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Within-Seller and Buyer–Seller Network Structures and Key Account Profitability

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Abstract

In business-to-business (B2B) markets, the success of key account management (KAM) teams depends on how they are structured and how they handle customer relationships. The authors conceptualize relationships among selling team members as a within-seller (intrafirm) network and the relationships between selling team members and buyer representatives as a buyer–seller (interfirm) network. Drawing on both structural (buyer–seller density, within-seller density, and within-seller centralization) and functional (buyer–seller similar function ties and within-seller cross-functional ties) composition attributes of these networks, the authors examine how the interplay between these networks drives seller account profitability. Using data from 207 key account managers across B2B industries, the authors uncover a nuanced pattern of interplay across the two networks. Densities in the two networks are mutually substitutive, but density in the buyer–seller networks and centralization in the within-seller networks serve complementary roles. Cross-function ties in the within-seller network serve a complementary role too, but only in relation to similar function ties in the buyer–seller network. In contrast, within-seller centralization supports both network density and similar function ties in the buyer–seller network and, thus, emerges as a valuable KAM team characteristic. These findings suggest multiple ways for firms to align interfirm and intrafirm KAM networks to improve account profitability.

Keywords

buyer–seller relationship, centralization, cross-functional ties, key account management, social networks

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Increasing specialization, fragmentation, and dynamism of business-to-business (B2B) markets (Cannon and Homburg 2001; Griffith et al. 2017) has motivated many B2B sellers to adopt a key account management (KAM) approach with priority customers. These strategically significant, long-term customers often purchase portfolios of goods, services, and solutions (Steenburgh, Ahearne, and Corsi 2012), and although they often represent 10% or less of a seller's accounts, they can account for more than half of its revenues. In the KAM approach, seller firm representatives from sales, financing, engineering, and executive functions interact, both with one another and with their counterparts in the buying organization. That is, effective KAM implementation involves managing teams or networks of interfirm and intrafirm actors. When implemented well, KAM can increase firm revenues by 5%–10% and margins by 3%–4% and lower costs by up to 20% (Lubkeman and Taneja 2010). Yet most KAM initiatives fail to achieve their objectives (Aronowitz, De Smet, and McGinty 2015), partly because of how they are structured. We therefore aim to determine both how the design of interfirm and intrafirm KAM teams affect KAM success and what firms can do to increase their chances of success.

Organizing successful key account teams involves several challenges. First, the configurations of buyer–seller teams are diverse (Cannon and Perrault 1999; Workman, Homburg, and Jensen 2003), and systematic assessments of their relative efficacy are scarce. For example, Kohler, the packaging materials firm, benefited from a cross-functional design with its Nestlé key account (Cheverton 2008), consistent with scholarly recommendations for "silo-busting" (Gulati 2007). Yet, Siemens, which similarly designed its KAM process to be "not silo-minded" (Steenburgh, Ahearne, and Corsi 2012, p. 3) by untethering managers from specific business units, struggled

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partly because the managers lacked unit-specific knowledge to effectively interact with customers. Second, KAM involves multistakeholder teams on both sides (Gonzalez, Claro, and Palmatier 2014). The KAM function for Procter & Gamble (P&G) thus involves both external interactions with Walmart's buying center and internal interactions among P&G's KAM team members from sales, operations, and logistics divisions (Cheverton 2008). As such, interactions within both the internal and external KAM teams should influence the seller's KAM outcome. However, the extant literature offers "surprisingly limited" (Homburg, Workman, and Jensen 2002, p. 38) insights into this topic even though the design of KAM teams represents a crucial aspect of account management, an aspect that suppliers simply "need to get right" (Ryals and McDonald 2010, p. 209). Therefore, we consider two critical, closely related research questions: First, how do specific attributes (e.g., functional similarity) of the interfirm buyer–seller KAM team influence account profitability for the seller? Second, how do the corresponding attributes of the selling (i.e., internal or within-firm) team moderate this profitability impact?

To capture a complex pattern of internal and external KAM interactions, we conceptualize key account teams as two interlinked networks: a buyer–seller (interfirm) network and a within-seller (intrafirm) network. The buyer–seller network involves interactions between personnel from the buyer and seller firms, who represent different functions (e.g., sales, engineering). This interfirm network supports the gathering and exchange of information and resources across the buyer–seller interface, enabling the parties to understand each other's needs, capabilities, and constraints. Then, the within-seller team, through internal consultations, processes and utilizes the information exchanged to develop offerings for the buyer (Wuyts and Dutta 2014). Thus, KAM success is shaped jointly by influences in both the buyer–seller information (and resource) gathering and exchange network and the within-seller information processing and utilization network. With this conceptualization of KAM teams as networks, we expect the nature of the network ties to affect the information exchange and usage processes.

