

**MARKETING STRATEGY BEYOND THE FIRM BOUNDARY: ESSAYS EXAMINING
THE EFFECTS OF SOCIAL NETWORKS ON FIRM PERFORMANCE**

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MARKETING STRATEGY BEYOND THE FIRM BOUNDARY: ESSAYS

EXAMINING THE EFFECTS OF SOCIAL NETWORKS ON FIRM

PERFORMANCE

Felipe Thomaz, PhD

This dissertation is comprised of two essays that incorporate social networks into the analyses of marketing strategies and phenomena to develop a deeper and more nuanced understanding of the marketing environment, and to enhance manager's ability to forecast a firm or brand's performance in the digital domain. The first essay explores the impact of marketing alliance announcements on firm equity risk given a network of previous strategic alliances for both a focal firm and its partner. Results confirm a widely held belief in the literature that marketing alliances have risk-reducing benefits, but only for those alliances involving a new partner. Furthermore, at high levels, the interconnectedness of partners or density of a firm's network can cause idiosyncratic risk to increase, while the density of a partner's network can also result in increases in systematic risk of a firm after alliance formation. The second essay proposes a novel method for using social media monitoring in a forward-looking manner to forecast brands' future online WOM valence. The method infers associative relations between brands from social media monitoring data by observing which brands are mentioned at the same time in the same social media sources. This is used to construct time-varying brand "networks" from which forecasting variables are extracted. The method is empirically validated on social media monitoring data for 77 major consumer electronics brands over 16 months, and provides reasonably accurate forecasts for positive and, in particular, negative WOM valence.

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PREFACE

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1.0 INTRODUCTION

From 1997 to 2010, MSI's research priorities pointed to the importance of linking marketing actions to financial results for the firm. The resulting research stream provided frameworks for the analysis of marketing's impact (Rust, Ambler, Carpenter, Kumar and Srivastava 2004; Srivastava, Shervani, and Fahey 1997, 1998), as well as extensive support for the notion that marketing activity impacts overall firm performance and value in financial markets, whether through advertising (Srinivasan, Pauwels, Silva-Risso, and Hanssens 2009; Joshi and Hanssens 2010), improvements to consumer satisfaction (Fornell et al 2006; Luo and Batthacharya 2006), developing a focus on service (Fang, Palmatier, and Steenkamp 2008), or focusing on brands (Morgan and Rego 2009; Mizik and Jacobson 2009).

However, the marketing concept holds that the marketing function is a consideration of relationships, and as such the discussion of marketing's impact on firm performance should benefit from the consideration of more complex relationships between entities outside of traditional firm boundaries. In fact, the most commonly thought-of assets under the control of a marketing manager, such as consumer, brand, and channel-equities are market-based (Hanssens, Rust, and Srivastava 2009); meaning that they don't reside within the firm, but are rather intangible items that are co-created with a variety of external entities.

For example, a consumer's brand equity is a function of the strength, valence and uniqueness of the associations the consumer has made with the brand (Keller 1993), under some

influence from the firm's marketing efforts. This equity value explains the propensity of purchase, and if aggregated across all consumers, will also offer a good explanation for the volume of goods sold, revenues generated, and any volatility observed (if we consider these revenues over time). However, consumers do not hold these brand-associations in a vacuum. Rather, consumers live in a world filled with interactions, where they can both influence and be influenced by other consumers, alternative brands, and competitive or cooperative marketing efforts. Therefore, it is not surprising that social network theory (which allows us to chart, quantify, and study these interaction) found applications in the marketing literature. In fact, network concepts should not be just useful to managers in connecting firm action to firm performance (Swaminathan and Moorman 2009, Stephen and Toubia 2010), but also in the development of managerial tools and procedures that allow them to generate at least temporary competitive advantage in the market and improve firm performance.

1.1 SOCIAL NETWORK INFORMATION: RELATIONAL AND STRUCTURAL

Information is one of the mechanisms by which a network has the ability to improve firm performance (Gulati 1998), meaning that membership, and perhaps position within a given network can give rise to a situation where there is asymmetry in information. This asymmetry then allows for arbitrage around the information itself, or creates a window of opportunity for competitive advantage to be created, thus generating value and enhancing performance. This information can arrive either due to relational or structural benefits (Granoveter 1992).

Relational benefits rely on the strength of the tie between two members of a network. Assuming, just momentarily for exposition, that we are dealing with a network of firms. A strong

tie between two firms would indicate a greater degree of collaboration, more integrated systems, a longer history of working together, etc. Strong ties facilitate the flow of information between these firms, allowing for more tacit knowledge transfers, and greater trust (Rowley, Behrens, and Krackhardt 2000). However, Granoverter (1973) argued that strong ties would also provide more redundant (rather than novel) information. In contrast, weak ties, exemplified by shallower and more infrequent inter-firm communications, represent connections to more dissimilar firms with access to more novel knowledge. Given this contradictory nature of the strength of ties (i.e., high quality connection with redundant information versus a low quality connection with novel information), Rowley, Behrens and Krackhardt (2000) explain that the firm's environment, and its intended goals at a specific point in time dictate the value of the strength of a tie.

Alternatively, informational benefits can be derived from a structural perspective, which takes into account the position of the firm relative to other members of the network. In this perspective, a firm might be positioned in such a way that it connects two groups, or clusters of other firms that would not have been connected otherwise. This position of brokerage allows the connecting firm the aforementioned arbitrage opportunity on information it receives from either of the separate groups (Gulati 1998).

1.2 THE SOCIAL NETWORK AS INFORMATION

Lastly, it is worth noting that additional information can be derived from analysis of the social network itself, given the accumulation and pattern of connections between all members. This shift in perspective from network-member benefitting from information flows within the network (relational or structural), to network-observer provides incremental benefits for the firm

when we consider the ability to absorb new information, even from networks where the firm does not directly participate in as a member, such as consumer or brand networks.

Assuming that connections in marketing-relevant networks, such as consumer, brand, or firm networks, are not randomly generated, but rather arise due to choice or strategic action; then, analyses of these network can yield relevant and actionable managerial information to aid in the development of marketing strategies that will drive firm performance, and value.

This dissertation builds on the research studying the impact of social networks on marketing practice in two meaningful ways. First, I add to the discussion on the impact of marketing alliances, and marketing alliance networks on firm risk. While much of the previous research has emphasized that strategic alliances contribute to reduction of risks because uncertainties are shared across firms, reducing the risk exposure of any one firm, empirical support for this view is limited. For example, Bucklin and Sengupta (1993, p. 43) argue “alliances provide a superior vehicle for gaining access to new complementary products or technologies without all the risks of internal development.” Rowley, Behrens, and Krackhardt (2000, p. 371) echo this view that “firms enter strategic alliances to gain access to external resources [and] share risks.” While Rindfleisch and Moorman (2003, p. 422) suggest that “advocates of interfirm cooperation argue that alliances, joint ventures, and other forms of cooperation are largely procompetitive because they help firms reduce risk.” Similar claims have been made in the strategy literature in which one of the touted advantages of strategic alliances is the “risk-sharing” component (Hagedoorn 1993; Rowley, Behrens, and Krackhardt 2000). Despite the widespread belief that strategic alliances are mechanisms for risk reduction, Das, Sen, and Sengupta (1998) find that marketing alliances contribute to an increase in risk. To resolve these incongruences, this dissertation provides an empirical examination of the marketing

alliance impact on separate components of equity risk, taking into consideration the pattern of connections in the alliance network where the firm is embedded.

I find that while a novel alliance reduces both the firm's systematic and idiosyncratic risks, any subsequent alliances with the same partner do not provide the same benefit. Furthermore, the clustering of a firm's ego network has an exponential impact on idiosyncratic risk, first decreasing but rapidly increasing as this interconnectivity grows. Conversely, systematic risk increases at a decreasing rate as a function of one's partner's clustering. So, contrary to the widespread belief that marketing alliances are good vehicles for risk reduction, this study demonstrates that they are only conditionally so, and highlights situations where managers could be unwittingly increasing the firm's risk exposure without a commensurate increase in value.

This analysis also suggests that a manager looking for a new marketing alliance partner (whether for a joint promotion, co-branding, or joint sales program) can adopt a network-as-information perspective and screen for potential partners on the additional basis of which network position each firm occupies, as well as which overall network structure would be created with the alliance. Careful selection of partners on this basis could give rise to greater abnormal returns in the financial markets (Swaminathan and Moorman 2009), as well as lower idiosyncratic risk.

Lastly, I explore the network-as-information concept in a different domain where enhanced marketing strategy can improve firm performance and create firm value: social media. Firms are currently facing decisions about an entirely new, and rapidly evolving environment in the digital space, comprised by ecommerce, online discussion forums, social media sites, blogs, file-sharing depots and torrents, etc. While few would now argue that this online digital space

has a small performance consequence for firms, it might be less obvious that this world has a direct and significant impact on real world, brick and mortar performance, be it through media use of social media for gathering news, the growing popularity of apps, and mobile interactions. As such, understanding and predicting the attitudes of consumers about a brand online should be a valuable activity for managers, opening up the possibility to take corrective action before small online shifts become larger offline problems. To address this need, this dissertation proposes a brand-network enhanced forecast model for online sentiment valence.

This novel approach to predict online word of mouth valence uses only standard, commercially available, social media monitoring data. By considering that brands being discussed online don't exist in vacuum, time varying networks of brands are built based on their coexistence in this digital space, and then this relational structure is used to reduce the forecast error for a focal brand. The incorporation of information from this digital environment, such as the brand's network degree centrality or ego network clustering, improves predictability and extends the forecast window, providing a valuable tool for managers interested in anticipating changes in consumers' positive or negative attitudes towards a brand.

2.0 WHAT GOES AROUND COMES AROUND: THE IMPACT OF MARKETING ALLIANCES ON FIRM RISK AND THE MODERATING ROLE OF STRUCTURAL EMBEDDEDNESS

In the past decade, the forces of globalization and competition have led to a significant shift in the organizational structure of firms, from a stiff hierarchy to a more fluid and disaggregated organizational structure comprising internal and external networks. Different from hierarchical forms of organization, networked organizations are structured such that innovation and marketing coordination takes place at the core and an increasingly large number of strategic alliance partners supplement the efforts of the firm in various crucial aspects (e.g., gaining access to new markets, developing new products). Achrol and Kotler (1999) predicted that as the organizational structure of firms shift from hierarchical forms to networked organizations, marketing outcomes would be increasingly determined by competition between networks of firms.

Literature on strategic alliances in marketing has primarily focused on the dyadic level of analysis (e.g., Bucklin and Sengupta 1993; Houston and Johnson 2000), though recent efforts have also explored how networks of interfirm agreements contribute to various aspects of performance (e.g., Cui and O'Connor 2012; Swaminathan and Moorman 2009; Wuyts, Stremersch, and Dutta 2004). This work is also consistent with the broader trend toward understanding how networks can be a source of value to the firm (Grewal, Lilien, and

Mallapragada 2006; Mallapragada, Grewal, and Lilien 2011). Despite these important findings, much of the previous work on strategic alliances in both marketing and the broader strategy literature has focused on value creation; far less research has examined the risk implications of strategic alliances.

This study examines whether marketing alliances, defined as alliances that enable a firm to gain access to new resources, markets, brands, and products (Bucklin and Sengupta 1993; Swaminathan and Moorman 2009), have an impact on firm risk. It also highlights the role of network characteristics (e.g., network density) as a moderator of the relationship between marketing alliance formation and firm risk.

Interfirm network characteristics have important implications for firm risk for three reasons. First, anecdotal evidence from financial and banking sector crises (e.g., subprime mortgage crisis, Greek debt crisis) indicates that contagion risk can cause whole industries to become vulnerable to problems emanating from one or two participants in the network. The implication is that a firm's risk is closely linked to the firms on which it depends for cash flows; these firms are strategic alliance partners in the network of interfirm relationships in which the focal firm is embedded. Second, the marketing function has a direct impact on the risk profile of a firm because volatility of cash flows is often linked to demand uncertainties, and demand generation is primarily a marketing function. Thus, understanding how marketing actions (e.g., marketing alliances) can affect the risk profile of the firm is crucial. Third, the dependence on external partners to fulfill the functions in the firm could lead to greater systematic risk, which again could lead to greater covariation of firms' cash flows with the overall industry; to the extent that a firm has chosen to embed itself in a network of tightly linked firms, the network could impose significant risks, particularly if the interconnections are so dense that volatility is

exacerbated.

The expectation that dependence on strategic alliance partners can be problematic for a firm stands in stark contrast with how extant literature examines risk implications of strategic alliances. Much of the previous research has emphasized that strategic alliances contribute to reducing risks because uncertainties are shared across firms, limiting the risk exposure of any one firm. For example, Bucklin and Sengupta (1993, p. 43) argue that “alliances provide a superior vehicle for gaining access to new complementary products or technologies without all the risks of internal development.” Echoing this view, Rowley, Behrens, and Krackhardt (2000, p. 371) state that “firms enter strategic alliances to gain access to external resources [and] share risks.” Finally, Rindfleisch and Moorman (2003, p. 422) suggest that “alliances, joint ventures, and other forms of cooperation are largely procompetitive because they help firms reduce risk.” Researchers in strategy literature have made similar claims, touting one advantage of strategic alliances as the “risk-sharing” component (Hagedoorn 1993; Rowley, Behrens, and Krackhardt 2000). Despite widespread agreement that strategic alliances are mechanisms for risk reduction, empirical support for this view is limited. Indeed, to our knowledge, only Das, Sen, and Sengupta (1998) consider the equity risk consequence of alliances (even if just briefly); in their work, they link strategic alliances to stock market returns and find that marketing alliances contribute to an *increase* in risk.

We aim to empirically examine the relationship between marketing alliances and risk to resolve the debate. In contrast with Das, Sen, and Sengupta’s (1998) work, we examine the impact of marketing alliances on two components of risk: idiosyncratic and systematic risk. More important, we argue that the relationship between strategic marketing alliances and firm risk is moderated by structural properties of the network of prior alliances. Our focus is

specifically on network density, or the level of interconnectivity among a firm's partners. We examine how a densely interconnected set of actors in a firm's strategic alliance network moderates the relationship between new strategic alliance formation and firm risk.

In summary, this research makes three key contributions to the literature. First, we examine how strategic marketing alliances contribute to firm risk by disentangling the impact on two dimensions of risk. In doing so, we contribute to recent findings regarding the impact of marketing actions, specifically advertising and brand equity, on risk (Bharadwaj, Tuli, and Bonfrer 2011; McAlister, Srinivasan, and Kim 2007; Morgan and Rego 2009; Rego, Billett, and Morgan 2009; Sorescu and Spanjol 2008; Tuli and Bharadwaj 2009). Second, we explore the moderating role of network density. Third, we examine how repeat partnering moderates the impact of alliances on risk. We test these using a database of marketing alliances across various industries. We use an event study methodology (similar to Das, Sen, and Sengupta's [1998] study) to measure risk by examining the change in risk before and after the announcement of a strategic alliance. We conclude with a discussion of the importance of networked-asset management as an emerging skill for marketing managers and the strategies that firms can undertake in the formation of their own marketing networks.

2.1 THEORY AND HYPOTHESES

Theory of Risk in Marketing

Scholars have increasingly recognized the importance of marketing actions in reducing risk. McAlister, Srinivasan, and Kim (2007) describe the impact of advertising and research-and-development expenditures on reducing the systematic risk of a firm. Rego, Billett, and Morgan

(2009) suggest that customer-based brand equity helps reduce idiosyncratic risk and can also buffer equity holders from downside systematic risk. Bharadwaj, Tuli, and Bonfrer (2011) show that brand quality reduces firm idiosyncratic risk. More recently, Tarasi et al. (2011) advocate incorporating the financial principles of risk to effectively manage a firm's customer portfolio. Taken together, these results suggest that marketing investments in brand building and advertising can act as mechanisms for risk reduction. Despite these important contributions, extant research has largely focused on marketing assets located within the firm; increasingly, firms are attempting to access resources located externally in partner organizations. How does the increasing propensity of firms to engage in interorganizational relationships and exchange marketing resources affect their equity risk and its two components, idiosyncratic and systematic risk? We examine this issue next.

Equity Risk

Equity risk, by definition, arises from and resides in the financial/equity market. Considered the volatility of a firm's stock returns, it exists because stock traders (either individual investors or institutions) disagree on the true underlying value of the firm (and, with it, its stock), thus enabling trades to occur, returns to be realized, and volatility to exist. To fall on the profitable side of these disagreements, traders use all the information available to them.

In line with this argument, Srinivasan and Hanssens (2009, p. 294) state that within this "well-known efficient markets hypothesis ... in finance, these investor reactions fully and accurately incorporate any new information that has value relevance. Thus, insofar as marketing drives product-market performance, new marketing developments could be value relevant." Kimbrough and McAlister (2009, p. 316) echo this statement by arguing that short-window event

studies are ideally suited to inferring causality and provide for “more direct causal inferences about the source of the information on which investors rely.”

Thus, a novel marketing alliance announcement should provide new information for the entire market on the firm’s ability and plans to generate future profits, allowing competing traders to model new alternative firm values and execute trades—giving rise to divergent amounts of equity risk. In hypothesizing the impact of marketing alliance announcements, we adopt this perspective of a trader/investor analyzing future performance consequences due to novel information.

