets and service other customers
Impact on the *Speed* of Cash Flows	**Positive** Impact (increase the speed of cash flows)	- Facilitate faster response to critical information (e.g., technological development) - Shorten NPD cycle	- Penetrate a bigger proportion of the world market in a speedy manner - Facilitate new product adoption	- Facilitate new product adoption - Enable faster reaction to market changes and reduce NPD cycle
	Negative Impact (decrease the speed of cash flows)		- Deter the development of young firms' own marketing capabilities if young firms over-rely on alliance partners' marketing capabilities	- Reduce the speed of converting sales revenue into cash flows, as young firms do not want to risk their relationships with key customers by imposing late-payment penalties
Impact on the *Volatility* of Cash Flows	**Positive** Impact (decrease the volatility of cash flows)	- Reduce the likelihood of R&D failures, thus increase the predictability and stability of future cash flows	- Promote better channel coordination and operations stability - Access to brand equity and customer base and reduce the variability in sales revenue and cost	- Reduce the variance in inventory and production costs - Provide smoother revenue streams due to loyalty
	Negative Impact (increase the volatility of cash flows)	- Reduce the predictability of future cash flows as the risk of equity relinquishment increases	- Increase the uncertainty of future marketing success if the young firms over-rely on alliance partners' marketing capabilities - Increase the risk of equity relinquishment	- Increase the vulnerability of cash inflows upon customers switching, as key customers contribute a significant proportion of sales - Increase the risk of credit concentration

Table 2
Descriptive Statistics and Correlation Matrix

	Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	Initial Offer Value	278.31	330.78																
2	Total Price to Public	78.13	137.19	**0.81**															
3	RAR Centrality	0.71	2.12	-0.05	-0.06														
4	MAR Centrality	0.84	2.02	0.07	0.13	**0.64**													
5	KCR Centrality	3.14	4.54	0.02	-0.02	0.00	0.05												
6	R&D Expenditures	11.75	61.02	**0.37**	**0.53**	**0.22**	0.16	-0.06											
7	Selling & Marketing Expenditures	22.46	96.86	**0.46**	**0.63**	0.05	**0.26**	0.13	**0.53**										
8	Assets	38.27	70.22	**0.52**	**0.58**	0.06	0.11	0.12	**0.62**	**0.67**									
9	Venture Capital Backing	0.57	0.50	-0.01	-0.12	0.01	0.05	-0.08	-0.16	**-0.22**	**-0.23**								
10	ROA	-0.19	0.57	0.08	0.06	-0.08	0.05	0.04	-0.06	**0.19**	0.16	**-0.22**							
11	Cash flows from Operation	3.94	43.85	**0.53**	**0.52**	-0.11	0.04	**0.17**	-0.35	**0.37**	0.14	**-0.19**	**0.33**						
12	% of shares held by insiders	37.74	27.17	-0.02	-0.03	0.10	-0.02	0.14	-0.13	**-0.19**	**-0.18**	-0.03	0.09	-0.12					
13	Underwriter Ranking	7.61	2.48	0.11	0.13	0.03	0.01	0.04	0.07	0.07	0.02	0.13	-0.12	-0.01	-0.16				
14	Upper Echelon Experience	2.75	1.38	0.04	0.04	0.02	0.05	0.03	**0.19**	0.10	-0.05	**0.16**	-0.12	0.00	-0.11	**0.21**			
15	RD_AC	28.11	29.64	-0.07	0.00	**0.18**	**0.17**	**0.19**	0.06	0.03	0.06	0.03	0.07	0.06	-0.02	-0.03	0.06		
16	MK_AC	85.35	13.98	-0.14	-0.04	0.08	0.10	0.06	0.05	0.09	0.14	**-0.17**	0.14	0.16	**0.18**	-0.14	-0.07	0.10	
17	C_AC	56.12	26.67	0.08	0.15	0.01	-0.10	-0.16	**0.12**	0.13	**0.27**	-0.12	0.15	0.00	0.00	0.00	0.06	**0.22**	**0.17**

- Variables 1, 2, 6, 7, 8, and 11 are in millions of USD.
- Correlations that are statistically significant at 5% level are presented in bold.
- R&D know-how absorptive capacity, marketing know-how absorptive capacity, and customer know-how absorptive capacity are derived from Stochastic Frontier Estimations.
- The value of variables reported in this table is the original value. Variables 1 through 7 and variable 11 will be scaled by Assets (variable 8) when used in model estimations.

Table 3
The Effects of Three Types of B2B Relationships, Three Types of Absorptive Capacity, and Their Interactions on IPO Value

		IPO Value Measure: Initial Offer Value		IPO Value Measure: Total Price to Public	
	Hypotheses	**Heckman 2-Stage Model 1**	**Heckman 2-Stage Model 2**	**Heckman 2-Stage Model 1**	**Heckman 2-Stage Model 2**
R&D Alliance Relationship (RAR) Centrality		0.26	0.15	-0.20	-0.38
Marketing Alliance Relationship (MAR) Centrality		0.14	0.54	0.09	0.40*
Key Customer Relationship (KCR) Centrality		0.20*	0.35*	0.31**	0.39***
R&D Know-how Absorptive Capacity (RD_AC)		0.00	0.00	0.00	0.01*
Marketing Know-how Absorptive Capacity (MK_AC)		0.01***	0.05**	0.01***	0.05***
Customer Know-how Absorptive Capacity (C_AC)		0.08*	0.10*	0.10**	0.10**
RAR Centrality x RD_AC	**H1 (+)**		**0.03**		**0.04****
MAR Centrality x MK_AC	**H2 (+)**		**0.07****		**0.06*****
KCR Centrality x C_AC	**H3 (+)**		**0.31*****		**0.19*****
Industry Dummy		-0.00	0.00	0.09	0.09
Lambda (inverse Mills ratio)		0.27	0.29	-0.05	-0.03
Cash Flows From Operations		0.53	0.85*	0.31	0.05
Return on Assets (ROA)		-0.82	-0.89	0.07	-0.09
R&D Expenditures		0.03	0.08	0.31*	0.37*
Selling & Marketing Expenditures		0.47	0.51*	0.69***	0.75***
Venture Capital Backing		0.40**	0.45**	0.04	0.04
% of Shares Held by Insiders		0.01*	0.01**	-0.00	0.00
Underwriter Ranking		0.56*	0.63**	0.51***	0.53**
Upper Echelon Experience		-0.02	-0.03	-0.09	-0.10
Year 1997		-0.06	0.09	-0.25	-0.14
Year 1998		-0.03	0.14	-0.34*	-0.20
Year 1999		0.54*	0.67**	0.45**	0.56***
Year 2000		0.55*	0.68*	0.61***	0.73***
Year 2001		-1.22	-1.07	0.10	0.21
Year 2002		(dropped)	(dropped)	(dropped)	(dropped)
Year 2003		-0.02	0.02	-0.21	-0.14
Year 2004		0.42	0.46	-0.09	-0.04
Year 2005		0.15	0.09	-0.16	-0.16
Year 2006		-0.42	-0.39	-0.40	-0.37
		R^2=41.28%	R^2=46.24%	R^2=62.68%	R^2=67.57%