We rely on social networks theory (Wasserman and Faust 1994) as well as the literature streams on customer relationship management (CRM; Palmatier 2008) and selling teams (Jones, Stevens, and Chonko 2005) to describe the information exchange and utilization aspects in these KAM networks. In the buyer–seller network, we use network density (i.e., the ratio of number of actual connections present to the maximum number of connections possible in a network) and similar function ties (i.e., similarity in the functional backgrounds of buyer and seller representatives) to capture the amount and richness, respectively, of information exchange (e.g., McPherson, Smith-Lovin, and Cook 2001; Palmatier 2008). In a parallel fashion, in the within-seller network, we use network density and cross-function ties (i.e., diversity in the functional backgrounds [sales, engineering, etc.] of the selling team members) to capture the amount and richness, respectively, of information utilization activities. Recognizing that centralization (i.e., the extent to which selling team activities are concentrated around a few central team members) plays an important role in KAM (e.g., Homburg, Workman, and Jensen 2002), we also incorporate the role of network centralization (i.e., the presence of central actors in the within-seller network who can coordinate information utilization efforts in the seller team; Mintzberg 1990).

We contend that the attributes of the two networks influence the seller's key account profitability in a complex, interactive fashion. To test such contentions, we use primary source data from 207 key account managers in a variety of B2B industries in the United States, applying a regression model to correct for unobserved heterogeneity and endogeneity. We find a subtle pattern of alignment across the two networks. First, cross-functional ties in within-seller and similar function ties in buyer–seller networks jointly enhance seller account profitability. However, the network density attributes reveal mixed effects: densities in the two networks are mutually substitutive, but centralization in the within-seller network and density in the buyer–seller network serve complementary roles.

We contribute to the CRM literature, of which the KAM research constitutes one facet, and to the sales management literature. As seen in Table 1, most existing research focuses on actor- or dyad-level analyses (Gonzalez, Claro, and Palmatier 2014). While valuable, this perspective is not entirely suited to examining KAM team–level issues (Murtha, Bharadwaj, and Van den Bulte 2014). Instead, we advance a network conceptualization, which enables us to uncover interplays across buyer–seller and within-seller networks. Recent research in the sales and CRM domains remains largely limited to one or the other network in isolation (see Table 1: Ronchetto, Hutt, and Reingen [1989] and Ustuner and Godes [2006] columns).

Second, beyond considering two different *types* of KAM networks, we also study the interrelationships between different *attributes* of these networks. Extant sales research has emphasized the role of network density, to the relative neglect of other network attributes such as functional composition (e.g., Ahearne et al. 2013; see Table 1). We address this gap by incorporating numerous network attributes, which yields several new insights. For example, centralization is usually detrimental to team outcomes (Ruekert, Walker, and Roering 1985), but we show that in KAM teams, within-seller centralization enhances profitability when combined with either increasing density or with similar function ties in the buyer–seller network. Such interactions involving distinct network attributes remain unexplored in prior KAM research (see Ahearne et al. 2013; Homburg, Workman, and Jensen 2002). Finally, unlike most extant work in the sales and CRM domains that has examined individual salesperson performance as its outcome (see Table 1), we consider key account profitability. Our work thus is the first to connect KAM network attributes to account profitability.

In the next section, we present our conceptual background and develop our research hypotheses. Next, we outline our research methodology and analysis approach and summarize

Table 1. Related Sales, CRM, and KAM Research.