Marketing Alliances and Idiosyncratic Risk

The idiosyncratic risk component of equity risk accounts for a firm’s own volatility and other firm-specific factors unrelated to the broader financial market (Rego, Billett, and Morgan 2009; Shin and Stulz 2000). Firms enter into marketing alliances to gain access to new resources, markets, brands, and products (Bucklin and Sengupta 1993; Swaminathan and Moorman 2009). Therefore, marketing alliances help diversify a firm’s product portfolio and expand its geographic reach, both of which reduce the volatility of the firm’s demand. Thus, investors evaluating a marketing alliance announcement will generate new value expectations based on firm-specific factors, which in turn will impact the firm’s idiosyncratic risk. But should idiosyncratic risk increase or decrease with information from a new alliance?

Marketing alliances can be a diversifying force, helping the firm gain access to new markets or products through external partnerships rather than through costly internal development. To the degree that these new acquisitions are unrelated to the firm’s previous market or product offerings, the firm’s cash flow volatility should decrease. For example, the U.S. toy manufacturer Hasbro partnered with Gameloft, a French game developer, to leverage

some of its intellectual property (My Little Pony and Littlest Pet Shop) on mobile gaming platforms (Hasbro 2012). This agreement extended Hasbro's portfolio into digital gaming, in which revenues increased more than 4% in 2011, while the toy industry in the United States experienced a 2% decline in the same period (NPD Group 2012; PricewaterhouseCooper 2012). In this case, Hasbro entered into an alliance to increase the number of product categories it operates in, making up for any downsides in one business with upsides in a different category. By combining unrelated (or, at least, imperfectly related) businesses or markets, a firm can reduce the volatility of its cash flows and, by doing so, reduce its idiosyncratic risk.

Marketing alliances can also strengthen a firm's positioning and increase its brand equity by acquiring new brand associations, as in the case of cobranding alliances. To the extent that these new associations increase the brand's equity, the firm's volatility and idiosyncratic risk should decrease (Rego, Billett, and Morgan 2009). This decrease in volatility comes from a more stable cash flow stream due to greater consumer loyalty (Chaudhuri and Holbrook 2001), repeat-buying patterns (Keller 2003), and a decrease in brand substitution (McAlister, Srinivasan, and Kim 2007).

Taken together, these arguments suggest that the benefits of alliances due to diversification and stronger brand equity have a significant impact on reducing idiosyncratic risk. Announcements of marketing alliances should signal greater stability of cash flows in the future brought by a diversified consumer base (Tarasi et al. 2011) and strong brands (Rego, Billett, and Morgan 2009). Therefore, when a marketing alliance is announced, investors should update their beliefs or expectations in such a way that helps reduce the firm's idiosyncratic risk. Thus:

H₁: A firm's idiosyncratic risk decreases after a marketing alliance announcement.

Marketing Alliances and Systematic Risk

The systematic component of equity risk is indicative of the firm's exposure to macrolevel economic risks, such as fluctuations in currency exchange rates, the price of energy, and interest rates (Brealey, Myers, and Allen 2008; Rego, Billett, and Morgan 2009). Firms can buffer themselves from these broader market shocks with certain marketing initiatives and assets, such as advertising (McAlister, Srinivasan, and Kim 2007) and brand equity (Rego, Billett, and Morgan 2009), but can also increase their exposure as a result of others, such as brand quality (Bharadwaj, Tuli, and Bonfrer 2011). How, then, do marketing alliances affect the firm's systematic risk?

If the alliance serves as a diversifying force for the firm (e.g., new markets, new products), the firm will enhance its economic footprint, in turn potentially increasing the number of macroeconomic forces to which it is susceptible. For example, the alliance between Hasbro and Gameloft, which stabilized Hasbro's cash flows through participation in the digital gaming market, might also have caused Hasbro to worry about the dollar/euro exchange rate, which has implications for the timing of currency exchanges and, thus, profitability between the firms. As such, the increasing responsiveness of firm performance and returns to macroeconomic forces translate into greater systematic risk (Brealey, Myers, and Allen 2008).

The increase in uncertainty from the reliance on partners can also increase systematic risk because an unrelated partner firm brings a different set of macroeconomic vulnerabilities (e.g., exchange rate, interest rate) to be "shared" in the alliance (Rowley, Behrens, and Krackhardt 2000). Therefore, underperformance from a partner due to a market-level event will affect the firm's own performance (conditional on its interdependencies) and, with it, the extent to which it

can respond to macroeconomic forces, increasing systematic risk. Thus, as a firm diversifies through its alliances and increases its reliance on partners, based on aforementioned arguments, investors will react to announcements of marketing alliances such that systematic risk increases.

H₂: A firm's systematic risk increases after a marketing alliance announcement.

Repeat Partnering

We move beyond dyadic relationships and consider a more complete network of alliances (Gulati 1998; Swaminathan and Moorman 2009). The alliance network perspective, originally suggested by Gulati (1998), incorporates the firm's direct partnerships and their interdependencies (similar to a portfolio) but also accounts for both the partner's connections and other accumulating connections, extending beyond the appropriate interdependencies. These types of networks paint a more complex picture and also provide a dynamic view of forces influencing the firm and partner actions (Granovetter 1985; Gulati 1998; Yang, Lin, and Lin 2010). Previous studies of firm networks have considered two types of additional information arising from the network structure: relational and structural (Rindfleisch and Moorman 2001; Swaminathan and Moorman 2009).

Relational characteristics are associated with the strength of ties between firms in a social network (Granovetter 1973), which determines the degree of trust in the relationship and the likelihood and ease of transferring information (Gulati 1995, 1998). Firms that share a strong alliance connection are also more likely to act, and react, in a similar manner (Gulati 1998). This similarity calls to question the portfolio assumption of stable correlations, especially as firms engage in repeated partnerships and agreements. How, then, does a repeat partnership affect the two types of risk important to investors?

Recall that we previously argued that idiosyncratic risk, or firm-specific risk, should decrease after a marketing alliance because of either a diversification or a brand equity–strengthening effect. Firms can achieve diversification by tapping into assets uncorrelated with their own (e.g., entering new markets, acquiring new products or brands). Brand equity can be strengthened through new brand associations in a cobranding relationship. Furthermore, new partnerships give firms access to novel information, and the knowledge acquired through such partnerships leads to new knowledge, which is critical to success in uncertain environments (Christensen and Raynor 2003; Duysters 1996; Goerzen 2007). However, none of these mechanisms apply when a firm forms an alliance with a preexisting/current partner. Because both proposed mechanisms rely on the acquisition of or access to a novel asset, increasing commitment to one specific asset already accessed should not have any beneficial effects of lowering a firm’s idiosyncratic risk.

We also hypothesized that a firm’s systematic risk exposure should increase because the firm is now exposed to various macroeconomic forces that can indirectly influence its cash flows. When a firm enters into a repeat partnership, the previously mentioned impact on systematic risk does not hold true, because the firm has already become susceptible to the broader forces that influence its partner, by virtue of a past partnership.

Although repeat alliances could involve different functional areas from firms in the original alliance, the mechanism by which risk arises is still dependent on whether the partners establish a correlation between their revenue streams. If the correlation has already been established (from a previously announced alliance), a level of dependence already exists between the partners in terms of their revenues. If the new repeat partnership involves a different functional area, new increases in correlation could arise, but this increase would likely to be

lower than in a brand-new partnership. Therefore, we expect that the hypothesized impact of marketing alliance formation on idiosyncratic and systematic risks will hold only for a firm's new connections.

H_{3a}: The decrease in idiosyncratic risk after a marketing alliance announcement holds only for a new partnership, not for a repeat partnership.

H_{3b}: The increase in systematic risk after a marketing alliance announcement holds only for a new partnership, not for a repeat partnership.

Network Density

Density refers to the connectivity among a firm's partners. In addition to relational benefits, the firm can benefit from its position in the alliance network. Maintaining connections with distinct parts of the alliance network can provide further diversification to the firm, giving it access to novel and nonredundant information, which is beneficial for remaining innovative (Baum, Calabrese, and Silverman 2000), enhancing its position from brokering the information transfer (Burt 1992, 2001), and sustaining performance levels during periods of environmental change and uncertainty (Koka and Prescott 2008). Achrol and Kotler (1999, p. 147) argue that networked firms experience a reduction in risk exposure because "environmental disturbances transfer imperfectly through loosely coupled networks and tend to dissipate in intensity as they spread through the system," resulting in a situation in which "each unit in the network must deal with a small component of the disturbance."

Among the many sociometric measures used to describe an actor's position in a network, prior research has shown that degree centrality (the number of direct partners) and density (the

number of connections between partners as a proportion of possible connections) have a significant impact on a firm's results and returns (Stephen and Toubia 2010; Swaminathan and Moorman 2009). So, what are the possible downsides of these network structures? Although prior research has highlighted many positive aspects of density, some of these recognized benefits can have a dark side in terms of a firm's risk exposure. Density increases the structural stability of the network (Baum, Shipilov, and Rowley 2003; Provan, Fish, and Sydow 2007), which is accomplished through the formation of cliques, or subgroups, that are more interconnected than linked to external partners. This cliquelike behavior facilitates the exchange of information between firms and increases the incidence of joint activity and cooperation (Coleman 1988, 1990; Uzzi 1996). Therefore, network density can lower idiosyncratic risk

However, at higher levels of network density, this joint activity and cooperation can translate into more incidences of overlapping markets, customers, and brands. Such an overlap can lead to an increase in the correlation in the performances of these firms; as this correlation increases, the diversification of their portfolios/networks decreases. Indeed, Achrol and Kotler (1999) contend that at very high levels of density, a clique of firms approximates a singular, undiversified superstructure or a "networked entity."

Furthermore, high levels of density works against Burt's (1992) concept of structural holes by erasing the brokerage positional advantage of the firm as its partners form direct connections to one another. This vanishing advantage compromises the value of the information the firm can access from its network, which affects its ability to navigate in uncertain environments. This also reduces the amount of power and control the firm can exert over its network, thus lowering its ability to use partnerships as tools in risk-mitigation strategies and rendering it more prone to operational uncertainty.

Thus, as partner firms become more interconnected, they first stabilize partnerships and facilitate the exchange of information, which can reduce uncertainty. However, as density increases, firms begin to act similarly and resemble each other, diminishing the impact of diversification and brand equity strengthening, which had originally contributed to a decrease in the firm's idiosyncratic risk, and lowering their ability to use their network as a protective barrier against operational uncertainty. Therefore, as the partner firm's network density increases, its idiosyncratic risk should initially decrease but then increase:

H₄: A firm's alliance network density has a curvilinear impact on its idiosyncratic risk following a marketing alliance announcement. Specifically, at low levels of network density, idiosyncratic risk decreases, and at high levels, idiosyncratic risk increases.

Partner Network Density

One factor that may exacerbate the risk inherent in a strategic alliance is the role of a partner's network characteristics. A large part of the uncertainty in alliances stems from the notion that a partner is an independent, active, and strategic actor (Das and Teng 2001; Yang, Lin, and Lin 2010). As an active player, the partner firm manages its own network of alliances to maximize its returns and minimize its risk exposure. Therefore, as the partner firm uses its network to change its own risk profile, it also changes the amount of risk it brings into the alliance to be "shared" (Rowley, Behrens, and Krackhardt 2000).

One such shared risk factor, as we have argued, is the number of additional vulnerabilities to market forces brought by the partner firm. When a firm diversifies through its partner, it also assumes its vulnerabilities, thus becoming more exposed to a wider variety of market forces and, by definition, suffering from greater systematic risk. That is, as the partner's

network density increases, the firm's systematic risk also increases because of the undiversification of the partner's position and a subsequent reduction in the differentiation provided by the alliance. However, at high levels of density, the detrimental impact of this reduction in differentiation should occur at a decreasing rate, simply because of the nature of network density itself. To approach its maximum level, network density requires that all firms have a connection with all other firms, which reduces the novelty of the macroeconomic forces. In addition, this connection exacerbates issues that were present in other previously established connections.

These arguments imply that while a partner's dense network exposes the firm to more market forces, the increase in systematic risk due to a dense partner network likely manifests at a decreasing rate owing to the process of network creation. Thus:

H₅: A partner's network density has a nonlinear impact on the firm's systematic risk following a marketing alliance announcement. Specifically, at low levels of network density, systematic risk increases, and at high levels of network density, systematic risk increases at a decreasing rate.

2.2 METHOD

Event Studies of Risk

To examine the relationship between strategic alliances and the risk profile of a firm, we use the event study approach to assess changes to a firm's risk. This methodology is new to marketing, though it has a long history in finance literature. For example, Kalay and Loewenstein (1985) examine the changes in equity risk surrounding dividend announcements,

using event windows extending 34 days before and after the announcement. Brown, Harlow, and Tinic (1988) analyze information uncertainty with a similar methodology but use event windows extending over 60 days. More recently, Carlson, Fisher, and Giammarino (2010) examine dynamics of risk before and after a seasoned equity offering. Across all these studies, an event study approach to risk involves comparing risk before and after a significant event. We employ this approach in a marketing context to examine how marketing alliance announcements influence a firm's risk exposure.

2.2.1 Data

Following Swaminathan and Moorman's (2009) work on the impact of alliance networks on returns, we collected data on strategic alliances from the SDC Joint Ventures/Strategic Alliances database, which provides descriptions of the alliance and participants. We gathered stock performance data from CRSP and other firm information from COMPUSTAT. We retrieved Fama–French factors from Kenneth French's web-based data library.

Our sample consisted of firms from five different industries (i.e., automotive, electronics, software development, telecommunications, and power generation) that announced marketing alliances from 1988 to 2008, while Swaminathan and Moorman (2009) focused on a single industry. From our original list of alliances, we extracted the results for all partners separately, which yielded two data points per partnership announcement. We deleted partnerships that included more than two partners or those that involved private partners. We also deleted firms for which we could not obtain network, partner network, or firm data. Finally, we deleted firms without a credit rating for the year of the alliance, which provides an indication of their cash flow

vulnerabilities (Rego, Billett, and Morgan 2009). This process yielded a final sample of 251 firm-specific results for analysis.

2.2.2 Measures

Idiosyncratic risk. Both our dependent variables are functions of the components of the total financial risk facing shareholders—that is, equity risk. We take equity risk as the standard deviation in the returns for a given security. We calculate the first component of equity risk, *idiosyncratic risk*, by taking the standard deviation of the residual of the Carhart- (1997) modified Fama–French model (Fama and French 1993, 1996):

$$r_{it} = \beta_i + \beta_i r_{mt} + s_i \text{SMB}_t + h_i \text{HML}_t + u_i \text{UMD}_t + e_{i,t}, \quad (1)$$

where r_{mt} is the market return, SMB_t are the differential returns to portfolios comprising small versus large capitalization firms, HML_t are the differential returns to portfolios comprising high versus low market-to-book ratio firms, and UMD_t are the differential returns to portfolios comprising firms with high versus low prior returns.¹

To determine the change in firm idiosyncratic risk, we followed the approach Das, Sen, and Sengupta (1998) use by first calculating the firm idiosyncratic risk for the period between –60 trading days and –10 trading days, using the alliance announcement as the day 0 reference point. This is the prealliance firm-specific risk. We then repeat the procedure for the period from +10 trading days to +60 trading days after the announcement, which gives us the postalliance

¹ Although the capital asset pricing model (Sharpe 1964) is a potential alternative to the Fama–French model used herein, it would require a significantly greater amount of data to generate the required market portfolio (which, in principle, should expand beyond stocks to include bonds, durables, real state, labor, and so on) to match or surpass the Fama–French model’s ability to predict returns. As such, our chosen model provides a more efficient approach to minimizing residuals and the most conservative estimates of risk.

firm-specific risk. The difference between these two measures is our first dependent variable to be used in Model 1.

Systematic risk. We calculate the second component, *systematic risk*, by subtracting the squared standard deviation in the errors from the squared standard deviation in returns (e.g., Lubatkin and Chatterjee 1994; Rego, Billett, and Morgan 2009). We follow an identical procedure to arrive at the change in systematic risk. That is, we calculate the preannouncement firm systematic risk for the period between –60 trading days and –10 trading days, before the alliance announcement (day 0). As previously, the calculation of the period from +10 trading days to +60 trading days is the postannouncement systematic risk component. The difference between the values in these two periods is our measure of the change in systematic risk, our second dependent variable, to be used in Model 2.

Independent Variables

When possible, we follow Swaminathan and Moorman's (2009) selection and specification of variables; they present the impact of alliance networks on returns, and we aim to present the counterpoint with respect to firm risk. However, this risk perspective also necessitates its own considerations that diverge from Swaminathan and Moorman's original work, as we discuss next.

Repeat partnership. To differentiate alliances that have a structural impact from those that reinforce preexisting network ties, we must account for the existence of these connections. Repeat partnership is an indicator variable that assumes a value of 1 if the two firms involved in the alliance announcement have previously engaged in a strategic alliance (given by any, related

or unrelated, alliance announcement containing both firms in the five years preceding this new announcement) and a value of 0 if otherwise.²

Network density. We calculate network density as the number of connections among all firms in a focal firm's network divided by the total number of possible connections among these firms (Rowley, Behrens, and Krackhardt 2000). We mean-centered this value by firm before entering it into the model.³ Network densities in our data range from 0 to 1, with the average firm having a value of .437. While 75% of the firms we observe have densities below .6, 10% of all firms in the data have network density values of 1.