Model 1 is the main effect model as specified in Equation (5). Model 2 includes interaction effects, as specified in Equation (6).

Entries are coefficients. One, two, and three asterisks indicate the two-tailed (one-tailed for interaction terms) significance at the 10%, 5%, and 1% levels, respectively.

Table 4: Robustness Check

IPO value is measured by the *total price to public* other than indicated. All models include control variables. Entries are coefficients. One, two, and three asterisks indicate the two-tailed significance (one-tailed for interaction factors) at the 10%, 5%, and 1% levels, respectively.

Table 4-1: Robustness check with alternative measures

	Altern. measure for the DV (End-of-1st Day Value)	Altern. Measure for the DV (90-Day Value)	Altern. measures for the IDV: Weighted B2B Network Centrality	Altern. measures for the IDV: Alternative KCR Measure	Altern. measures for the IDV: Alternative Absorptive Capacity Estimates	Altern. measure for VC involvement (VC ownership)
R&D Alliance Relationship (RAR) Centrality	-0.59	-1.10	-0.18	-0.41	-0.29	-0.38
Marketing Alliance Relationship (MAR) Centrality	0.62	-0.03	-0.27	0.30	0.38*	0.41*
Key Customer Relationship (KCR) Centrality	0.39*	0.69**	0.34***	0.37***	0.57***	0.39***
R&D Know-how Absorptive Capacity (RD_AC)	0.01	0.00	0.01*	0.01*	0.02*	0.01*
Marketing Know-how Absorptive Capacity (MK_AC)	0.04*	0.01	0.01*	0.04***	0.06**	0.05***
Customer Know-how Absorptive Capacity (C_AC)	0.05	0.12*	0.04	0.07*	0.16***	0.10**
RAR Centrality x RD_AC	**0.04**	**0.01**	**0.03***	**0.04****	**0.05***	**0.04****
MAR Centrality x MK_AC	**0.05***	**0.01**	**0.04****	**0.06*****	**0.01*****	**0.06*****
KCR Centrality x C_AC	**0.21****	**0.20***	**0.06*****	**0.08***	**0.27*****	**0.18*****

Table 4-2: Robustness check with alternative modeling approaches

	Heckman 2-Stage Model (1st-stage controlling for self-selection of B2B relationship formation)	Hierarchical Bayes Model (Industry group): With B2B centrality effects constant	Hierarchical Bayes Model (Industry group): With B2B centrality effects varying un-conditionally	Hierarchical Bayes Model (Industry group): With B2B centrality effects varying conditionally: Firm-level coefficients	Hierarchical Bayes Model (Industry group): With B2B centrality effects varying conditionally: Coefficients γ of industry concentration in explaining B2B centrality effects	Hierarchical Bayes Model (Age group): With B2B centrality effects constant	Hierarchical Bayes Model (Age group): With B2B centrality effects varying unconditionally
R&D Alliance Relationship (RAR) Centrality	-0.41	-0.41	0.22	0.26	0.19	-0.42	-0.06
Marketing Alliance Relationship (MAR) Centrality	0.28	0.46*	0.20*	0.18	-0.09	0.38	0.40
Key Customer Relationship (KCR) Centrality	0.46***	0.41***	1.31*	1.35**	0.21**	0.48***	0.50*
R&D Know-how Absorptive Capacity (RD_AC)	0.01*	0.01*	0.01*	0.01*		0.01*	0.01*
Marketing know-how absorptive capacity (MK_AC)	0.04***	0.05***	0.05**	0.05**		0.05***	0.04***
Customer Know-how Absorptive Capacity (C_AC)	0.10**	0.10*	0.09*	0.09**		0.08*	0.08*
RAR Centrality x RD_AC	**0.05****	**0.05****	**0.06*****	**0.06*****		**0.04***	**0.04***
MAR Centrality x MK_AC	**0.06*****	**0.06*****	**0.07*****	**0.07*****		**0.06*****	**0.06*****
KCR Centrality x C_AC	**0.21****	**0.20*****	**0.22*****	**0.23*****		**0.14****	**0.15****

Table 5
Summary of Hypotheses in Essay 2

Hypotheses	Relationship	Result
H1	B2B network size → C2C WoM volume	Supported (coefficient is significant in later stages of the pre-release period)
H2	B2B network size x B2B strength-of-ties → C2C WoM volume	Supported (coefficient is significant in later stages of the pre-release period)
H3	B2B strength-of-ties → C2C WoM's impact on sales	Not supported (coefficient is not significant)
H4	B2B network size → C2C WoM's impact on sales	Supported (coefficient is significant in the beginning and ending stages of pre-release period)
H5	Early-stage C2C WoM → New product quality	Not supported (coefficient is not significant)
H6	Early-stage C2C WoM → Overall sales	Supported
H7	Late-stage C2C WoM → Opening sales	Not supported
H8	C2C WoM velocity → Overall sales	Supported (coefficient is significant in earlier stages of the pre-release period)
H9	C2C WoM volume → Change in firm value upon new product release	Supported (coefficient is significant near the end of the pre-release period)