Partner firm network density. Partner firm network density is identical to the focal firm's network density, except that the partner firm is at the center of the network. We treat firms as both focal (when explaining own returns and risk differencing) and partners (when explaining partner firm's return and risk differencing). We account for the nonindependence created by these observations by the use of hierarchical linear modeling.

Control Variables

Alliance returns. To capture the risk differencing arising solely from the connection between firms, we control for the expected risk differencing arising from the extra value generated during the event window of the alliance announcement. This control absorbs any change in equity risk expected from the changes to the underlying value of the assets in question, thus accounting for the higher risk associated with greater returns (Markowitz 1952). We calculate the abnormal returns arising from the alliance announcement by subtracting the

² This dichotomous approach to repeat alliances is meant to capture only the structural component of the connection between the firms. An alternative, continuous measure (e.g., number of previous alliances) would instead capture a relational component that begins to approach measures of tie strength. Although our study does not address relational considerations, we provide some insights using this alternative specification as a robustness check.

³ Mean-centering by group is a standard practice in hierarchical linear modeling designed to simplify interpretation of the results, especially for models containing variables for which values of 0 are either impossible or nonsensical. Under this centering option, an intercept π_{0jk} is equivalent to the unadjusted mean for firm j , and the variance is modeled around each firm's individual position (Raudenbush and Bryk 2002).

expected returns from the observed returns in an event window of -1 and $+1$ days surrounding the announcement of the new alliance. We calculate the expected returns by applying the Carhart-modified Fama–French model given in Equation 1, using a window of -300 to -60 days to the alliance announcement as an estimation period for each firm’s coefficients.

Horizontal alliances. The type of alliance could have a significant impact on firm risk, and strategic alliances have traditionally been distinguished between vertical and horizontal strategic alliances (Rindfleisch 2000). Vertical alliances involve strategic alliances with either upstream suppliers or downstream customers of the focal firm (Dyer 1996; Lorenzoni and Lipparini 1999). In contrast, horizontal relationships are typically within-industry alliances, such that both partners occupy a similar point on the value chain (Ahuja 2000; Jap 1999). We include an indicator variable that assumes a value of 1 if both partners are active in the same industry, as determined by a two-digit Standard Industrial Classification code, and a value of 0 if otherwise.

Marketing alliance types. Using detailed alliance announcement information, each alliance was coded by two MBA students. The coders were instructed to indicate any and all the types of alliances described below that matched the description of the alliance given in the official announcement. Note that the same alliance could have multiple types assigned to it. The overall interrater agreement was 83%, and disagreements were resolved by a third coder. The following points summarize the distribution of alliances in our sample and provide a brief description of the different types of alliances. Broadly, the alliance motives revolve around product development–/integration-based motives and market development–/access-based motives:

1. *Product development* (27%): The alliance was formed so that the two companies could develop a joint product.
2. *Product integration* (20%): The alliance was formed for the purpose of integrating two

products (e.g., hardware, software).

3. *Joint marketing* (53%): The firms jointly market their offerings to the target customers.
4. *Market access* (21%): The alliance helps the firm gain access to new geographic regions or target markets.
5. *Other*: Other motives for the alliance include licensing (2%), customer service (4%), sales (12%), bundling (4%), and international (5%).

Prior firm credit rating. To conduct a more complete assessment of the firm's overall risk, we include its credit rating in the year before the alliance announcement. This quantifies the firm's default risk to debt holders. The variable ranges from 2 (equivalent to a credit rating of AAA) to 27 (equivalent to a credit rating of D); the higher the value, the more risk the firm has.

Network centrality. Network centrality refers to a firm's degree centrality, or the number of firms with which the focal firm is directly connected (Freeman 1979). This is an important variable in the alliance context (e.g., Gulati and Gargiulo 1999; Gulati, Lavie, and Madhavan 2011; Yang, Lin, and Peng 2011) because it enables us to control for the effect of the size of a firm's network on firm risk.

Network efficiency. The efficiency of a network serves as an indication of the nonredundant knowledge available in a network (Baum, Calabrese, and Silverman 2000; Granovetter 1973; Mason and Watts 2012) and has been shown to influence various firm outcome measures, such as innovation and sales (e.g., Yu, Gilbert, and Oviatt 2011). We calculate this measure with a variation of the Hirschman–Herfindahl index, capturing the proportion of partners in the firm's network from nonoverlapping industries (determined by the two-digit Standard Industrial Classification code).

Network strength. The strength of a network is an indication of the quality of the alliance portfolio. We measure network strength on the basis of the average quality of a partner in a

network. We construct the measure by using a firm's membership in *Fortune's* Top 100 list, which assumes a value of 1 on an appearance and 0 otherwise. The final value of network strength is the average reputation score across partners in a firm's network (Houston and Johnson 2000).

Selectivity bias. We model selectivity bias in two stages: the bias in a firm's propensity to enter into alliances and the bias in selecting partners with specific characteristics. In the first stage, we use a probit equation to account for the firm's propensity to enter into alliances (for details, see Appendix A). We then employ the inverse Mills ratio from this equation and include it in the second stage.

In the second stage, we specifically control for selection bias to rule out the possibility that the results we observe are primarily due to the selection of partners with specific characteristics. To do this, we calculate an inverse Mills ratio by estimating a selection equation in which we model the probability of choosing a particular partner from a set of available similar partners in that industry in that year (again, for details of this estimation and results, see Appendix A).

2.2.3 Model Development

We apply a three-level specification of a hierarchical linear model to test our hypotheses. Hierarchical linear modeling is an appropriate methodology in this case because (1) our data are nested, so that multiple alliances involving the same unique firm can occur in the same calendar year; (2) the data are unbalanced, in that some firms repeatedly engage in alliances throughout our observation period, while others engage in a single partnership during the same period; and (3) it allows for a direct interpretation of our coefficients as well as a simpler but robust test of

our hypotheses. We also considered the application of a vector autoregressive model, given its growing acceptance in marketing literature and its strength in dealing with questions on market performance. Thus far, however, this specification is unable to handle the panel structure required for our analysis. We estimate the model individually for each of our dependent variables, which are represented by Y_{ijk} . In the simpler hierarchical notation, the model employed is as follows:

Level 1: Alliance

$$Y_{ijk} = \pi_{0jk} + \pi_{1jk}(\text{Abnormal returns})_{1ijk} + \pi_{2jk}(\text{Horizontal alliance})_{2ijk} + \pi_{3jk}(\text{Repeat partner})_{3ijk} + \pi_{4jk}(\text{Product development})_{4ijk} + \pi_{5jk}(\text{Product integration})_{5ijk} + \pi_{6jk}(\text{Joint Marketing})_{6ijk} + \pi_{7jk}(\text{Market Access})_{7ijk} + \pi_{8jk}(\text{Other Alliances})_{8ijk} + e_{ijk},$$

where each variable is given for alliance i , firm j , in year k and e_{ijk} is the deviation of the alliance from its predicted score based on the Level 1 model.

Level 2: Firm

$$\pi_{pjk} = \beta_{p0k} + \beta_{p1k}(\text{Credit rating})_{p1k} + \beta_{p2k}(\text{Centrality})_{p2k} + \beta_{p3k}(\text{Density})_{p3k} + \beta_{p4k}(\text{Density}^2)_{p4k} + \beta_{p5k}(\text{Efficiency})_{p5k} + \beta_{p6k}(\text{Strength})_{p6k} + \beta_{p7k}(\text{Partner density})_{p7k} + \beta_{p8k}(\text{Partner density}^2)_{p8k} + \beta_{p9k}(\text{Partner selectivity bias})_{p9k} + r_{pjk},$$

where the intercept β_{p0k} indicates the change in firm risk (idiosyncratic or systematic) arising from the alliance and r_{pjk} is the random effect representing the firm's deviation in these risk differences.

Level 3: Year

$$\beta_{pqk} = \gamma_{pq0} + u_{pqk},$$

where $q = 0$ through 8, indicating each of the Level 2 variables, and u_{pqk} is the random effect representing the yearly deviation in each Level 2 coefficient.

We also estimated additional models to account for the interaction between alliance types and firm network characteristics. These models are also hierarchical linear models following the specification of our main models, similarly estimated for systematic and idiosyncratic risk. However, they differ in two ways: First, we simplify alliance types into a product type (combining product development and integration) and market type (combining joint marketing and market access); second, we include additional terms for the interaction of the simplified types with the four network density measures (Network density, Network density², Partner firm's network density, and Partner firm's network density²).⁴

2.3 RESULTS

Table 1 reports the correlations between variables in our study. Table 2 presents the coefficients, t-values, and associated significance levels estimated for our model, repeated for differences in idiosyncratic and systematic risks. To test out hypotheses, we model the change of

⁴ This simplification is necessary for the models to converge because the across-level interactions add 4 new parameters by type of alliance (simplified classification adds 8) to the original specification's 20 new parameters.

risk as a function of the alliance announcement, the type of alliance, firm network characteristics, and the change in value derived from the alliance.

Table 1 Correlation Table

Variable	M	SD	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	13.	14.	15.	16.
1. Δ Idiosyncratic	-0.086	0.017															
2. Δ Systematic	0.051	0.005	.022														
3. CARs	0.009	0.052	.127	.125													
4. Credit rating	4.993	4.890	.106	.043	.147												
5. Horizontal	0.128	0.335	.025	-.075	.032	.098											
6. Repeat	0.865	0.341	.066	.039	.087	.183	-.151										
7. Centrality	62.72	84.87	.022	.046	-.004	.035	-.046	.070									
8. Density	0.401	0.344	-.045	.044	.013	.065	-.156	.258	.124								
9. Efficiency	0.094	0.164	-.001	-.002	-.026	-.072	.086	-.455	.068	.044							
10. Reputation	0.409	1.271	.059	.001	-.018	-.060	-.031	.026	-.059	-.018	.033						
11. Partner density	0.430	0.308	.050	.145	.007	.102	-.096	.008	.108	.402	.134	-.009					
12. Product dev.	0.268	0.443	.060	.052	-.080	.118	-.088	.123	.184	.084	-.058	.030	.115				
13. Integration	0.201	0.499	-.017	.109	-.055	-.050	.004	-.143	-.081	.020	.155	-.071	.104	-.068			
14. Joint mktg.	0.528	0.401	-.024	-.052	.100	.083	.062	.071	-.019	-.004	.026	-.045	.027	-.087	-.082		
15. Market access	0.206	0.404	-.022	.046	.022	.042	-.006	.075	.077	.009	-.050	.060	-.031	.003	-.092	.114	
16. Other alliance	0.215	0.403	.055	.001	-.011	.061	-.014	.143	-.050	-.023	-.141	-.067	-.055	-.058	-.104	-.029	-.002

Notes: Bold values are significant at $p < .05$. CARs = cumulative abnormal returns. Mean values for Δ in risk components are multiplied by 10^{-4} . (N = 251)

2.3.1 Change in Idiosyncratic Risk (Model 1)

Model 1, which explores the factors influencing the change in idiosyncratic risk in Table 2, is a significant improvement ($-2LL = 770$, d.f. = 18, $\chi^2 = 44.27$, $p < .01$) over the null specified model ($-2LL = 1238$, d.f. = 4). The random components of the model are also significant ($\chi^2 = 38.16$, $p < .001$), providing support for the appropriateness of modeling the alliance, firm-, and time-specific factors that affect the change in idiosyncratic risk after an alliance announcement. Furthermore, the addition of our predictors enables us to explain approximately 98.77% of the variability observed between alliances, 98.59% of the variability between firms, and 21.58% of the variability over time (as a reduction in the residuals e_{ijk} , r_{pjk} , and s_{pjk}). The intercept is significant and negative ($\pi_{0jk} = -.026$, $p < .01$), indicating that a firm in

Table 2 Change in Firm Equity Risk Following a Marketing Alliance Announcement

Change in Idiosyncratic Risk (Model 1)			Change in Systematic Risk (Model 2)		
Variable	Parameter	t-value	Variable	Parameter	t-value
Intercept	-0.026**	-3.01	Intercept	-0.011	-1.53
<u>Network Characteristic</u>			<u>Network Characteristic</u>		
Network Centrality	-0.000	-0.10	Network Centrality	-0.000	-0.52
Network Density	-0.006*	-2.44	Network Density	0.000	-0.38
Network Density ²	0.015*	2.03	Network Density ²	0.001	-0.71
Network Efficiency	-0.003	-0.55	Network Efficiency	-0.001	0.35
Network Strength	0.002#	1.66	Network Strength	0.001	0.35
Partner Firm's Network Density	0.006	0.78	Partner Firm's Network Density	0.009**	3.14
Partner Firm's Network Density ²	-0.004	-0.53	Partner Firm's Network Density ²	-0.006*	-2.27
<u>Marketing Alliance Type</u>			<u>Marketing Alliance Type</u>		
Product Development	0.003#	1.77	Product Development	0.001	1.47
Product Integration	0.000	0.17	Product Integration	-0.001*	-2.28
Joint (Co-) Marketing	-0.001	-0.70	Joint (Co-) Marketing	0.001	1.57
Market Access	0.003*	1.93	Market Access	0.001	0.99
Other	-0.002	-0.98	Other	0.000	0.09
<u>Control Variables</u>			<u>Control Variables</u>		
Alliance Abnormal Returns	0.042**	2.72	Alliance Abnormal Returns	0.000	-0.63
Horizontal Alliance	0.000	0.12	Horizontal Alliance	-0.001	-1.30
Repeat Alliance	0.022**	2.47	Repeat Alliance	0.009	1.21
Firm Credit Rating	0.000	0.09	Firm Credit Rating	-0.000	-0.63
Partner Selectivity Bias	-0.001	-0.22	Partner Selectivity Bias	0.000	0.07
Random Effects			Random Effects		
<i>Alliance (Level 1 residual)</i>	0.0002*		<i>Alliance (Level 1)</i>	0.0002*	
Repeat Alliance	0.0000*		Repeat Alliance	0.0002*	
<i>Firm (Level 2)</i>	0.0002*		<i>Firm (Level 2)</i>	0.0001*	
Partner Selectivity Bias	0.0000*		Partner Selectivity Bias	0.0000*	
Firm Credit Rating	0.0000*		Firm Credit Rating	0.0000*	
Network Reputation	0.0000*		Network Reputation	0.0000*	
<i>Year (level 3)</i>	0.0001*		<i>Year (level 3)</i>	0.0000*	
-2LL	770		-2LL	1029	
Pseudo-R ²	0.378		Pseudo-R ²	0.418	

*** $p < .001$, ** $p < .01$, * $p < .05$, # $p < .10$.

an average network position experiences a decrease in its idiosyncratic risk after an alliance announcement. This finding provides support for H₁.

Of the control variables, alliance abnormal returns are significant and positive ($\pi_{1jk} = .042, p < .01$), confirming the expected relationship between greater returns and increased risk. Several of the variables are not significant, including horizontal alliances ($\pi_{2jk} = .000$, n.s.); network efficiency ($\beta_{p5k} = -.003$, n.s.); alliance-type dummies, including product integration ($\pi_{5jk} = .000$, n.s.); and joint marketing ($\pi_{6jk} = -.001$, n.s.). Only the market access dummy variable is significant ($\pi_{7jk} = .003, p < .05$), although the product development alliance dummy is positive and marginally significant ($\pi_{4jk} = .003, p < .10$). Firm credit rating ($\beta_{p1k} = .000$, n.s.) and degree centrality ($\beta_{p2k} = .000$, n.s.) are not significant. The relationship between network strength and change in risk is marginally significant ($\beta_{p6k} = .002, p < .10$).

Furthermore, we find that repeat partnerships have a significant and positive coefficient ($\pi_{3jk} = .022, p < .001$), which negates the risk reduction advantages of strategic alliances. This result provides support for H_{3a}. We posited that network density would have a significant, nonlinear impact on the change in idiosyncratic risk. We find evidence of a nonlinear impact; network density has a negative and significant impact ($\beta_{p3k} = -.006, p < .05$) on the change in idiosyncratic risk after an alliance announcement, and squared network density has a positive and significant impact ($\beta_{p4k} = .015, p < .05$). Figure 1 graphs these results. As this representation shows, firms experience a decrease in their idiosyncratic risk at the lowest levels of density in their networks, but as density increases, so does their idiosyncratic risk. This result provides support for H₄.

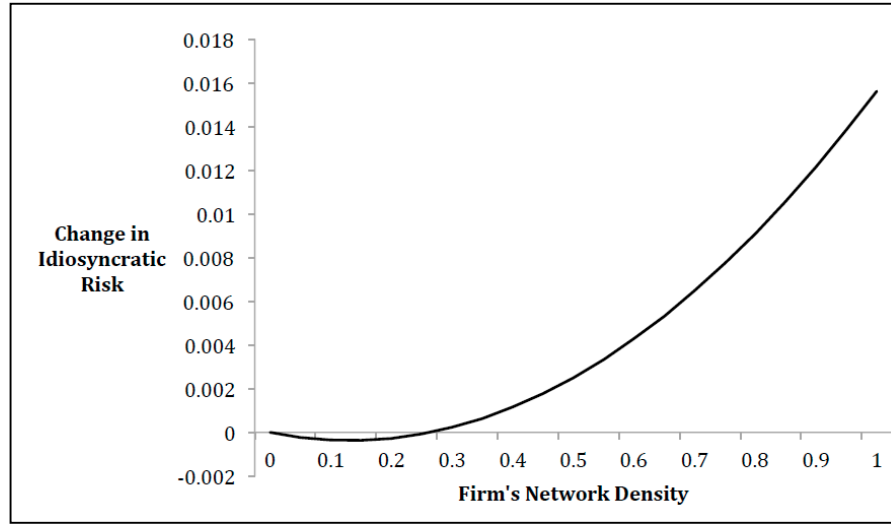


Figure 1 Impact of Network Density on Focal Firm's Idiosyncratic Risk

2.3.2 Change in Systematic Risk (Model 2)

Model 2, which explores the change in systematic risk after a strategic alliance, is also a significant improvement ($-2LL = 1029$, d.f. = 18, $\chi^2 = 29.87$, $p < .001$) over the null model ($-2LL = 1768$, d.f. = 4). In this specification, the random components are also significant, and the proportion of variance explained by our independent variables is essentially unchanged from that in Model 1.

In Model 2, the impact of alliance abnormal returns on risk is not significant ($\pi_{1jk} = .000$, n.s.), which suggests that increases in returns are not necessarily associated with greater levels of systematic risk. The intercept for Model 2 is not significant ($\pi_{0jk} = -.011$, n.s.), indicating that a firm in an average network position experiences no change in systematic risk after an alliance announcement, offering no support for H_2 . Repeat partnership has no impact on systematic risk ($\pi_{3jk} = .009$, n.s.), which offers no support for H_{3b} , a hypothesis that was conditional on the

unsupported H₂ discussed above. Firm credit rating, horizontal alliance, and partner selectivity bias are also not significant.

Among alliance types, we find that product development type, joint marketing type, market access type, and other type of marketing alliance are all not significant. Only product integration is negative and significant ($\pi_{5ijk} = -.001, p < .05$). Furthermore, for the changes in the firm's systematic risk, the partner firm's density has a significant and positive impact ($\beta_{p7k} = .009, p < .01$); consistent with our hypothesis, higher levels of partner network density also have a significant and negative impact ($\beta_{p8k} = -.006, p < .05$). Figure 2 presents the combination of these relationships. In light of our previous results, we find that a partner's network density increases the extent to which systematic risk increases after an alliance announcement, but at a decreasing rate, eventually reversing this downside at higher levels. This finding provides support for H₅. Ultimately, a firm will experience an increase in its systematic risk following a marketing alliance announcement, which is consistent with our theorizing; however, the extent of this increase doesn't appear be determined by formation of the alliance itself (as argued by H₂ and H_{3b}) but rather by the density of the partner's network.

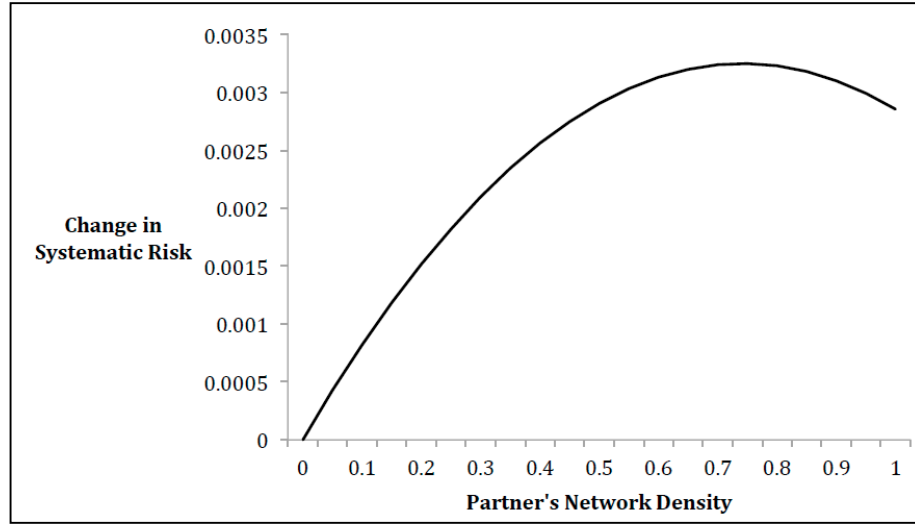


Figure 2 Impact of Network Density on Focal Firm's Systematic Risk

2.3.3 Interaction Models

Table 3 contains the results of the two additional models that further investigate the role of alliance type in the change in firm risk given a marketing alliance announcement. Model 3 explores the change in idiosyncratic risk and provides similar insights. First, the intercept is negative and significant ($\pi_{0jk} = -.025, p < .001$), which conforms to the previous finding that, on average, a marketing alliance announcement reduces idiosyncratic risk. Second, our indicator for a repeat alliance is positive and significant ($\pi_{3jk} = .019, p < .01$), indicating a diminished risk benefit of engaging with a preexisting partner. A significant increase in risk also occurs with increases in the alliance's abnormal returns ($\pi_{1jk} = .041, p < .01$) and the strength of the firm's network ($\beta_{p6k} = .001, p < .01$). Regarding the interaction of alliance types with the firm's network density, a similar pattern results, albeit weaker than the general case in Model 1. Product-related alliances show a negative (though not quite strong) effect of density of change in

idiosyncratic risk ($\beta_{p3k} = -.008$, n.s.), followed by an increase in risk at higher levels of network density ($\beta_{p4k} = .027$, $p < .05$). Following the same pattern, market-related alliances have a negative and significant impact on risk for network density ($\beta_{p3k} = -.010$, $p < .05$) but a positive (and, again, not strong) impact on risk at higher levels of density ($\beta_{p4k} = .016$, n.s.).

Model 4 extends this analysis to the interaction effect of alliance types and network density on the change in systematic risk given a marketing alliance announcement. The intercept is negative and significant ($\pi_{0jk} = -.014$, $p < .001$), providing some support for arguments counter to H_2 in that, on average, a marketing alliance announcement reduces systematic risk (after we control for the interactions). Again, our indicator for a repeat alliance is positive and significant ($\pi_{3jk} = .008$, $p < .01$), countering the advantage gained by forming the alliance, and providing support for the notion that a novel connection is required to obtain a risk benefit from an alliance announcement. Even if these findings are contrary to our original diversification-based hypotheses, they support a brand-equity based view whereby engaging in cobranding alliances firms can gain brand equity and reduce their systematic risk (Rego, Billett, and Morgan 2009). By building brand equity and stimulating loyalty, the firm creates a situation in which consumption of its products suffers less from downturns in the economy. This insulation from the broader markets translates into lower firm systematic risk.

Similar to our previous findings, the partner firm's network density has an inverse U-shaped relationship to the change in systematic risk, first increasing at lower levels of density ($\beta_{p7k} = .026$, $p < .001$) and then decreasing at higher levels ($\beta_{p8k} = -.021$, $p < .001$). However, this pattern is inverse for product-related alliances in the interaction coefficients ($\beta_{47k} = -.021$, $p < .001$; $\beta_{48k} = .020$, $p < .001$, respectively), thus resulting in a net zero impact of partner firm network density on systematic risk for these alliances.

Table 3 Change in Firm Risk Following a Marketing Alliance Announcement: Network Interactions with Type of Marketing Alliance

Change in Idiosyncratic Risk (Model 3)			Change in Systematic Risk (Model 4)		
Variable	Parameter	t-value	Variable	Parameter	t-value
Intercept	-0.025 ***	-3.48	Intercept	-0.014 ***	-5.06
<u>Network Characteristics</u>			<u>Network Characteristics</u>		
Network Centrality	0.000	0.35	Network Centrality	-0.000	-0.30
Network Density	0.004	0.83	Network Density	0.000	0.14
Network Density ²	-0.016	-1.15	Network Density ²	0.003	0.54
Network Efficiency	-0.001	-0.27	Network Efficiency	-0.001	-0.39
Network Strength	0.001 **	2.37	Network Strength	0.000	1.42
Partner Firm's Network Density	0.012	0.76	Partner Firm's Network Density	0.026 ***	4.11
Partner Firm's Network Density ²	-0.009	-0.52	Partner Firm's Network Density ²	-0.021 ***	-3.36
<u>Alliance Types and Interactions</u>			<u>Alliance Types and Interactions</u>		
Product (Development/Integration)	0.001	0.31	Product (Development/Integration)	0.004 *	2.42
× Network Density	-0.008	-1.61	× Network Density	0.000	0.00
× Network Density ²	0.027 *	1.99	× Network Density ²	-0.008 #	-1.64
× Partner Firm's Network Density	-0.006	-0.36	× Partner Firm's Network Density	-0.021 ***	-3.45
× Partner Firm's Network Density ²	0.013	0.81	× Partner Firm's Network Density ²	0.020 ***	3.39
Joint Marketing/Market Access	0.002	0.56	Joint Marketing/Market Access	0.003 #	1.64
× Network Density	-0.010 *	-1.94	× Network Density	-0.000	-0.17
× Network Density ²	0.016	1.19	× Network Density ²	0.001	0.17
× Partner Firm's Network Density	-0.002	-0.11	× Partner Firm's Network Density	-0.009	-1.37
× Partner Firm's Network Density ²	-0.008	-0.44	× Partner Firm's Network Density ²	0.006	0.87
<u>Controls</u>			<u>Controls</u>		
Alliance Abnormal Returns	0.041 **	2.63	Alliance Abnormal Returns	0.009	1.49
Horizontal Alliance	0.001	0.45	Horizontal Alliance	-0.001	-1.45
Repeat Alliance	0.019 **	2.91	Repeat Alliance	0.008 ***	3.33
Firm Credit Rating	-0.000	-0.04	Firm Credit Rating	-0.000	-0.71
Partner Selectivity Bias	0.000	0.03	Partner Selectivity Bias	0.000	0.36
<u>Random Effects</u>			<u>Random Effects</u>		
<i>Alliance (Level 1 residual)</i>	0.0001 *		<i>Alliance (Level 1)</i>	0.0000 *	
<i>Firm (level 2)</i>	0.0000 *		<i>Firm (level 2)</i>	0.0000 *	
<i>Year (level 3)</i>	0.0001 *		<i>Year (level 3)</i>	0.0000 *	
-2LL	778		-2LL	1017	
Pseudo-R ²	0.371		Pseudo-R ²	0.425	

*** $p < .001$, ** $p < .01$, * $p < .05$, # $p < .10$.

We provide no formal hypotheses for the differential impact of network density on changes to risk (idiosyncratic or systematic) across different alliance types, but Models 3 and 4 are useful in two ways. First, they validate the general underlying pattern of results found in Models 1 and 2, and second, they provide evidence of a richer set of circumstances that affect marketing alliances' effect on firm risk, offering opportunities for further research on the topic.

2.3.4 Robustness Checks

Longer risk calculation window: six months. To calculate our measures of idiosyncratic and systematic risks, we follow the work of Das, Sen, and Sengupta (1998) by examining 50 trading days before and 50 trading days after the alliance announcement (from –60 days to –10 days and then from +10 days to +60 days, around the announcement at day 0). These windows give us roughly two and a half months of data for each firm with which to calculate their risk exposure. To test the sensitivity of our results to the choice of this particular window, we expanded the firm observation period to six months before and six months after the alliance announcement.

The findings relative to the expected decrease in idiosyncratic and systematic risks, as well as the detrimental impact of repeat partnerships, remain unchanged. However, the coefficients related to network position become nonsignificant, with the exception of the partner's network density, which remains positive and significant ($\beta_{p7k} = .017, p < .001$). This loss of significance, combined with the loss of significance of the alliance's abnormal returns and the increasing significance of both a firm's credit rating and alliance type, leads us to conjecture that the increase in the risk window captures events beyond the singular alliance

announcement we measure. As such, the extended window models should be less reliable than those we presented previously.

Alliance experience. Another possible moderating force for the impact of marketing alliance announcements on a firm's idiosyncratic and systematic risk is the firm's experience in forming alliances. While the inclusion of abnormal returns controls for any disproportionate gains from experienced firms, the amount of experience itself could be indicative of an underlying firm strategy.

When we incorporate the firm's experience into our models of change in risk exposure, we find that experience is a nonsignificant predictor of change in both idiosyncratic risk ($\beta_{p10k} = .000$, n.s.) and systematic risk ($\beta_{p10k} = .000$, n.s.). As such, we can conclude that a firm's experience and the strategies it indicates have no effect on the impact of alliance on market risk exposure beyond that which accompanies any expected disproportionate returns from the alliance itself.

Repeat alliances as a continuous measure. We use a dichotomous measure of repeat partnerships to capture structural change, but the entire concept of repeat partnerships is more complex. Essentially, the generation of zero values in repeat partnerships follows a different process than nonzero values. Firms must first decide whether to reenter a partnership and then determine how often to do so. With these two processes, the repeat concept taps into two distinct constructs: (1) structural, which pertains to the first decision of whether to reengage with a preexisting partner, as captured by the dichotomous measurement of "repeat," and (2) relational, which captures the frequency with which the partners choose to cooperate, captured by a continuous treatment of "repeat." If we include this alternative (continuous) measure of repeat partnerships in our models of equity risk, the impact of repeated partnerships on

idiosyncratic risk is nonsignificant ($\pi_{3jk} = -.002$, n.s.); however, repeated partnership has a negative and significant impact on systematic risk ($\pi_{3jk} = -.0015$, $p < .05$). For our study, given our focus on explaining the impact of structural changes in the network, the dichotomized repeat measurement is more appropriate.

2.4 DISCUSSION

The results from this research show that the announcement of a marketing alliance is a significant event with implications for the firm's risk. In contrast with prior research, we focus on the impact of marketing alliances on both idiosyncratic and systematic risk. By disentangling the impact of marketing alliances on these components of risk and by examining the impact of networks on marketing alliances, we shed new light on how and why marketing alliance formation influences firm risk. A basic argument underlying our study lies in the expectation that firms become more similar as they interconnect through alliances, which leads to non-stable correlations and necessitates network-level, rather than portfolio-level, analysis when examining the implications of a broad set of partners on a firm's systematic and idiosyncratic risks.

Theoretical Contributions

Our contributions to theory are fourfold. First, we advance understanding of the mechanisms by which marketing alliances change the volatility of a firm's equity, thereby building on the initial work of Das, Sen, and Sengupta (1998). We show that idiosyncratic risk decreases after a marketing alliance, which implies a reduction in volatility of cash flows, perhaps because of the diversification benefits marketing alliances afford. Indeed, most marketing alliances are formed to access either new markets (or customer segments) or new

products, both of which help reduce risk. More important, this result holds after we control for the magnitude of alliance returns; this suggests that the reduction in risk after a marketing alliance cannot be accounted for by the belief that marketing alliances are inherently less risky (and also linked to low returns). Instead, we find that even after controlling for variations due to the magnitude of returns, marketing alliances are heralded by the stock market as contributing significantly to reducing equity volatility. Therefore, in conjunction with previous research that shows increased returns after a marketing alliance announcement (e.g., Houston and Johnson 2000; Swaminathan and Moorman 2009), we demonstrate that marketing actions can create value by helping control the volatility of a firm's stock. These findings regarding the reduction in risk after marketing alliances are contrary to those by Das, Sen, and Sengupta (1998), who find that risk actually increases after a marketing alliance. One reason for this difference might be that in their examination of marketing alliances, they do not disentangle systematic and idiosyncratic risk components or explore conditions that can increase risk exposure (e.g., network position). Furthermore, we account for the previous level of risk for firms entering an alliance, which suggests a noteworthy path for further research regarding optimal alliance seeking and network-building decisions of firms under different risk scenarios. Ultimately, our findings provide new insights into the role of marketing alliances in influencing the systematic and idiosyncratic components of firm risk.

Second, this research also provides new insights into the role of repeat partnerships, thus extending previous research examining the impact of repeat partnerships on alliance returns. Previous research has highlighted advantages of repeat partnerships from the perspective of strengthening trust and thereby reducing transaction costs (Gulati 1995). However, repeat partnerships can also increase redundancies and reduce performance when technological

uncertainty is high (Goerzen 2007). We demonstrate how repeat alliances can influence the risk facing a firm. A marketing alliance announcement seems to reduce idiosyncratic risk, but only if it is a new partnership. As might be expected, repeat partnerships do not change the diversification and brand equity benefits accruing to a firm after a marketing alliance and therefore have no significant impact on firm risk.

Third, we find that the network of prior alliances in which a firm has engaged has implications for firm risk. In particular, network density, or the interconnectedness of a firm's partners, can significantly influence the idiosyncratic and systematic risk benefits a firm can reap after a marketing alliance. At very high levels, network density can reduce flexibility (Rowley, Behrens and Krackhardt 2000); the implication is that benefits to idiosyncratic risk due to marketing alliance formation are limited to settings in which a firm is not embedded in a densely interconnected network.

Fourth, partner network density also has implications for systematic risk benefits accruing to a firm after marketing alliance announcements. Every strategic alliance connects a firm with the broader stock market and makes it vulnerable to shocks experienced by the economy as a whole. However, to our knowledge, this is the first empirical demonstration of the impact of a partner's network density on the firm's own risk. By connecting a firm with new sources of interconnectedness embedded in a partner's network, alliance formation can become a double-edged sword. Specifically, while alliances can be instrumental in reducing risks, they can also expose a firm to various economywide shocks, which may render it unstable and more risky. Therefore, managers should carefully evaluate the risks and benefits associated with strategic alliance partners before embarking on alliances. More important, they should examine partners'

own network density and its implications for the firm's own risk before entering into strategic alliances.