Figure 1
Conceptual Framework

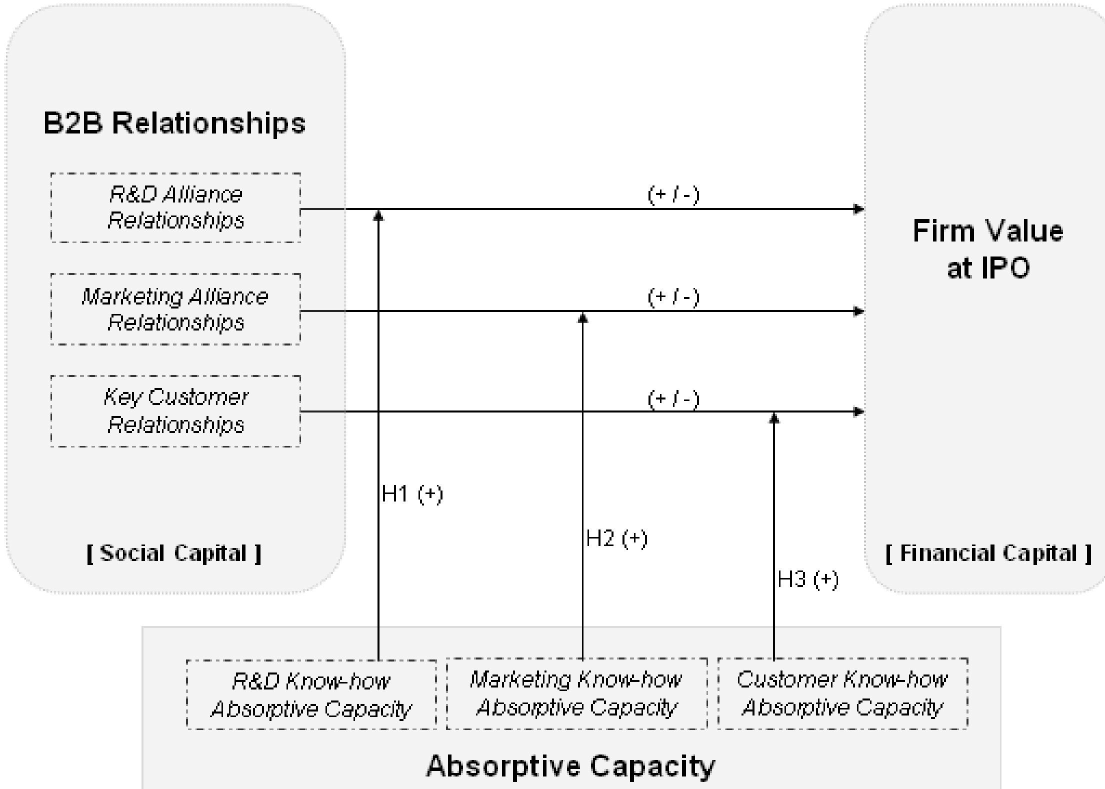
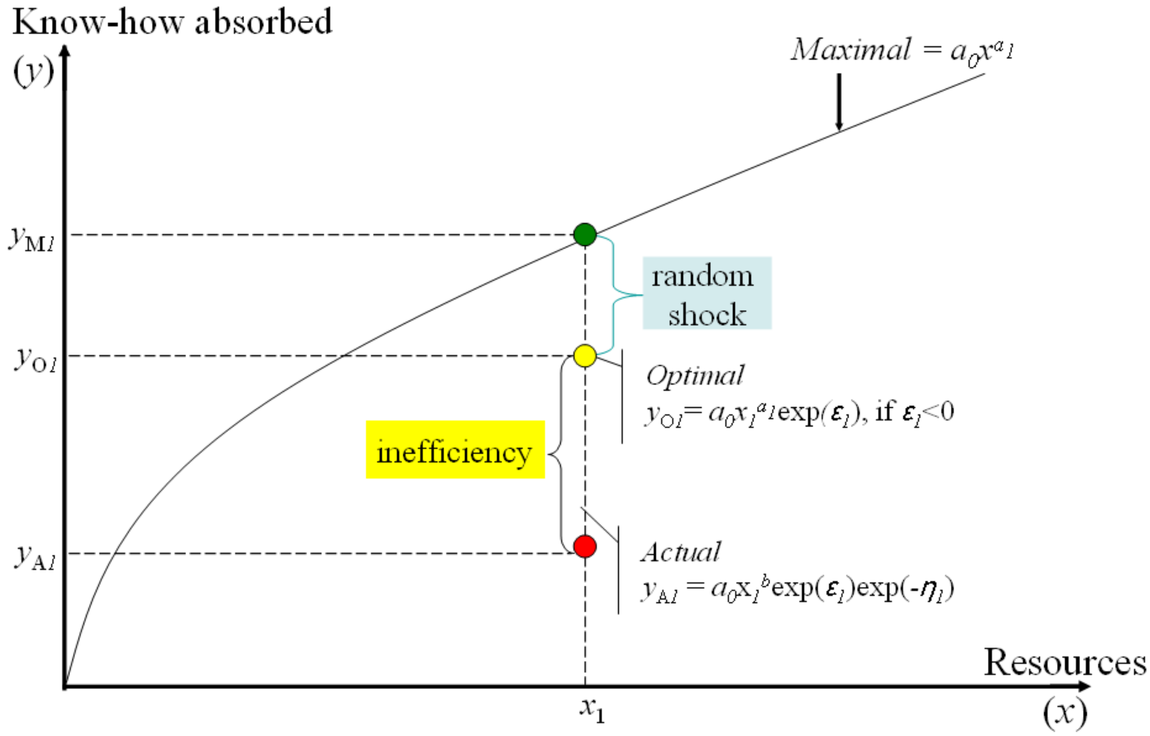