The results with regard to alliance type are informative, and add to the literature that has focused on returns from alliance types such as product development and co-marketing (e.g., Bucklin and Sengupta 1993; Kalaighnam, Shankar and Varadarajan 2007). First, we find that the reduction in idiosyncratic risk holds for most marketing alliance types, except market access alliances. We argued previously about a potential increase in uncertainty when outsourcing marketing actions, which might help explain the positive impact of market access alliances on idiosyncratic risk. Second, we find that marketing alliances help reduce systematic risk, and this result is even greater for product integration alliances. It is possible that the combinations of complementary products made possible through product integration further protect a firm against broader macroeconomic forces. For example, integrated or bundled products might stimulate greater brand loyalty and act as an insurance against broader market forces. The models in which alliance type interacts with network density (own and partner's) also generate important insights. Product development and integration alliances increase the nonlinear impact of own network density on idiosyncratic risk, likely because information redundancies and technological lock-ins that occur at high levels of density contribute to increases in idiosyncratic risk. Conversely, the benefits of network density in lowering idiosyncratic risk at lower levels of density are more likely in the case of joint marketing and market access alliances, perhaps because the diversification benefits afforded at lower levels of network density occur more when jointly marketing a product or accessing new markets.

Taken together, the current findings call into question the risk-reduction benefits touted in extant literature (Rowley, Behrens, and Krackhardt 2000; Rindfleisch and Moorman 2003).

Our research demonstrates that though a firm may attain risk-reduction benefits after forming a marketing alliance, these benefits can be erased by the firm's own and the partner's network of alliances. In a "network economy," strategic alliances can be beneficial in reducing the costs associated with internal development, but they can also foster greater uncertainty and expose a firm to greater economywide shocks, particularly under certain conditions. By spotlighting the role of network density (own and partner's), this research goes beyond the findings of Das, Sen, and Sengupta (1998) to demonstrate how network characteristics moderate the risk benefits of marketing alliances.

Managerial Implications

Alliances are a necessary part of business, but their success rates continue to be low. For example, according to Lunnan and Haugland (2008), alliance termination rates hover around 50%. Much of the discussion surrounding alliances has centered on their ability to strengthen competitive position, increase efficiency, or help a firm gain access to new resources. The current research sheds light on an overlooked benefit of marketing alliances—namely, their ability to minimize firm risk. On average, we show that marketing alliances reduce the amount of volatility of cash flows (i.e., lower idiosyncratic risk) and also protect a firm against broader shifts in the stock market (i.e., lower systematic risk, after we account for specific alliance type). Both benefits are increasingly important to managers, particularly in a network economy. Indeed, the collapse of the housing industry led to far-reaching impacts and almost brought down the financial sector. The Greek debt crisis further highlights the dangers of a network economy, in which many countries are tied together because of a unified currency; in such an economy, no firm or industry can exist in isolation. Thus, managers should increasingly focus on ways to minimize exposure to negative movements in the stock market while also finding ways to reduce

volatility of cash flows. This research highlights one approach that might be helpful in this regard—namely, marketing alliances. We demonstrate that by pooling marketing resources, firms in an average position in the marketplace can reduce their risk.

However, there are some conditions in which reduction in risk cannot be obtained. According to this research, managers should carefully examine the density of their own network as well as their partner's network before initiating a marketing alliance. If a firm's own density is high, the expected reduction in firm risk after a marketing alliance may not occur. This suggests that managers must have an overall strategy to help them manage their entire portfolio of interfirm relationships. The risk implications of network density are significant, and managers should strategically manage the structural aspects of their network of strategic alliance partners to prevent increases in volatility of cash flows arising from the lack of diversification in the network. Furthermore, managers should examine the network density of their partner firms before entering into an alliance because partner network density at moderate levels may reduce the benefits of the alliance, particularly with regard to systematic risk.

This does not mean that strategic construction and management of their local or broader network is possible for all firms; the ability to do so will vary from case to case. Large, powerful, and successful firms are likely to have a disproportionally larger number of possible partners, while smaller, less successful firms will have fewer choices and thus are more likely to accept their naturally occurring network position. However, a firm's position will still provide a manager with information about the risk consequences of a marketing alliance, which in the case of a low-positioned firm constitutes the first step in generating mitigation strategies.

Managers should also realize that when following a risk-minimizing strategy, they will face a trade-off between idiosyncratic and systematic risk. To reduce idiosyncratic risk, they

should seek novel connections; however, these new connections increase firms' exposure to novel macroeconomic forces and increase systematic risk. Balancing this trade-off is important, and the optimal solution will vary depending on the firm's situation at any point in time and its stakeholders.

Last, our study focuses on equity risk (and observed firm risk based on long term cash flow volatility and credit risk; see Appendix B), but this is not the only way managers perceive or act on their preferences for risk. Both March and Shapira (1987, 1992) and Miller and Chen (2004) examine different conceptualizations of risk, mostly pertaining to downside consequences and the monetary value of potential losses. Although these perspectives can guide decision making, such as alliance seeking and partner selection, the risks we discuss herein also affect day-to-day operations through the firm's ability to meet debt obligations, secure further funding, or increase its desirability and value in the financial market.

The success of an alliance hinges on many factors, ranging from partner selection to alliance management. This research suggests that managers can benefit from marketing alliances by reducing volatility of cash flows. By ensuring that the right network conditions are present for risk reduction benefits to accrue or by understanding the consequences of their given position, managers will be in a better position to improve the outcomes from marketing alliances.

3.0 USING SOCIAL MEDIA MONITORING DATA TO FORECAST ONLINE WORD OF MOUTH VALENCE: A NETWORK-BASED PERSPECTIVE

Social media monitoring is a fast-growing and increasingly specialized area of marketing research. Firms use social media monitoring services to track brand and product mentions across various online social media sources, such as online social networking platforms exemplified by Facebook and Twitter, as well as blogs and online discussion forums. These services typically provide firms with two types of brand-level time series data: *volume*, which counts the number of times a given brand (or keyword, more generally) is mentioned in various social media sources, and *valence*, which quantifies the extent to which these brand mentions are positive or negative (i.e., sentiment). A large number of companies provide this service (e.g., Crimson Hexagon, Conversition, Cymphony, Nielsen, and Radian6), which firms see as valuable because it allows them to track consumer sentiment toward their brands and products. Compared to traditional marketing research methods for tracking brands over time (e.g., surveys), social media monitoring data has the advantage of being observational and unobtrusive, which makes it potentially more attractive from a research perspective, and also tends to be cheaper to collect.

Similar to traditional brand tracking research, a standard use of social media monitoring data, particularly valence, is *backward looking* in the sense that managers use it to evaluate past performance. While this can provide useful insights, managers also want to predict the future and therefore seek *forward-looking* uses for social media monitoring data. For example, while it is

useful for a manager to know that over the last three months positive mentions of her brand decreased and negative mentions increased, it would be more useful for her to know *in advance* that over the next three months she can expect increasing negative and decreasing positive mentions. In other words, it would be useful if social media monitoring data could be used as an early-warning system to forecast, with reasonable accuracy, consumer sentiment as indicated by online word-of-mouth (WOM) valence.

This paper shows how standard, commercially available, brand-level social media monitoring time-series data can be used to build reasonably accurate valence-forecasting models. Despite the increasing numbers of social media sources and social media monitoring services that extract data from those sources, the data these services collect is relatively standardized. A typical social media monitoring dataset for a single brand is a time series data that documents, by source (specific social media website), the number of positive and the number of negative mentions of that brand per time period.⁵ Because social media monitoring services typically provide time series data at regular intervals, these data can be used to build valence-forecasting models. Interestingly, however, although marketers often try to forecast other variables such as demand, market size, sales, and new product adoption, they typically do not apply forecasting methods to consumer attitudes or online WOM valence. Historically, this may have been due to a lack of frequently collected data. Social media monitoring valence data fortunately has the potential to overcome this problem.

A challenge when forecasting consumer attitudes toward brands, irrespective of the data source used, is that brands typically do not exist alone neither in consumers' minds nor in social media; i.e., brands are, to some degree, interdependent or related. Indeed, central to the concept

⁵ Note that these data could be for a single brand or for a brand broken down into a set of relevant keywords. Total mentions (positive + negative + neutral) are also usually tracked.

of brand equity is the notion that the perceived value of a given brand is shaped by associations between it and competitive alternatives (Keller 1993). Consumers' perceptions of brands are likely to be formed in a relative, not absolute, sense. This is consistent with the notion that consumers store information (including brand-related information) in cognitive associative networks, where the "nodes" in these networks contain information (e.g. brands) and the links contain associative information between the nodes (e.g., similar brands; Krishnan 1996). It is therefore not surprising that prior research emphasizes the importance of understanding how brands are related to other brands (Henderson, Iacobucci, and Calder 1998), and argues that inter-brand associations can be represented as networks and modeled using methods from the network analysis literature (Henderson, Iacobucci, and Calder 2002).

This implies that a reasonably accurate valence-forecasting model for a single brand will need to incorporate information from other brands, or at least take into account associative relations between brands in the same industry or product category. Although this could be done using traditional marketing research data (e.g., tracking surveys), it is likely to be expensive because it would require firms to collect time-series data for many brands instead of just for their own brand and possibly a limited number of competitors. The cost of multi-brand, time-series valence data from social media sources is typically substantially lower, which makes it potentially viable from a forecasting perspective.

We propose a method for building valence-forecasting models that account for associative relations between brands in order to get better forecasts of positive and negative brand mentions in social media. Our method leverages standard, commercially available social media monitoring data to represent a brand's associations with other brands as a time-varying network where brands are nodes and ties exist between pairs of brands if they are mentioned

together in the same time period in the same source or sources (e.g., social networking sites, blogs, forums).⁶ We then use these networks to compute time-varying brand-level “network” metrics that are used in models as predictors of future positive and negative valence. We show that the inclusion of these predictors—which incorporate information on inter-brand associations—improves the accuracy of valence forecasts.

This research makes two main contributions to the literature on social media marketing and marketing research methodology more broadly. First, we show how social media monitoring data—which is affordable and widely available—can be used for a forward-looking manner to calibrate valence-forecasting models. This can help managers anticipate changes in positive and negative social-media brand mentions and allows them to build early-warning systems as part of their social media monitoring activities. Further, it helps to extract additional insights from what has now become a common, but under-utilized, type of marketing research data. Second, we show that incorporating information on brands’ associations with each other (inferred from social media monitoring data) into forecasting models has value because it reduces forecast error. By taking into account the fact that brands do not exist in a vacuum and that consumer attitudes toward brands tend to be relative and comparative we show that our ability to forecast valence of social media mentions can be improved.

⁶ Although this is an imperfect proxy for brand relatedness or “connections,” we show that it is sufficient in that including this information significantly reduces forecast error in our empirical application.

3.1 BACKGROUND

Prior research has examined the implications of online WOM and brand mentions in social media channels with respect to both volume (i.e., number of mentions) and valence (i.e., sentiment or positivity/negativity of mentions). This stream of research has examined the dynamics of online WOM and how it impacts marketing outcomes such as sales and new product adoption (e.g., Godes and Mayzlin 2004, 2009; Liu 2006; Chevalier and Mayzlin 2006; Trusov, Bucklin and Pauwels 2009; Schmitt, Skiera, and Van den Bulte 2011; Stephen and Galak 2012; Moe and Trusov 2011). Related research has also attempted to link online brand/firm mentions to stock market performance (e.g., Luo 2007, 2009; Tirunillai and Tellis 2011; McAlister, Sonnier and Shively 2012).

Extant studies have generally shown that online WOM affects marketing performance. Godes and Mayzlin (2004) link discussions of new TV shows to TV show ratings. Chevalier and Mayzlin (2006) examine online book reviews with respect to volume and valence and find that valence has a significant impact on retail sales, with negative valence having a stronger effect than positive valence. Liu (2006) studies movie box office revenues and finds that online review volume, as opposed to valence, drives revenues. Also in the movie context, more recent work by Chintagunta, Gopinath, and Venkataraman (2010) has found that valence is also a key driver of box office revenues. Finally, in a meta-analysis, de Matos and Rossi (2008) find that WOM valence is associated with consumer loyalty and satisfaction. Clearly, the valence of brand mentions in social media is important since it has been repeatedly shown to be a key predictor of important marketing performance outcomes. However, while the literature has used online sentiment to forecast future buying behavior, sales (Sonnier, McAlister, and Rutz 2011), and the

stock market performance of firms (Tirunillai and Tellis 2012), to the best of our knowledge no prior studies have focused on forecasting the valence of online WOM itself.

With respect to using social media data or online WOM data to derive marketing insights, in addition to linking WOM to product consumption (TV show ratings), Godes and Mayzlin (2004) also introduced the concept of entropy, which is a measure of how concentrated or dispersed the “conversation” about a brand is across sources. In their case, Godes and Mayzlin (2004) captured the extent to which conversations about new TV shows were concentrated in a one or a few online discussion rooms or dispersed over many. In our case, we apply this concept to whether a brand’s mentions in a given time period are concentrated in a few *sources* (e.g., just on a particular Facebook page) or dispersed over many sources (e.g., Facebook, multiple discussion boards, blogs, and Twitter). We do this because prior work has demonstrated the importance of accounting for entropy in a multi-source online WOM context.

Finally, we note that literature on extracting associations between brands from social media-type data—which is a key step of our method—is scant. A notable exception is Netzer et al. (2012), who used data from an online discussion forum and subjected it to text-mining algorithms that allowed them to build associative inter-brand networks. They used these networks to show how this method could be used to infer market structure. Similar to their approach, we use social media data to construct associative networks for brands. However, our research extends Netzer et al. (2012) in at least two ways. First, we build time-varying brand networks using co-occurrences of brands across a large number of social media sources. Second, our primary purpose lies not in showing how such networks can be inferred, but rather how future brand valence can be reliably forecast using such information. Importantly, our approach

shows how marketing research insights can be improved (i.e., more accurate forecasts) without increasing firms' data requirements.

3.2 DATA AND METHOD

3.2.1 Social Media Monitoring Data

Valence data. We use commercially available social media monitoring data from Nielsen's BuzzMetrics service. The dataset covered 77 consumer electronics and technology brands over 16-months from November 2009 to February 2011. Examples of brands included in the dataset are Amazon, Apple, Motorola, and Sony. Nielsen provided, for each brand, monthly counts of positive and negative brand mentions. Table 4 reports some descriptive statistics. We focus on the number of positive messages and the number of negative messages as the indicators of brand valence that we attempt to forecast.

Table 4 Descriptive Statistics: Monthly Positive, Negative, and Neutral Comments

Valence of Comment	Average Count	Standard Deviation
Positive	1,105	2,504
Negative	380	1,131
Neutral	13,929	32,351

Nielsen BuzzMetrics uses proprietary algorithms that mine a large number of social media sources, from online social networks to blogs to discussion forums, and identify brand-related posts or mentions. They then analyze the text using natural language processing and sentiment analysis algorithms to identify which posts/mentions are predominantly positive, which are predominantly negative, and which are neutral (everything else that is not positive or negative). Thus, the raw dataset provides monthly counts of positive and negative mentions by social-media source for each brand. We did not perform sentiment analysis ourselves to determine the valence of the brand mentions, and instead relied on the commercial dataset from Nielsen (as a manager would do). This is appropriate since this paper focuses on using data that managers can readily access to forecast valence, and not on validating the computer science and machine learning methods used to extract valence from social media monitoring data.

Social-media source data. In addition to the cross-sectional time-series data counting positive and negative mentions of brands, Nielsen provided data on the sources of the brand mentions in social media. For each month and each brand we knew how many times it was mentioned across 7,376 unique sources. In this context a source is a specific social media site (indicated by a URL), such as a social networking site, a blog, or a discussion forum. The sources represented in the data range from relatively unknown blogs and forums to well-known destinations such as mashable.com, endgadget.com, facebook.com, and twitter.com. At the source level, there was large variance in monthly brand mentions, ranging from zero mentions to 122,948 mentions.

An important caveat of the source data, however, is that it does not break the brand mentions down by valence within each source. Thus, while we know, for each brand and each month, the numbers of positive and negative mentions *aggregated across all sources* and

numbers of mentions irrespective of valence *for each source*, we do not have brand-source-level valence data. We use the source-level *volume* (but not valence) data to construct time-varying networks that describe how brands are related or similar to each other based on being mentioned in the same sources at the same time. Although this is not perfect, our network-construction method based on the unvalenced source data still yields improvements in our valence forecasts.

3.2.2 Brand Network Data from Source Data

The source data counting brand mentions by source type by month can be thought of as affiliation data that shows how each brand is affiliated with each source in each month. In this context, a brand is affiliated with a source if that brand is mentioned in that source at least once. Affiliation data can be represented mathematically by affiliation matrices, and are often used to summarize bipartite graphs, otherwise known as two-mode networks (Harary 1969). In our context, for period t we define an N -by- M affiliation matrix \mathbf{A}_t to represent the affiliations between N brands and M sources. Element $a_{ikt} \geq 0$ is the number of times in period t that brand i is mentioned in source k (for $i = 1$ to N and $k = 1$ to M).

As mentioned earlier we need to infer “connections” or associations *between brands*, not between brands and sources. A measure of inter-brand association must capture the extent to which online WOM overlaps across sources for each pair of brands. Following Borgatti and Halgin (2011), representing this type of association as a network tie can be justified from two perspectives. First, a brand-pair coexisting in a similar space of online discussion or conversation provides an opportunity for these brands to be compared in the minds of consumers. Second, a brand-pair coexisting in a similar space of online discussion or conversation occurs due to some

unobservable underlying relationship between the brands or unobservable characteristics that the brands have in common, which manifests in where and when consumers choose to discuss them online in social media.

To represent inter-brand associations in a network form we must convert the brand-by-source *affiliation* matrices \mathbf{A}_t to brand-to-brand *association* matrices. A number of possible approaches could be used to determine the extent of association based on contemporaneous overlapping brand mentions across social-media sources. Two straightforward possibilities are to count the number of sources where both brands appear in the same period, or to normalize this count by dividing it by the total number of sources. A third possibility is to compute the Jaccard coefficient for each brand-pair in each period, which would be the total number of shared sources divided by the total number of sources where at least one of the brands in the pair appears. A fourth possibility is the Bonacich normalization, which calculates the extent to which the overlap exceeds an expected amount of overlap given the number of sources where each brand is present. A disadvantage of each of these four possible approaches is that they result in lost information when the brand-by-source affiliation matrix is converted to a brand-by-brand association matrix, since each method accounts for only those sources where the brands were present, but ignores the potential information available in the not-present space, where brands were not discussed even though they had the opportunity. Put simply, there may be information in two brands *not* appearing the same sources at the same time, just as there is likely information in two brands appearing together at the same time.

A fifth possibility—which we use—addresses this limitation of the other four approaches, preserves information, and is more straightforward because it is based on Pearson correlation coefficients. We convert each brand-by-source affiliation matrix \mathbf{A}_t to a corresponding brand-by-

brand (N -by- N) association matrix \mathbf{B}_t that can then be analyzed using familiar network analysis methods. Off-diagonal element b_{ijt} in \mathbf{B}_t (for $i \neq j$, and $b_{ijt} = b_{jit}$) is the Pearson correlation coefficient computed across all M sources for brand i and j in period t ; i.e.,

$$b_{ijt} = \frac{\sum_{k=1}^M (a_{ikt} - \bar{a}_{it})(a_{jkt} - \bar{a}_{jt})}{\sqrt{\sum_{k=1}^M (a_{ikt} - \bar{a}_{it})^2} \sqrt{\sum_{k=1}^M (a_{jkt} - \bar{a}_{jt})^2}}$$

Where $\bar{a}_{it} = \frac{1}{M} \sum_{k=1}^M a_{ikt}$, the mean number of mentions per source for brand i in period t . A higher correlation (b_{ijt}) between a pair of brands means a higher degree of association between them in that period because of a greater extent of overlapping mentions (or non-mentions) across sources. This accounts for being mentioned or not mentioned in the same sources at the same time *and* the volume of mentions. Importantly, this takes into account instances where a brand-pair is jointly absent, which is not fully taken into account by the other methods we considered.

For subsequent network analysis we followed standard network analysis procedures by transforming each \mathbf{B}_t such that diagonal elements were zero and off-diagonal elements (measures of brand association strength) were dichotomized to be 1 for $b_{ijt} > .70$ and 0 otherwise. The squared Pearson correlation coefficient of .70, gives us a coefficient of determination of .49, meaning that to be “connected” in our dichotomized association matrix, roughly 50% of the variability in one brand’s social media presence is explained by the variability in the other brand in the pair, which can be viewed as a better-than-chance likelihood of a meaningful inter-brand association. This value of Pearson correlation coefficient provides a more conservative network dichotomization, and a more sparse network structure, to the common methodology used by default in standard network analysis software, where a meaningful association is assumed to exist if $b_{ijt} > 0$.

Our brand association network does not necessarily imply that a brand-pair are mentioned in *precisely* the same post (e.g., where a consumer compares a Sony TV to a similar Samsung TV). Rather, it simply indicates that a pair of brands was mentioned in the same place at approximately the same time (i.e., in the same discrete time period). We acknowledge that this is not a perfect measure of association between brands, however, as we show later, incorporating this information into forecasting models is enough to significantly reduce forecast error. Further, this is the best that can be done with standard social media monitoring data provided by companies like Nielsen and without more thorough text mining analysis (cf. Netzer et al. 2012).

Table 5 Descriptive Statistics

	Mean	Std. Dev.	1	2	3	4	5	6	7	8	9	10
1 Positive Messages	1,105	2,504	-									
2 Negative Messages	380	1,131	.722	-								
3 Lagged Positive Msg.	1,121	2,527	.960	.679	-							
4 Lagged Negative Msg.	381	1,121	.683	.940	.703	-						
5 Volume	3,991,527	5,671,532	-.002	.049	-.003	.040	-					
6 Time Trend	10.95	4.295	.021	-.003	.035	-.016	.154	-				
7 Owned media	0.412	0.217	-.002	.065	.001	.063	.106	.061	-			
8 Entropy	0.012	0.566	.056	.086	.052	.087	.172	.190	.139	-		
9 Degree	1.222	2.132	.145	.053	.158	.050	.016	.209	-.114	-.053	-	
10 Clustering	0.211	0.383	.170	.062	.190	.074	-.035	.080	-.190	-.069	.703	

3.2.3 Variables Used In The Forecasting Models

We now list and define each of the variables used in our forecasting models. We report descriptive statistics and correlation coefficients in Table 5.

Positive messages (valence). The number of positive messages mentioning each brand per month. We use this as a dependent variable.

Negative messages (valence). The number of negative messages mentioning each brand per month. We use this as a dependent variable.

Lagged valence. We use one-period lagged positive and negative messages mentioning each brand as control variables in our models.

Lagged volume. We use the one-period lagged total number of messages mentioning each brand (positive + negative + neutral) as a control variable in our models. This controls for the total amount of online WOM for each brand.

Entropy. This variable follows the measure of entropy introduced for online WOM modeling by Godes and Mayzlin (2004, p.551). It captures the extent to which mentions of a brand in a month are concentrated in a small number of sources or equally dispersed over a large number of sources. If all of the mentions are in from a single source in a month, then entropy = 0. Entropy increases, and approaches entropy = 1 as the number of sources with mentions increases and the overall volume of mentions becomes evenly distributed across all sources.

Degree centrality. This is computed from the dichotomized brand network in each time period and is the number of other brands a brand is directly associated with (“connected” to) in a given month in the network. For example, if brand i in month t is associated directly with four other brands then $\text{degree}_{it} = 4$.

Clustering coefficient. This is also computed from the dichotomized brand network in each time period and is another standard node-level social network metric. In a social network, a person’s clustering coefficient is the proportion of her friends that are also friends with each other (Watts and Strogatz 1998). In our context, clustering is a measure of the interconnectedness of the other brands that brand i is associated with in month t . Clustering ranges between 0 and 1, with higher values indicating that a brand is part of a denser local network or tightly

interconnected cluster of brands. We compute brand i 's clustering coefficient on the month t network as the total number of links between the brands that brand i is connected to divided by the total number of such possible links.

Owned media. This is a control variable that measures the percentage of a brand's posts that come from brand-owned websites (i.e., "owned" media; Stephen and Galak 2012).

Brand extension. This is a dummy variable that controls for the fact that some of the brands in our sample were new products introduced as brand extensions during the observation window (1), whereas others were established brands (0).

Seasonality. Consistent with standard practice in time series modeling, we control for seasonality with two dummy variables, one indicating the month of December, and another indicating the (northern hemisphere) summer months of July and August. Similar to Trusov et al. (2009), we find that these periods correspond with certain holidays (e.g. Christmas), and periods (e.g. summer) with online activity that is inconsistent with the remainder of the calendar year.

Time trend. Finally, we included a time trend variable to captures any systematic variation due to time in the 16-month timeframe of our sample, consistent with standard practice in time series modeling.

3.3 FORECASTING MODELS

Model Considerations

We now develop a forecasting model that accounts for a number of characteristics specific to our dataset and are therefore likely to be present in many commercial social media monitoring datasets that in essence are multi-brand, multi-period dynamic panel datasets.

First, we account for brand-level unobserved heterogeneity in our panel dataset since we have multiple observations for each brand. We use a straightforward random-intercept specification with brand random effects. An alternative would be brand fixed effects, however with 77 brands it is unlikely to be as efficient as the random effects specification. In any case, we checked both random- and fixed-effects specifications for each of our models and confirmed that the random-effects specification is preferred in all cases with Hausman tests.

Second, the forecasted (dependent) variables of positive and negative valence are counts of the numbers of posts of each valence, and these vary over time. Thus, they are time series count variables. As a first step we must determine whether each is a stationary or evolving time series, consistent with standard practice in multivariate time series modeling. If these variables are stationary then they should be modeled as counts (i.e., non-negative integers), however if these variables are evolving then should be transformed (first-differenced) and will then have different distributional properties. Based on an augmented Dickey-Fuller unit root test for panel data using a variety of lags for robustness (0-, 1-, and 2-period lags) it appears that both positive valence and negative valence are stationary ($ps < .001$).

Third, given that the dependent variables are stationary they should be modeled as counts. Two typical distributions used to model count data are Poisson (assuming equidispersion; i.e., mean = variance) and negative binomial (allowing for overdispersion; i.e., mean \leq variance). Based on unconditional means and variances for these two variables it appears that they are overdispersed. This suggests that a negative binomial model will be more appropriate, however we tested both random-effects Poisson and random-effects negative binomial models.

Fourth, there may be an excess number of observations where the dependent variables equal zero, which would necessitate using a zero-inflated model. We estimated regular and zero-

inflated random-effects Poisson and negative binomial models. Vuong tests suggested that a zero-inflated random-effects Poisson model is preferable to a regular random-effects Poisson model ($Z = 4.51$, $p < .001$). However, a regular random-effects negative binomial model is preferable to a zero-inflated version ($Z = -3.68$, $p < .001$).⁷ Based on these comparisons, we use a random-effects negative binomial model (without zero-inflation) since it allows us to handle overdispersion without added model complexity due to zero-inflation.

Fifth, we need to account for potential endogeneity. This is particularly likely for the two network-based variables—degree and clustering—since network variables are often endogenous in prior research. This could be due to, for example, more positively or negatively discussed brands attracting additional online WOM that compares them to other brands, which would affect a brand’s network position (degree and clustering). We checked all the non-dependent variables with Durbin-Wu-Hausman tests (Davidson and MacKinnon 1993) and found that degree, clustering, and entropy are endogenous. To address this we follow an approach suggested by Wooldridge (2002) for dealing with endogeneity in exponential-family generalized linear models (such as the Poisson and negative binomial models used here). The approach is a straightforward two-stage procedure, which we describe below.

3.3.1 Model Specification and Evaluation

Based on these considerations, our model is a two-stage dynamic panel model with a random-effects negative binomial regression. In simple terms, our model regresses the number of

⁷ For these Vuong tests, a positive (negative) test statistic indicates that a zero-inflated model is preferable (not preferable).

positive (or negative) mentions of a brand in the current period on a series of lagged predictors and control variables (e.g., time-invariant brand characteristics as fixed effects). Importantly, since we are interested in forecasting a brand's online WOM valence, we consider how a brand's prior-period valence, WOM volume, and network position affect current-period valence.

Specifically, for the random-effects negative binomial model, let y_{it} be the number of positive (or negative) mentions of brand i in month t and has the following probability distribution function:

$$P(y_{it}) = \left(\frac{\phi}{\phi + \lambda} \right)^{\phi} \frac{\Gamma(\phi + y_{it})}{\Gamma(y_{it} + 1)\Gamma(\phi)} \left(\frac{\lambda}{\phi + \lambda} \right)^{y_{it}}$$

Where λ is the mean and the variance is $\lambda + \lambda^2/\phi$, and ϕ is the dispersion parameter. We use a generalized linear model to model the conditional mean of y_{it} as a function of predictors/covariates \mathbf{X}_{it} and such that $\log \lambda = \alpha_i + \mathbf{X}_{it} \beta$. We use gamma random effects (α_i). Since some of our covariates are endogenous (degree, clustering, entropy), we partition \mathbf{X}_{it} into exogenous (\mathbf{W}_{it}) and endogenous (\mathbf{Z}_{it}) components.

As mentioned above, we use a two-stage method described by Wooldridge (2002) for handling endogeneity. In the first-stage regression we use a random-effects Gaussian model to regress \mathbf{Z}_{it} on \mathbf{W}_{it} , and recover the residuals δ_{it} . In the second-stage regression we use the random-effects negative binomial model to regress either positive or negative mention counts (y_{it}) on \mathbf{W}_{it} , \mathbf{Z}_{it} , and δ_{it} —the exogenous predictors, endogenous predictors, and residuals from the first-stage regressions. In both stages we use maximum likelihood estimation.

We consider three nested model specifications. Model 1 (base) predicts current positive or negative valence using lagged valence and volume as predictors, and controlling for brand characteristics with fixed effects. Additionally, we include as an additional control variable the other current-period valence variable (e.g., for the regression with positive valence as the

dependent variable this control variable is negative valence). We include this as a control variable since the counts of same-period positive and negative valence are highly correlated ($r = .72$; see Table 5). Model 2 (base + entropy) adds as an additional predictor, following Godes and Mayzlin (2004), lagged entropy as a measure of how concentrated or dispersed the conversation across sources. Finally, model 3 (base + entropy + network) adds as additional predictors a brand's lagged degree and clustering (as well as their interaction). We include the degree x clustering interaction to account for the difficulty in increasing the clustering coefficient at high levels of degree centrality.⁸ Note that in Models 2 and 3 the entropy, degree, and clustering variables used are after having controlled for their endogeneity using the two-step procedure described above.

To evaluate model performance we first examine model fit using likelihood-based metrics (-2 log-likelihood, Akaike Information Criterion [AIC], and Bayesian Information Criterion [BIC]). We then examine forecasting performance using adjusted Mean Absolute Percentage Error (MAPE). Unadjusted MAPE is computed as:

$$MAPE = \frac{1}{T} \sum_{t=1}^T \left| \frac{O_t - F_t}{O_t} \right|$$

Where O_t is the actual, observed value in period t , and F_t is the forecasted value from the model for period t , and there are T periods in total. This is infeasible here (as is often the case) because we observe $O_t = 0$. Following Voronin and Partanen (2012), we instead use adjusted MAPE where O_t is replaced by the three-period moving average value of O_t . This eliminates the division-by-zero problem, except in the case of three consecutive periods of zero values, which we never observed.

⁸ We thank David Krackhardt for this suggestion.

3.4 RESULTS

Table 6 presents the results of the first-stage regressions (used when applicable), and Tables 7 and 8 present the results of the second-stage regressions for positive and negative WOM for all three nested models. In this section we briefly discuss the estimated effects (focusing on the main, second-stage model), although our primary interest lies in model comparisons and forecasting performance, which we subsequently discuss.

Table 6 First-Stage Models

	Entropy		Degree		Clustering	
Variable	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value
First Lag	0.5693 ***	14.63	0.4437 ***	12.74	0.1089 ***	3.43
Second Lag	0.2385 ***	6.41	0.1896 ***	4.75	0.1172 ***	3.75
Time Trend	0.0002	0.05	0.0483 ***	2.85	-0.4562	-1.32
December	0.0542	0.94	-0.1020	-0.51	-3.4908	-0.86
Summer	0.0062	0.17	-0.3370 **	-2.47	9.7310 ***	3.54
Brand Extension	-0.0396	-1.32	0.1357	1.22	0.9551	0.42
Owned Media	-0.0279	-0.41	0.5537 *	2.14	-11.0871 *	-2.21
Positive Messages	0.0001	0.94	-0.0000	-0.43	-0.0003	-0.19
Lagged Positive Messages	-0.0001	-0.87	0.0000	0.24	0.0014	0.80
Negative Messages	-0.0000	-0.11	0.0001	1.05	-0.0031	-0.88
Lagged Negative Messages	0.0000	0.22	0.0001	-1.12	0.0033	1.02
Lagged Volume	0.0000	1.09	0.0000 *	2.36	-0.0000	-0.69
Model Fit						
-2LL	446		3896		1842	
AIC	477		3927		1873	
BIC	544		3987		1937	

*** $p < .001$, ** $p < .01$, * $p < .05$, # $p < .10$. Random-effects Gaussian models.

Table 7 Second-Stage Models: Positive Valence

	Model 1		Model 2		Model 3	
Variable	Coefficient	z-value	Coefficient	z-value	Coefficient	z-value
Time Trend	0.0392 ***	5.53	0.0362 ***	5.04	0.0332 ***	5.04
December	-0.0880	-1.14	-0.1246 #	-1.61	0.0077 #	-1.61
Summer	0.2415 ***	4.10	0.2903 ***	4.84	0.0259 ***	4.84
Brand Extension	-1.0973 ***	-8.00	-0.9078 ***	-6.38	-0.9899 ***	-6.38
Owned Media	1.7029 ***	9.15	1.4560 ***	7.60	1.5087 ***	7.60
Lagged Positive Messages	0.0001 ***	4.87	0.0001 ***	3.70	0.0001 ***	3.70
Lagged Negative Messages	-0.0001 *	-2.09	-0.0001 #	-1.63	-0.0001 #	-1.63
Concurrent Negative Messages	0.0001 ***	4.41	0.0001 ***	3.49	0.0002 ***	3.49
Lagged Volume	0.0000	-0.94	0.0000	-1.00	0.0000	-1.00
Lagged Entropy			0.9484 ***	6.45	1.1211 ***	6.45
Lagged Degree					-0.2629 ***	-2.93
Lagged Clustering					0.0246 ***	5.03
Lagged Degree x Lagged Clustering					0.0001	0.16
$\hat{\sigma}$ (residual) Entropy			-0.6158 ***	-4.33	-0.7010 ***	-4.78
$\hat{\sigma}$ (residual) Degree					0.0404	1.01
$\hat{\sigma}$ (residual) Clustering					-0.0224 ***	-5.09
Random effect variance	0.3181		0.3454		0.3604	
Negative binomial dispersion	1.5947		2.1049		2.2134	
Model Fit						
-2LL	6320		6276		6242	
AIC	6342		6302		6278	
BIC	6390		6358		6355	

*** $p < .001$, ** $p < .01$, * $p < .05$, # $p < .10$. Random-effects negative binomial models.

3.4.1 Positive Valence

Model 1 in Table 7 is our baseline positive-valence model. This forecasts the number of positive brand mentions per month based on prior-month positive mentions, same- and prior-month negative mentions, prior-month total WOM volume, and controls for seasonality, time, and time-invariant brand characteristics. We find that over time we can expect a brand to be mentioned positively more times ($b = .0392$, $p < .001$), and that positive mentions increase during summer ($b = .2415$, $p < .01$). Brand extensions on average have fewer positive mentions

($b = -1.0973$, $p < .001$), and positive mentions increase as the percentage of messages from a brand's owned media increases ($b = 1.7029$, $p < .001$). Not surprisingly, the first-order autoregressive effect (i.e., prior-month positive mentions) is significant and positive ($b = .0001$, $p < .001$). In other words, prior-month positive valence predicts next-month positive valence. Prior-month negative valence has the opposite effect ($b = -.0001$, $p < .001$), while same-month negative valence has a small positive effect ($b = .0001$, $p < .001$). These effects stay relatively consistent as we build more complex models on top of this baseline specification.