Figure 2
Measure of Absorptive Capacity

2-1: When random shock is unfavorable (ε_i<0)



2-2: When random shock is favorable (ε_i>0)

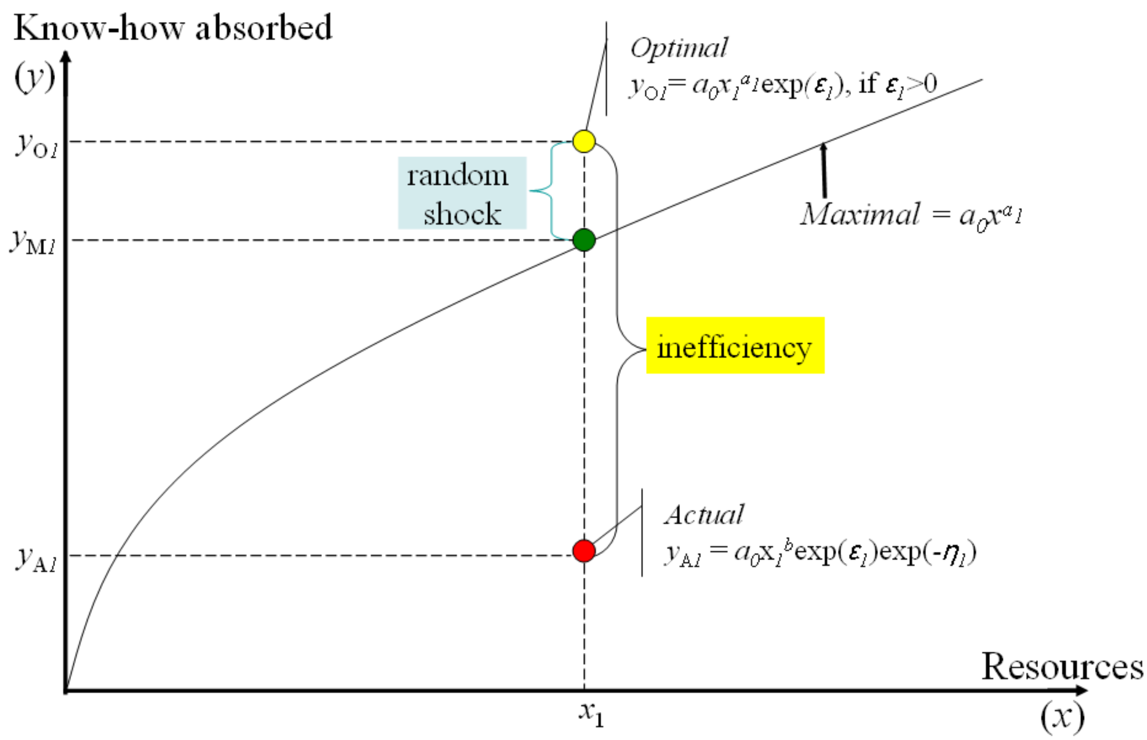
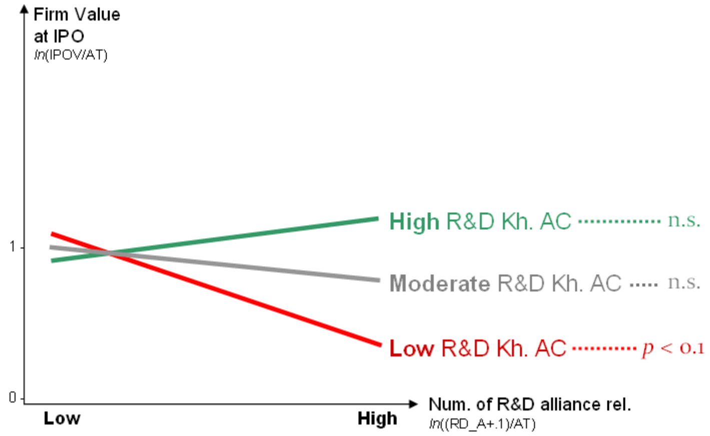
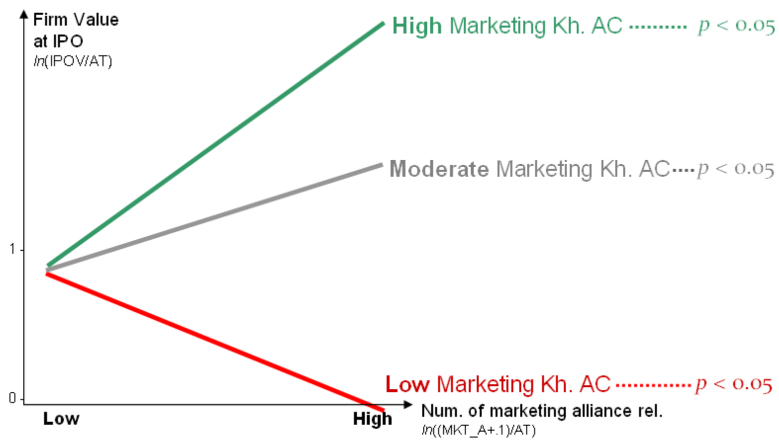