Model 2 in Table 7 adds entropy (and uses the two-stage estimator described above since entropy is endogenous). Entropy has a positive effect on positive valence ($b = .9484$, $p < .001$). As the social-media-based conversation about a brand becomes more dispersed across sources, we can expect there to be more positive mentions of the brand in the next month. This model fits better than Model 1 based on AIC and BIC.

Model 3 in Table 7 adds the brand-association network position measures—degree and clustering to Model 2 (and again uses the two-stage estimator). Degree and clustering are significant predictors of positive valence. Degree has a negative impact on next month's positive mentions ($b = -.2629$, $p < .001$), while clustering has a positive impact ($b = .0246$, $p < .001$). This model fits better than Models 1 and 2 based on AIC and BIC.

Table 8 Second-Stage Models: Negative Valence

	Model 1		Model 2		Model 3	
Variable	Coefficient	z-value	Coefficient	z-value	Coefficient	z-value
Time Trend	0.0364 ***	4.63	0.0287 ***	3.55	0.0118	1.45
December	-0.2164 **	-2.52	-0.2225 **	-2.62	-0.0280	-0.37
Summer	0.2881 ***	4.94	0.3479 ***	5.83	0.0374	0.54
Brand Extension	-1.0568 ***	-6.65	-0.9005 ***	-5.43	-0.9311 ***	-5.60
Owned Media	1.5124 ***	8.10	1.4380 ***	7.62	1.5675 ***	9.19
Lagged Positive Messages	0.0000	1.07	0.0001	1.14	-0.0000	-0.55
Lagged Negative Messages	-0.0001 #	-1.76	-0.0001 *	-2.13	-0.0002 ***	-5.06
Concurrent Positive Messages	0.0001 ***	10.55	0.0001 ***	9.96	0.0002 ***	15.13
Lagged Volume	0.0000	1.42	0.0000	1.18	0.0000 ***	3.70
Lagged Entropy			0.8047 ***	5.21	1.0419 ***	6.96
Lagged Degree Centrality					-0.1907 ***	-3.19
Lagged Clustering Coefficient					0.0294 ***	7.86
Lagged Centrality*Clustering					-0.0007 #	-1.68
δ Entropy			-0.5924 ***	-3.96	-0.6699 ***	-4.66
δ Degree Centrality					0.0196	0.65
δ Clustering Coefficient					-0.0262 ***	-7.68
Random effect variance	0.3487		0.3636		0.3985	
Negative binomial dispersion	0.7326		0.8235		0.8910	
Model Fit						
-2LL	4854		4826		4750	
AIC	4877		4854		4787	
BIC	4925		4909		4864	

*** $p < .001$, ** $p < .01$, * $p < .05$, # $p < .10$. Random-effects negative binomial models.

3.4.2 Negative Valence

Model 1 in Table 8 is the baseline negative-valence model with a parallel specification to positive-valence Model 1 in Table 7. We observe a similar pattern of results. We can expect more negative mentions over time ($b = .0364$, $p < .001$), and these increase during the summer months ($b = .2881$, $p < .001$), but decrease in December ($b = -.2164$, $p < .01$). Brand extensions can expect fewer negative mentions ($b = -1.0568$, $p < .001$), but once again, more as the percentage of mentions from the brand's owned media increases ($b = 1.5124$, $p < .001$). The

number of prior-month positive mentions has no impact on the number of negative messages in the next month ($b = .000$, n.s.). Prior-month negative valence has a marginally significant negative effect ($b = -.0001$, $p < .10$). Lastly, there is a positive effect of same-month positive mentions on negative valence ($b = .0001$, $p < .001$).

Model 2 in Table 8 adds entropy to Model 1 and uses the two-stage estimator. Entropy has a significant positive effect on next-month negative valence ($b = .8047$, $p < .001$). Thus, as the conversation becomes more dispersed across sources, then the brand can also expect more negative messages. This model fits better than Model 1 based on AIC and BIC.

Model 3 in Table 8 adds the two network position variables to Model 2 and uses the two-stage estimator. Degree has a negative effect on next-period negative valence ($b = -.1907$, $p < .001$), while clustering has a positive effect ($b = .0294$, $p < .001$). The degree x clustering interaction is negative but marginally significant ($b = -.0007$, $p < .10$). This model fits better than Models 1 and 2 based on AIC and BIC.

3.4.3 In- and Out-of-Sample Fit

In Table 9 we report adjusted MAPE for the three positive and the three negative valence models. For in-sample fit we estimated each model using all 77 brands and all 16 months. We then compared predicted to observed values by computing adjusted MAPEs. Consistent with the likelihood-based model fit indices reported in Tables 7 and 8, for both positive and negative valence we found that Model 3 had the lowest error and thus the best in-sample predictive fit. For out-of-sample fit we randomly allocated each of the 77 brands into either an estimation set (39 brands) or a holdout set (38 brands). We estimated each model using observations from all

months on the brands in the estimation set, and then used these parameter estimates to compute predicted positive and negative valence counts for the brands in the holdout set. We compared the holdout-brands' predicted values to observed values to compute adjusted MAPEs. For both positive and negative valence Model 3 had the lowest error and thus the best out-of-sample fit. Based on predictive and likelihood-based fit indices, Model 3—which includes the brand association network predictor variables—is the superior model.

Table 9 In- and Out-of-Sample Fit: Adjusted Mean Absolute Percentage Errors

Models	In-Sample		Out-of-Sample	
	Positive Messages	Negative Messages	Positive Messages	Negative Messages
Model 1: Base	96.36	94.06	101.62	97.78
Model 2: Base + Entropy	98.45	93.12	103.77	97.70
Model 3: Base + Entropy + Network	80.94	78.74	91.98	90.73

Table 10 Forecasting Results: Adjusted Mean Absolute Percentage Errors

Number of Months Forecast	Positive Mentions			
	Naïve Model	Model 1	Model 2	Model 3
1 Month	107.31	99.06	97.25	79.54
2 Months	111.54	94.99	94.55	77.91
3 Months	111.03	94.70	94.81	77.72
4 Months	114.21	94.00	93.54	76.65
	Negative Mentions			
	Naïve Model	Model 1	Model 2	Model 3
1 Month	85.760	25.45	21.73	17.89
2 Months	106.76	20.67	18.60	18.60
3 Months	104.91	17.95	15.31	11.67
4 Months	108.34	17.24	14.64	11.77

3.4.4 Forecasting

We now consider our primary objective of testing how well our models perform when forecasting future numbers of positive and negative social-media brand mentions. Table 7 reports forecasting results (adjusted MAPEs) for positive and negative valence and each of the three model specifications. To compute these measures we estimated our models using all 77 brands over a reduced number of time periods and then used the estimates to compute predicted values for the future holdout time periods. Specifically, we estimated the models on K periods (where K

was less than the full number of periods available for estimation⁹), with $K = \{10, 11, 12, 13\}$. In other words, we varied the length of the estimation time window between 10 and 13 periods and therefore tested our ability to forecast between one and four months ahead. Our goal was to see how robust our models—particularly Model 3 including network predictors—were in shorter- and longer-range social-media valence forecasting.

In addition to comparing our three model specifications, we added a fourth model specification (naïve) in which the expected future values (y_{it+1}) were equal to the current period's observed values (y_{it}). While such models have long been a common and adequate benchmark for forecasting models (Granger and Newbold 1974), the naïve model also resembles what is often seen in practice whereby managers assume that prior valence is a decent predictor of future valence in the absence of any exogenous shocks or events (e.g., marketing campaigns). Although we never expect the naïve model to provide reliable forecasts, including it allows us to highlight the extent to which our proposed approach improves on current managerial practice.

The results in Table 7 can be interpreted in two ways. First, we consider, for each number of months forecast, which model performs best from a forecasting perspective (i.e., in Table 7 comparing across columns within each row). For all forecasting ranges (1 to 4 months) and for both positive and negative valences we see that Model 3, which incorporates the network predictors, performs the best. On average (across forecasting ranges), for positive valence, we see improvements in adjusted MAPEs between Model 3 and the naïve model, Model 1, and Model 2 of, respectively, 29.73%, 18.52%, and 17.97%. In the case of negative valence, the average improvements in adjusted MAPEs between Model 3 and the naïve model, Model 1, and Model 2 are, respectively, 84.93%, 26.61%, and 15.26%. Given our focus on using inferred

⁹ The full number of available estimation periods was 14 months. This is because the first two months in the 16-month dataset were used for lags.

inter-brand associations to help forecast valence (i.e., Model 3), we see that, irrespective of the valence of a brands' mentions in social media, adding this information substantially increases forecast accuracy. Specifically, compared to the next-best model (Model 2), we see reductions in forecast error in the 15-20% range. This is impressive given that going from Model 2 to Model 3 only entailed including two brand network position variables (and their interaction), which came from a relatively straightforward procedure using the source data.

The second approach to interpreting the adjusted MAPE forecasting results in Table 7 is to see how robust a given model is to changes in the length of the forecasting range (i.e., in Table 7 comparing across rows within each column). For Models 1 through 3 we see that forecast error decreases as the forecasting range is increased from one month to four months, albeit only slightly. For positive valence Model 3, increasing the forecasting range from 1 month to 4 months reduces error by 3.63%, and by 7.86% in the case of negative valence Model 3. The fact that forecast error does not increase as the forecasting window increases (and the estimation window commensurably decreases) suggests that our models are robust for forecasting future values, at least within a few months into the future. Up to four months is likely sufficient from a managerial perspective in the context of social media marketing planning. Lastly, for the naïve model we notice that the forecast error increases as the forecasting range increases. This is because the naïve model simply uses prior valence to predict future valence and forecast errors carry through from period to period. This would not be expected if a brand's WOM valence in social media was stable, however, at least for the sample of brands used in our analysis, this is apparently not the case. The poorer performance of this naïve benchmark as forecasting ranges increase also underscores the importance of using sophisticated forecasting.

3.5 DISCUSSION

In this paper we proposed and empirically validated a relatively straightforward method for using brand-level, social media monitoring time-series data that extends what managers have typically been doing with this relatively new source of data. As we mentioned earlier, social media monitoring is often used only for backward-looking “listening” purposes. Or, if managers do use it for forward-looking purposes such as forecasting future “buzz” (or valence of that buzz), their models tend to be naïve or do not account for interdependence and associations between brands in a common product category or industry. Our findings show that accounting for these types of “connections” or “linkages” between brands can substantially improve forecasting ability with respect to social-media WOM valence, even if the inter-brand associations are inferred using relatively simple methods. Overall, our findings show that it is possible to build reasonably reliable models for managers to use to forecast positive and negative brand social-media-mentions and that the accuracy of these models improves when inter-brand associations is accounted for.

Our focus has been on the valence of WOM about brands in social media and not the volume (total count) of those mentions. As we discussed above, extant research suggests that WOM valence is often a more important predictor of consumers’ actions (e.g., purchasing) than WOM volume. Managers also likely care more about forecasting valence than volume since how they react to expected changes in positive valence and negative valence is likely to be different. Further, valence is important in the social media monitoring context because it gives managers insights into consumers’ attitudes toward brands, as expressed by consumers’ opinions in social media posts. Since consumers’ opinions are unlikely to be generated in a vacuum and instead are relative to other brands and products, considering how brands are in some way connected to each

other is therefore also important. Although not the focus of the current research and best left for more detailed investigation in future research, this is possibly one reason why Model 3, which included the network predictors, outperformed the other models.

The current study is not without limitations. First, since we do not have data on the text of consumers' brand-related posts in social media sources we cannot validate the valence data provided to us by Nielsen. However, Nielsen is one of the world's leading sources of social media monitoring data and a market leader in this industry, which gives us confidence in the validity of their data.

Second, we were only able to examine the valence of the posts and not other potentially interesting variables. As natural language processing and sentiment analysis methods become more sophisticated it is becoming possible not only to quantify positive and negative mentions of brands, but also to capture more specific variables such as mentions by underlying topic or theme, or mentions by specific type of emotion (e.g., happiness-related mentions, anger-related mentions). This could be interesting for managers to forecast to see, for example, whether aspects of their brand positioning are picked up consistently over time in social media posts. For example, Coca-Cola is positioned around the emotional theme of happiness. It would be interesting for Coca-Cola to know if social media mentions of their brand are not only positive but also related to happiness. We expect that our method for forecasting WOM valence could be applied to forecasting other types of social media mentions given the appropriate data.

Third, our study examined a single general product category (consumer electronics and technology). Since our focus was on proposing and testing a method and not testing a specific theory, we feel that the generalizability of the current research is less of a concern. Nevertheless, it would be interesting to test our method on other product categories, and we encourage others

to do so. We selected the consumer electronics industry since it is a broad category with general appeal. In the U.S. in 2012 consumer electronics was worth approximately \$91 billion as an industry (Research and Markets Report 2012). Of course, a caveat is that our method is possibly most applicable to product categories that have more general appeal and are talked about in social media more commonly and frequently.

Finally, while our method for using source information to identify which brand-pairs are associated with each other is straightforward, it is not perfect. As we mentioned earlier, inferring that two brands are associated with each other does not imply that they are closely related because they were mentioned *jointly* in social media posts at the same time and in the same place. Unlike Netzer et al. (2012), who used online forum post data and text mining methods, we could not identify whether brands were mentioned jointly or just in the same sources in the same month. Thus, our network is an imperfect estimate of the true underlying associative connections between brands. Nevertheless, we showed that even when these inferences are imperfect they still improve forecast accuracy. We expect that if we used brand networks based on finer-grained co-mentions (e.g., with full-text data for each post) our forecasts would further improve. Thus, while this is a limitation of the current work, it suggests that our results may be a lower-bound estimate of what is possible. We hope that future research considers these and other related issues in an attempt to find valuable forward-looking uses for social media monitoring data.

4.0 CONCLUSION

Taken together, the two essays that make up this dissertation add to the discussion of marketing strategy beyond the traditional boundaries of the firm by considering the effect of firm relational positions on their financial risk, and by providing a relationship-enhanced forecasting tool for brand sentiment valence in the digital environment, a known leading indicator of firm performance.

Consistent with previous works incorporating social networks into the analyses of marketing strategies and phenomena (Swaminathan and Moorman 2009; Stephen and Toubia 2010; Mallapragada, Grewal, and Lillien 2011), the inclusion of this broader and more complex perspective provides a deeper and more nuanced understanding of the marketing environment.

For example, in the first essay I find that marketing alliances do reduce two components of equity risk: idiosyncratic and systematic risks. This result falls in line with much of the existing belief in the marketing and alliances literatures. However, there is also empirical support for situations where marketing alliances can increase firm risk. This increasing level of risk is explained by the expanded perspective provided by the incorporation of data on the broader network of firm alliances while examining the consequences of alliance announcements. The models presented suggest that firms experience risk-reduction benefits from alliance announcements when they engage with novel partners and forge new connections in their networks. This finding does suggest the structure (i.e. the pattern of connections in the network)

is important, given that the alternative, or the relational repeated partnerships offer no risk-reduction benefits in the equity market. The caveat, of course, is that while a relational focus does not help the firm if the goal is risk minimization; it is likely central to other managerial concerns, such as the development of trust with the partner firm (Wuyts, Stremersch, and Dutta 2004), the implementation of alliance-related initiatives, etc.

Furthermore, by incorporating other measure of network position, both for a focal firm and its partner, I was able to show that equity risk can change as a function of the network structure. For example, a firm whose direct partners are highly interconnected occupies a dangerous position. Referred to as a high ego-network density position, this firm relies on non-diversified partners for its business processes (from previous alliance formation), while its partners also rely on one another. While this clique-like structure of firms is efficient, any failure or issue arising within a single firm will be quickly felt by all network members, and then felt again as aftershocks through its other network partners as they also suffer due to this unique failure. This inability to “dissipate” unanticipated shocks through more diversified connections appears in this study as an exponential increase in firm-specific (idiosyncratic) risk, as it is unrelated to the broader financial market.