Figure 3
Johnson-Neyman Plots of the Interaction Effects

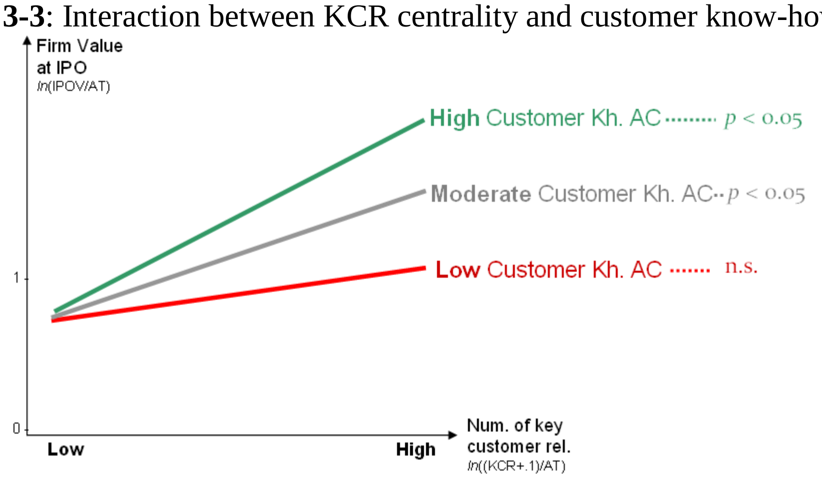
3-1: Interaction between RAR centrality and R&D know-how absorptive capacity



3-2: Interaction between MAR centrality and marketing know-how absorptive capacity



3-3: Interaction between KCR centrality and customer know-how absorptive capacity



Notes for interpreting the plots: For example, in Figure 3-1, under the condition of "low R&D know-how absorptive capacity", the down-sloping line shows a negative relationship between RAR centrality and IPO value, and "p<0.1" indicates that the impact is statistically significant at 10% level.

Figure 4

B2B Strength-of-Ties and C2C Network Density

Figure 4a: Weak B2B ties

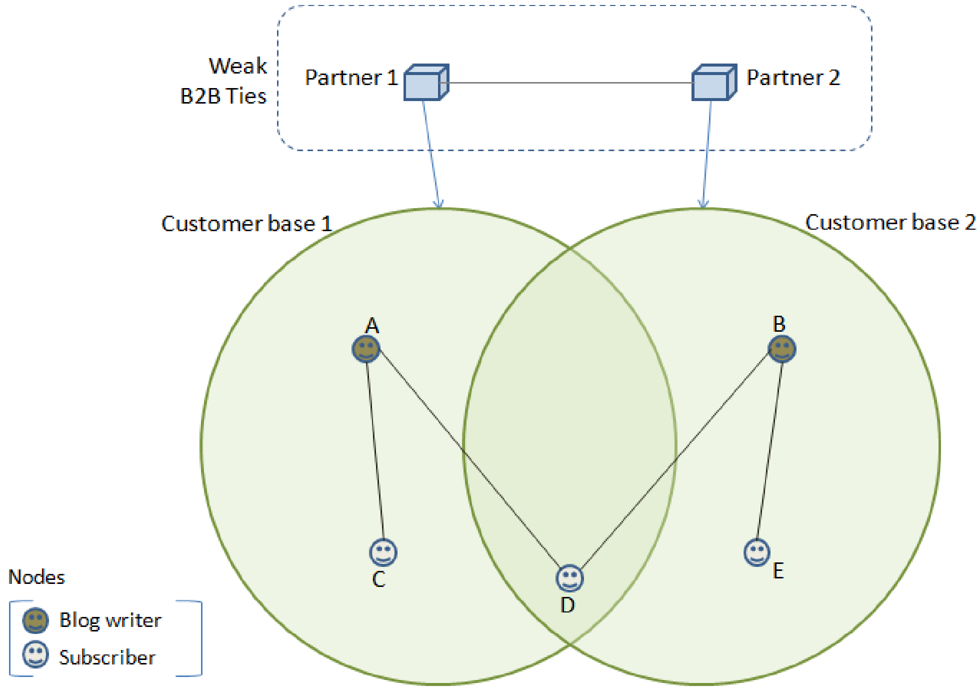


Figure 4b: Strong B2B ties

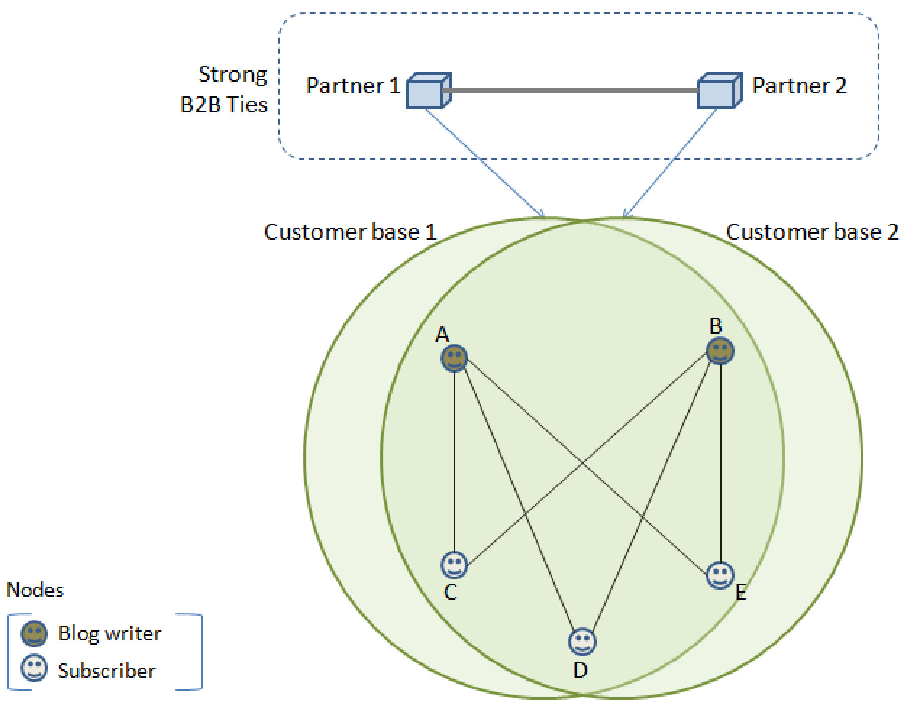


Figure 5

Smoothing Splines

Figure 5a: C2C WoM volume (logged)