That is not to say that the structure of the alliance network has no information on the firm’s relationship with the broader financial market in macro-economic forces. In fact, a firm’s selection of a partner is crucial in this connection, as it is the partner’s increasing ego-network density (interconnectivity) that leads us to expect greater levels of exposure to market level risk. The intuition again lies in the fact that an allying partner suggests connections with novel areas of the economy, and as exposure increases, so does risk. Interestingly, this perspective sets up a trade-off in the selection of partners and network formation relative to

expected risk consequences: a novel connection might alleviate firm-specific risk, while increasing the firm's exposure to market and economy-level risk.

Marketing managers can make use of this information in the process of selecting the correct partner for the intended alliance by augmenting the requirement of a potential partner firm's resources and capabilities with an understanding of both firm's alliance network positions, and the equity market consequences of the choice. However, these finding can be seen as particularly worrisome because practitioners are not currently trained to observe and account for their own, or much less their partner networks, but rather only their own immediate connections under a portfolio assumption. This difference could lead to a prediction of risk benefits arising from an alliance formation, while the actual result might turn out quite differently. Given this different managerial perspective, it is possible that many firms operate under much greater risk than they account for.

As an attempt to place to power of information from social networks at the hands of marketing managers, the second essay provides a novel way to utilize data the firm already own and metrics managers already track, by enhancing an online sentiment valence prediction model with brand network information.

While the popular use of social media and other digital communication methods have skyrocketed, marketing researchers have been preoccupied with linking the dynamics of this online conversation to important marketing outcomes. Research in this domain has shown that the quantity and nature of online word of mouth can impact both future sales and new product adoption (e.g., Godes and Mayzlin 2004, 2009; Liu 2006; Chevalier and Mayzlin 2006; Trusov, Bucklin and Pauwels 2009; Schmitt, Skiera, and Van den Bulte 2011; Stephen and Galak 2012; Moe and Trusov 2011). And while these sales would impact firm performance and

firm value through an traditional firm valuation pathway, additional research as also shown that online firm mentions can also impact stock market performance by influencing investors, who value timely information (e.g., Luo 2007, 2009; Tirunillai and Tellis 2011; McAlister, Sonnier and Shively 2012).

Marketing managers do increasingly recognize the value of monitoring online conversations around their brands, and in taking an active role in shaping this conversation for the benefit of the firm. However, forming predictions for the volume and valence of this conversation can be tricky, leading to often inaccurate and marginally useful forecasts.

While naïve forecasting models can be improved by incorporating autoregressive components, they can also be further improved by the addition of structural and relational brand network information. While the relationship between brands is not something we can observe directly, we can extract a time varying brand-by-brand relational network structure from the pattern of online conversations about these brands. From these networks, we can then extract information about number of other brands it is connected with, as well as how interconnected these brands are, with the ultimate goal of using this knowledge to improve forecast accuracy.

By providing a more accurate forecasting model for this leading performance indicator, managers can, for the first time, get ahead of this fast moving online conversation and take corrective action in case of a negative forecast, potentially saving eventual sales, and avoiding loss of value.

4.1 NETWORKS AND FIRM VALUE

In response to an increasing pressure on managers to demonstrate marketing's ability to provide financial returns and improve firm value, this dissertation highlights the benefit of incorporating a network perspective to marketing management and the pursuit of improved firm performance and greater firm value.

The marketing literature concerned with the financial performance of marketing activities has adopted a framework for value surrounding the manager's ability to generate cash flows for the firm that are either greater in volume, realized sooner, or more certain in nature (Srivastava, Shervani and Fahey 1998), with the additional understanding that improvements along any of these characteristics would also be valued by investors, and firm value would also increase in the financial market. The work presented here showcases the impact of two distinct networks under the purview of the marketing manager: one composed of marketing alliance partners, and a second composed of competing brands in the marketplace; each with the potential to alter firm cash flows, and ultimately, firm value.

First, the network of alliance partners (reflecting past connections and interconnections) has already been shown to improve firm value through greater abnormal returns given certain network configurations (Swaminathan and Moorman 2009). This work expands upon this view by highlighting the conditions under which marketing alliances and the network of previous alliances gives rise to lower or greater levels of firm uncertainty, which is tied to firm performance, survival, and overall value. This goes beyond the classic financial expectation of greater risk accompanying greater returns, and exposes scenarios where marketing is able to generate greater returns while simultaneously lowering the firm's risk exposure, and thus providing greater firm value through two proposed avenues.

Secondly, this work also shows that a network of brands connected in social media can aid in the understanding of word of mouth. This is significant because word of mouth volume and valence is informative of future intent to purchase (Godes and Mayzlin 2004, 2009; Liu 2006; Chevalier and Mayzlin 2006), which has a clear and direct connection to the volume and volatility of cash flows generated by the firm. By utilizing a network of brands to understand future word of mouth valence, a manager can then generate expectations for future-future cash flow performance, and take corrective actions if necessary, which leads to improved performance and increased value.

Even if marketing performance has not appeared as a MSI research priority in the previous two years, this understanding continues to be important for academics and practitioners alike. Now, more than ever, the performance of marketing activity and the firm by consequence is conditional on what the firm faces outside of its boundaries, whether it be through networked partners and their assets and capabilities, how the brand is perceived online and how that conversation is shifting. Looking beyond the firm and understanding these complex relationships as well as their implications for firm decision-making and performance should only help managers; not only now, but as the business environment continues to grow in interconnectivity and complexity.

APPENDIX A

CORRECTING FOR SELECTION BIASES

Our first-stage selection model has firm's entry into strategic alliances as a function of various factors, including firm size, firm profitability, prior alliance experience, etc. We use the entire sample of public firms within the industries we are focusing on and examine whether a firm announced a marketing alliance within each firm-year combination. We conducted a probit regression of the propensity to form alliances. We then calculated an inverse Mills ratio from this selection equation and included it in the second-stage selection correction, which focuses on partner selection. In the first-stage, we find that the overall model was significant ($-2LL = 1769.663$, $\chi^2 = 642.6923$, $p < .0001$). As Table 11 shows, the results indicate a significant impact of firm sales ($b = .00001$, $p < .0001$), net income ($b = .00014$, $p < .001$), intangible assets ($b = .00001$, $p < .01$), leverage ($b = -.309$, $p < .001$), and number of prior alliances ($b = -.002$, $p < .10$). Some variables were not significant, including strategic emphasis, marketing resource intensity, solvency, and return on assets. We also controlled for year dummy variables. We used this probit estimation procedure to estimate the inverse Mills ratio selectivity parameter, which is included in the next selection bias estimation model as a control variable.

Table 11 First-Stage Selection Bias: Propensity to Form Alliances

Parameter	Estimate	Standard Error	Significance
Intercept	3.0591	3.328	
Firm sales	.00001	0.0000	***
Net income	0.00014	0.0000	***
Intangible assets	0.00001	0.0000	**
Strategic emphasis	-0.023	0.042	
Marketing resource intensity	-0.001	0.005	
Solvency	-0.012	0.009	
Leverage	-0.309	0.065	***
Return on assets	0.003	0.003	
Number of past alliances	-0.002	0.001	#
Year dummy variables (included but not shown)			
-2 LL	1769.663		
Likelihood ratio	642.6923 ($p < .0001$)		

Note: N=36771

The second-stage selection model involves modeling the likelihood of selecting a specific partner. We focus on the firms that actually announced an alliance. We then controlled for the likelihood of choosing a specific partner. To do this, we calculated an inverse Mills ratio by estimating a selection equation, in which we model the probability of choosing the particular partner from a set of potential available similar partners in that industry in that year. Because data on potential partners were not directly available, we constructed a set of similar partners in the same industry and assumed that these were potential alternatives to the chosen partner. The

selection equation involved identifying partner firms with a similar size and asset base (firms whose size was $\pm 25\%$ of the selected partner) in the same industry as that of the partner firm. Then, we estimated a probit model in which the dependent variable was whether a given firm was selected versus not selected from among the various firms that could be potential alliance partners. The independent variables for the probit estimation included (1) the relative size of partners, (2) horizontal alliances, (3) repeat partnerships, (4) alliance with product development, and (5) alliance experience. We also controlled for time effects through a series of year dummies. We conducted separate analyses, controlling for firm effects. Specifically, we estimated selectivity parameters in a model in which we did not control for firm effects and another model in which we controlled for firm effects. Both models yielded selectivity parameters that were highly correlated ($r = .95$); therefore, we used the more parsimonious specification in which we did not include firm-level random effects (for results, see Table 12). We used the estimated parameters from the probit estimation to calculate the inverse Mills ratio, which we then entered into the models to account for possible selection bias.

As Table 12 shows, network density was significant ($\beta_1 = .569, p < .001$), network density² was significant ($\beta_2 = -1.283, p < .0001$), network efficiency² was negative and significant ($\beta_4 = -1.609, p < .001$), network strength was negative and significant ($\beta_5 = -.162, p < .001$), network centrality was negative and significant ($\beta_6 = -.006, p < .001$), horizontal alliance was negative and significant ($\beta_7 = -.617, p < .001$), product development component was positive and significant ($\beta_8 = .739, p < .001$), firm size was positive and significant ($\beta_9 = .008, p < .001$), repeat alliance was positive and significant ($\beta_{11} = .713, p < .001$), and the alliance formation probability was also positive and significant ($\beta_{12} = .093, p < .001$).

Table 12 Second-Stage Selection Bias: Partner Selection Bias (Probit Estimates)

Parameter	Estimate	Standard Error	Wald χ^2	Pr > χ^2
Intercept	1.774	0.437	16.500	***
Network Density	0.569	0.186	9.400	***
Network Density ²	-1.283	0.257	24.904	***
Network Efficiency	0.195	0.345	0.321	
Network Efficiency ²	-1.609	0.604	7.115	***
Network Strength	-0.162	0.053	9.439	***
Network Centrality	-0.006	0.0008	50.525	***
Horizontal Alliance	-0.617	0.153	16.348	***
Product Development/Research-and-Development Component	0.739	0.156	22.558	***
Firm Size (Number of employees)	0.008	0.001	64.186	***
Partner Tobin's q	0.0206	0.013	2.554	
Repeat Alliance	0.713	0.253	7.976	***
First Stage Selection Parameter	0.0928	0.0368	6.3458	**
Year Dummy Variables (Included but not shown)				
Model Fit Statistics				
Akaike information criterion	969.96			
-2 LL	913.96			
Likelihood ratio χ^2	559.59	P<.0001		

Note: N=2259

APPENDIX B

OBSERVABLE LONG-TERM IMPACT OF MARKETING ALLIANCE FORMATION ON FIRM RISK

While our main study involves the impact of marketing alliance announcements on a firm's equity risk and employs the financial market as an incentive-compatible crowd-sourced indicator of expected firm consequences, we also analyzed actual observed risk consequences for the firm. By doing so, we can examine how the realities of equity risk created by investors' decisions in the financial market can differ from two dimensions of risk the firm experience:¹⁰ cash flow volatility and credit risk (which incorporates a measure of financial health and probability of default).

¹⁰ These two additional dimensions of risk are distinct from idiosyncratic and systematic risks. These measures are not related to measures of equity and do not rely on the financial market but rather arise from operational considerations. While idiosyncratic and systematic risk pertain to the "source" of risk (firm-specific and broad economy forces, respectively), these measures are more closely related to notions of firm uncertainty (cash flow volatility) and vulnerability (credit rating).

B.1.1 Dependent Variables

Cash flow variability. We calculate cash flow variability as the standard deviation of a firm's net income normalized by its assets, over 12 reporting quarters following a marketing alliance announcement, thus covering three calendar years from the time of announcement.

Long-term firm riskiness. We calculate the firm's long-term riskiness as the average credit rating held over the three-year period (36 issued reports of credit worthiness) following a marketing alliance announcement. This variable ranges from 2 (equivalent to a credit rating of AAA) to 27 (equivalent to a credit rating of D); the higher this value, the riskier is the firm.

B.1.2 Model Estimation

Modeling the long-term volatility of cash flows presents an additional complication in that the dependent variable is not normally distributed. Therefore, we log-transform this dependent variable before regressing it on the same independent variables presented in our main study. Clustered errors accounted for the lack of independence.

Last, we model the long-term credit risk of the firm, which is an ordinal measure, meaning that a AAA credit rating is less risky than a AA+ rating; however, we cannot assume that the “distance” between these two values is equivalent to the “distance” between the next interval of ratings (i.e., AA+ rating in relation to a AA rating). To account for the characteristics of this dependent variable, we employ an ordinal logit model with clustered errors. Again, we used the same independent variables presented previously in the final model.

B.1.3 Results

Future (three-year) cash flow volatility. Table 13 presents the results from the model examining the impact of marketing alliance formation on the firm's long-term cash flow volatility. Cumulative abnormal returns are positive and significant ($\pi_{1jk} = 6.283, p < .001$), which we expected because future volatility is priced in the market and should be accompanied by increased returns as recompense. Repeat alliance is significant and negative ($\pi_{3jk} = -3.541, p < .001$). The firm's network centrality is both significant and negative ($\beta_{p2k} = -.002, p < .001$), as is its network efficiency ($\beta_{p5k} = -.736, p < .001$). These results are consistent with the notion presented previously that a firm creating a larger local network with partners in diverse industries can lower its cash flow volatility. A partner's network density also affects the firm's cash flow volatility, which is significant and negative at lower levels ($\beta_{p7k} = -1.846, p < .01$) but significant and positive at higher levels ($\beta_{p8k} = 1.744, p < .05$). For alliance types, the indicator for "other" alliance types (e.g., licensing, customer service, sales, bundling, international) is negative and significant ($\pi_{8jk} = -.132, p < .05$), while joint marketing and market access alliances are negative and only marginally significant ($\pi_{6jk} = -.219, p < .10$; $\pi_{7jk} = -.260, p < .10$, respectively). Last, the latent variable capturing partner selectivity bias is both negative and significant in this model ($\beta_{p9k} = -.098, p < .001$).

Future (three-year) credit risk. Table 14 presents the results for the model examining the impact of marketing alliance formation on long-term credit rating. Again, cumulative abnormal returns are positive and significant ($\pi_{1jk} = 7.091, p < .001$), while repeat partnerships are negative and significant ($\pi_{3jk} = -1.768, p < .01$). A firm's previous credit rating is a significant and positive predictor of its future credit rating ($\beta_{p1k} = .134, p < .001$). The firm's centrality is a significant and negative ($\beta_{p2k} = -.009, p < .001$), as is the firm's own network density ($\beta_{p3k} = -$

.740, $p < .05$). Furthermore, the firm's network efficiency is negative and significant ($\beta_{p5k} = -2.531$, $p < .01$). Last, for alliance types, only joint marketing alliances reduce future credit risk, but only marginally ($\pi_{6jk} = -.443$, $p < .10$).

When we incorporate alliance experience into the models of future risk performance, we find that it has no impact on credit risk ($\beta_{p10k} = .000$, n.s.) but is a significant contributor in reducing long-term cash flow variability ($\beta_{p10k} = -8.133$, $p < .05$).

Table 13 Long-Term Cash Flow Volatility (Three Years) Following a Marketing Alliance

Variable	Parameter	t-Value
Cumulative abnormal returns	6.283 ***	3.2
Horizontal alliance	0.209	1.06
Repeat alliance	-3.541 ***	-18.61
New product development alliance	-0.075	-0.67
Product integration alliance	0.051	0.39
Joint marketing alliance	-0.219 #	-1.8
Market access alliance	-0.260 #	-1.9
Other alliance	-0.132 *	-0.84
Firm credit rating	-0.022	-1.56
Network centrality	-0.002 ***	-2.96
Network density	0.085	0.35
Network density ²	-0.209	-0.32
Network efficiency	-0.736 **	-2.69
Network strength	-0.016	-0.5
Partner's network density	-1.846 **	-2.63
Partner's network density ²	1.744 *	2.41
Partner selectivity bias	-0.098 ***	-3.4
R ²	0.181	

*** $p < .001$, ** $p < .01$, * $p < .05$, # $p < .10$.

Notes: The model uses $\ln(\text{volatility})$ as the dependent variable.

Table 14 Future Credit Rating (Three Years) Following a Marketing Alliance

Variable	Parameter	t-Value
Cumulative abnormal returns	7.091 ***	3.28
Horizontal alliance	0.400	1.37
Repeat alliance	-1.768 **	-2.69
New product development alliance	-0.151	-0.52
Product integration alliance	0.362	1.25
Joint marketing alliance	-0.443 #	-1.67
Market access alliance	-0.440	-1.46
Other alliance	0.285	0.91
Firm credit rating (lagged)	0.134 ***	4.33
Network centrality	-0.009 ***	-8.34
Network density	-0.740 *	-2.04
Network density ²	-0.124	-0.13
Network efficiency	-2.531 **	-2.86
Network strength	-0.036	-1.19
Partner's network density	0.554	0.39
Partner's network density ²	0.278	0.21
Partner selectivity bias	-0.114	-1.19
Pseudo-R ²	0.074	0.066

*** $p < .001$, ** $p < .01$, * $p < .05$, # $p < .10$.

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