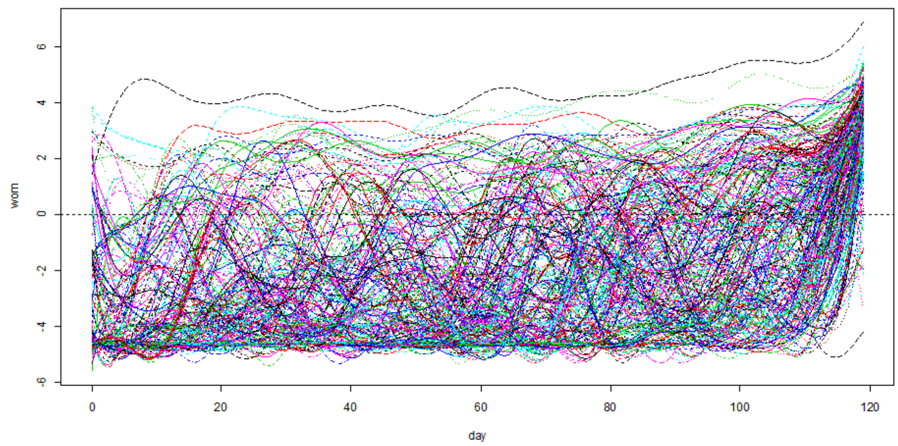


Figure 5b: Velocity of C2C WoM

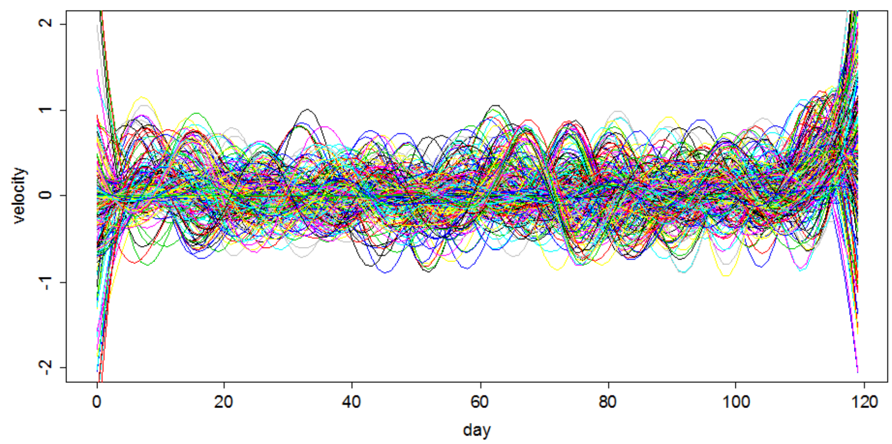


Figure 6

The Impact of B2B Network Characteristics on C2C WoM Evolution

Figure 6a: Impact of B2B network size

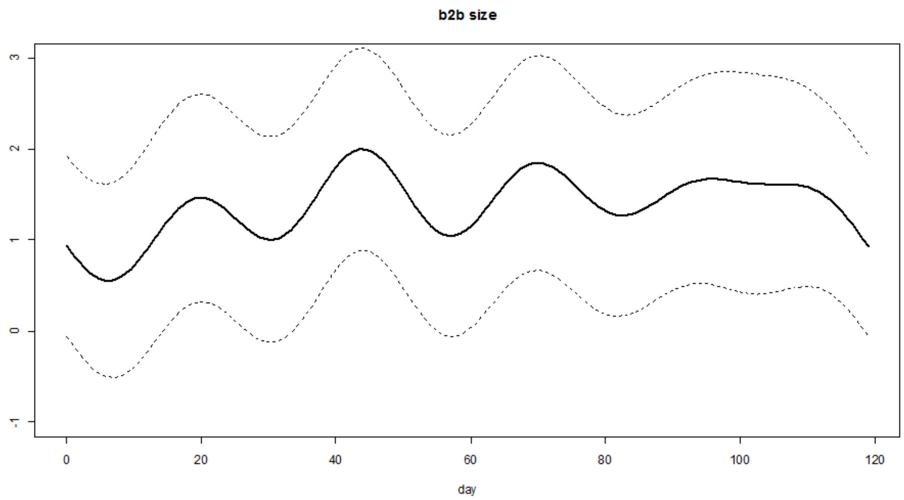


Figure 6b: Impact of the interaction between B2B network size and strength-of-ties

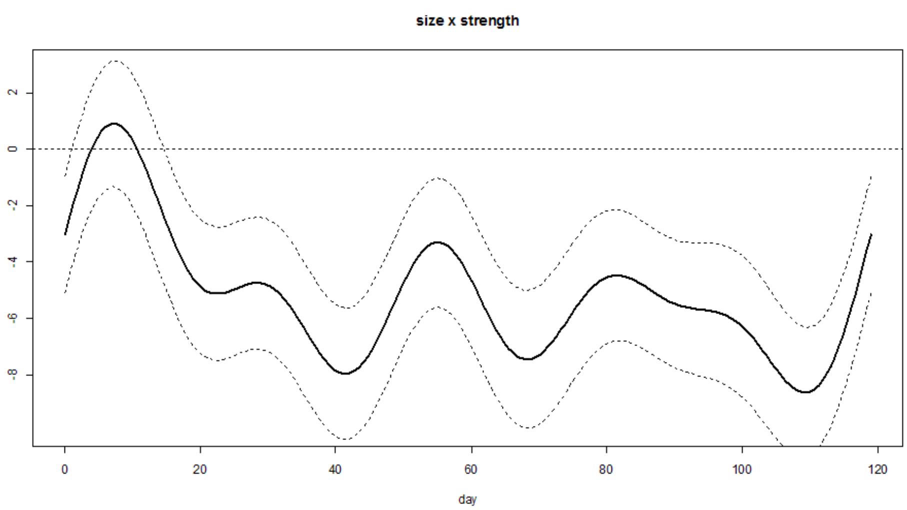


Figure 7

Other Variables Explaining the Heterogeneity in WoM Evolutions

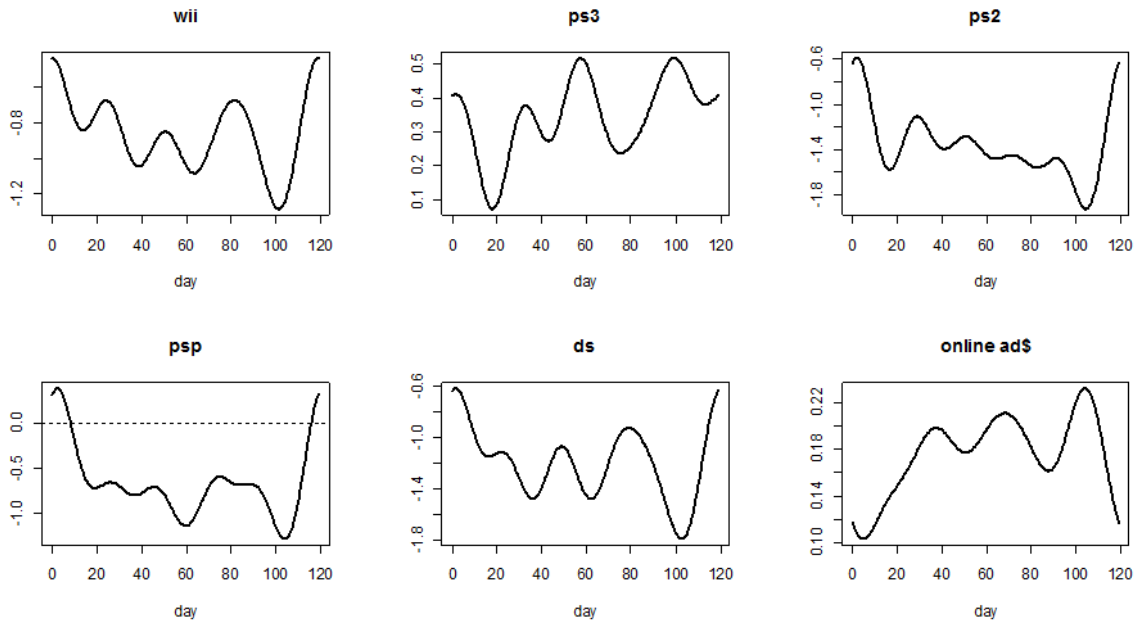


Figure 8

Effects of C2C WoM Evolution Pattern on Sales

Figure 8a: Impact of C2C WoM volume on opening sales

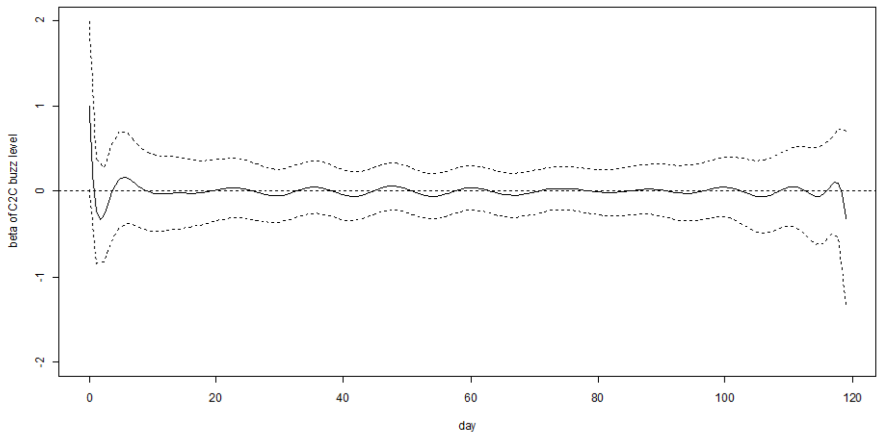


Figure 8b: Impact of C2C WoM volume on overall sales

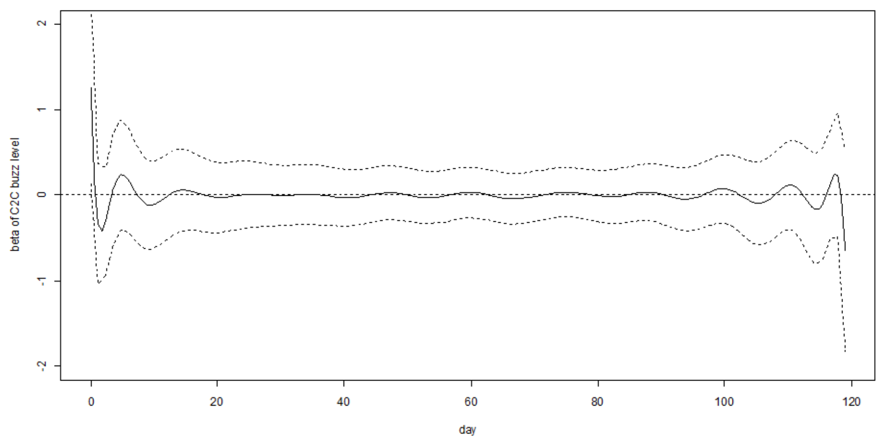


Figure 8c: Impact of C2C WoM velocity on overall sales

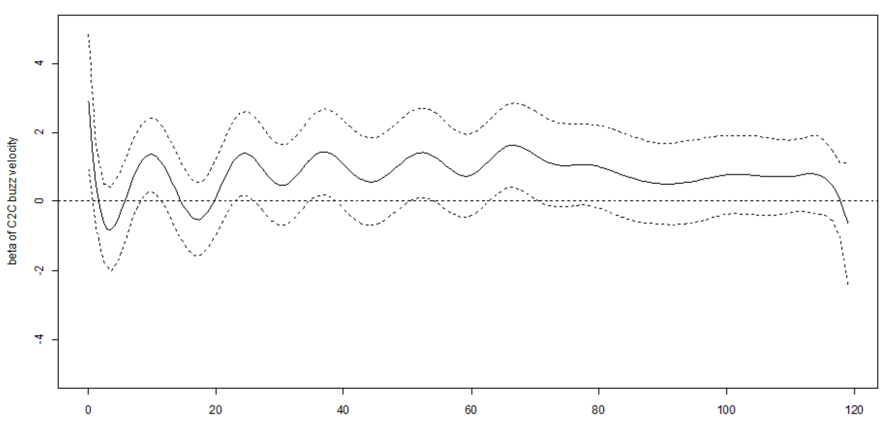


Figure 9

Figure 9a: Impact of C2C WoM evolution on product quality

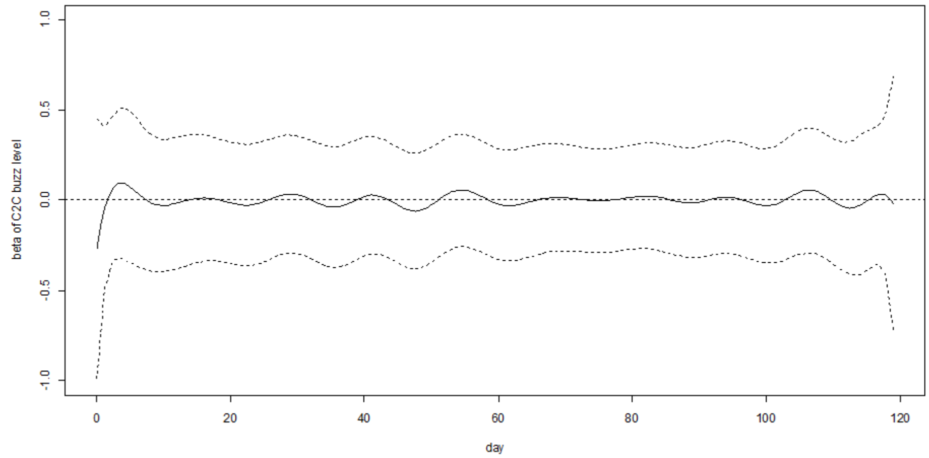


Figure 9b: Impact of C2C WoM evolution on the change in firm value on the product release day

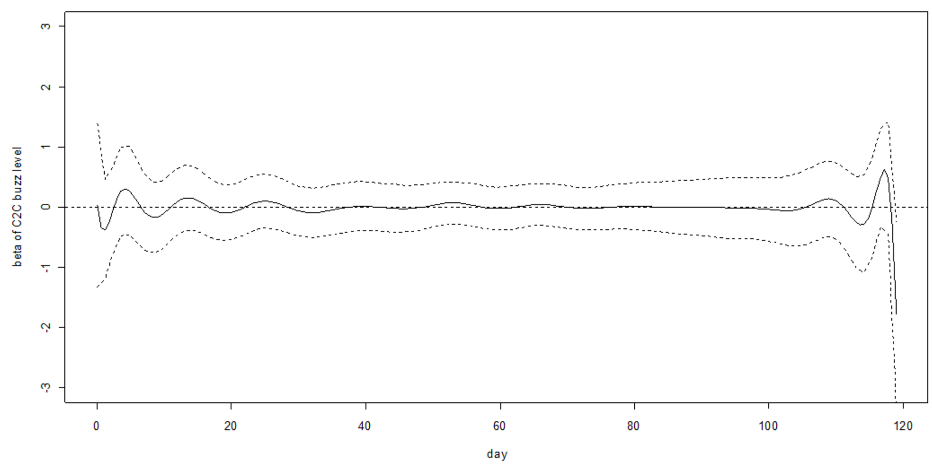


Figure 10

How B2B Network Characteristics Influence C2C WoM's Impact on Sales

Figure 10a: Impact of B2B strength-of-ties

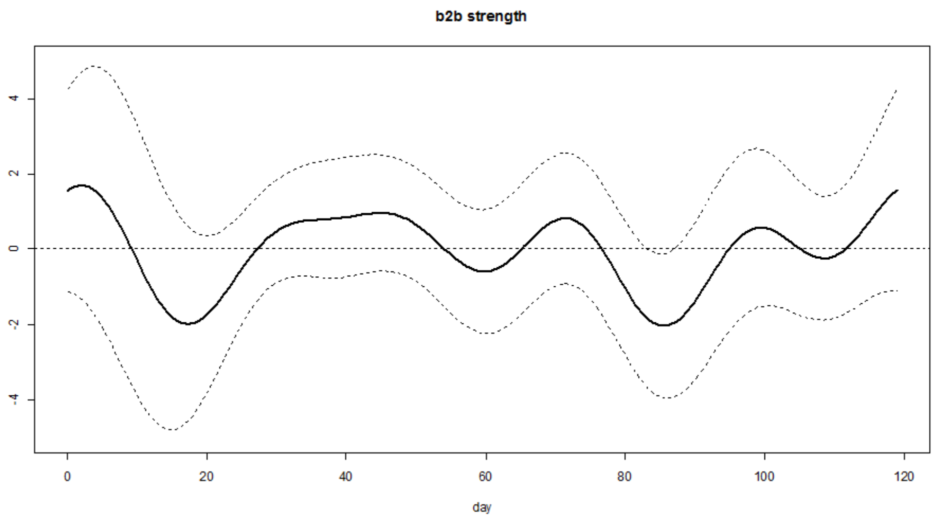


Figure 10b: Impact of B2B network size