	Sales Research				CRM and KAM Research				
Study	Ahearne et al. (2013)	Bolander et al. (2015)	Ustuner and Iacobucci (2012)	Ahearne, Lam, and Kraus (2014)	Ronchetto, Hutt, and Reingen (1989)	Homburg, Workman, and Jensen (2002)	Gonzalez, Claro, and Palmatier (2014)	Murtha, Bharadwaj, and Van den Bulte (2014)	This Research
Theoretical context	Impact of salesperson and district manager competitive intelligence on sales performance; network characteristics moderate this effect	Development of intraorganizational relationships and impact on salesperson performance.	Work and social networks have different effects on salesperson effectiveness at different stages of the sales process	Relationship between middle managers' adaptive strategy implementation (leveraging social capital embedded in networks) and business unit performance	How individual influence in buying centers derives from the position of actors in workflow (formal) and communication (informal) networks	A configurational perspective of key account management is used to develop a taxonomy of KAM teams	Effect of relationship manager's formal and informal networks on sales performance	Effect of connections between buying and selling teams on customer solution effectiveness and timeliness	Interplay between buyer–seller interfirm network and within-seller network on seller's account profitability from key accounts
Unit of analysis	Multilevel: Individual salesperson, sales district, and cross-level interactions	Actor level: Salesperson	Actor level: Salesperson	Actor level: Salesperson	Actor level: Buyer side	Team level	Actor level: Relationship manager	Network/dyad level	Network/dyad level
Empirical context	Sales organization within a U.S. media company	Outside sales force of a U.S. business-to-consumer firm selling high-end items	Twelve regional offices of a U.S.-based electronics component distributor	Largest unit of a *Fortune* 500 firm in industrial cleaning and sanitizing industry	Firm with 800 employees, owned by eastern-based parent company	U.S. and German B2B firms in five industrial sectors	A B2B distributor and manufacturer of industrial goods	Members of seven chapters of the Institute for Supply Management	Multi-industry sample of B2B firms with at least 500 employees.
Key outcome variable	Salesperson's monthly sales quota achievement (company records)	Average monthly units sold by salesperson (company records)	Salesperson performance across opportunity identification, solution creation, and deal closing tasks	Composite measure of sales quota achieved, sales growth, and such	Summed measure of individual influence derived from an individual's latent and manifest influence.	Firm profitability (% brackets), KAM effectiveness, performance relative to competitor	Relationship managers' sales growth	Effectiveness of customer solutions	Seller key account profitability (brackets in % terms)
Networks	Two intrafirm advice networks: • Within the unit, salesperson's advice network (seeking advice from district manager) • Informal network as peer network of district managers across units seeking advice from peers	Aggregate advice networks reported by individuals in a firm-wide network graph, used to calculate network measures for each salesperson	Two types: work network and social network	Manager's advice networks, both upward and downward	Workflow and communication network ties captured from 171 members in the buyer organization	None	Intrafirm networks: Formal network (from organizational chart) and informal network	Pseudo-network diagrams presented as conjoint experiment scenarios with three fixed actors from buyer and seller sides	Buyer–seller information exchange (communication) network as a two-mode network, and within-seller information use (consultation or advice network) as a one-mode network
Network constructs	District manager's in-degree centrality in within-unit and across-unit advice networks	Eigenvector centrality (relational centrality) and betweenness centrality (positional centrality)	Number of ties and number of frequently activated ties	In-degree centrality, E-I index (importance of external ties outside the district vs. internal ties within the district), and network size	Centrality, distance from upper management group, and distance from firm boundary	None; measures activities, actors, resources, and formalization using multi-item scales	Density, brokerage	Manipulates attributes but does not directly measure network constructs to capture matching ties, more than matching ties, and communication frequency	• Buyer–seller network: density, similar function ties • Within-seller network: density, cross-functional ties, and centralization

(continued)

Table 1. (continued)

	Sales Research				CRM and KAM Research				
Study	Ahearne et al. (2013)	Bolander et al. (2015)	Ustuner and Iacobucci (2012)	Ahearne, Lam, and Kraus (2014)	Ronchetto, Hutt, and Reingen (1989)	Homburg, Workman, and Jensen (2002)	Gonzalez, Claro, and Palmatier (2014)	Murtha, Bharadwaj, and Van den Bulte (2014)	This Research
Collection methodology; Network is complete or egocentric	• Free recall (based on nomination by informant) • Egocentric network	• Free recall (list people influential in salesperson's work life) • Egocentric network of salespeople, aggregated	Full sociometric network	• Free recall method • Egocentric network	Snowballing name generation, asking 13 members in buying roles for names of other employees who provided input or used output of these 13 people	None	Full sociometric network	Pseudo-network	• Free recall method for name generation • Egocentric network along with cognitive map reporting of ties for other selling team members
Intrafirm networks considered?	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
Interfirm networks considered?	No	No	No	No	No	No	No	Yes	Yes
Both inter- and intrafirm networks considered jointly?	No	No	No	No	No	No	No	Yes (in experimental setup)	Yes
Structural influences hypothesized?	Yes	Yes	Yes	Yes	Yes	No	Yes	No	Yes
Functional composition influences hypothesized?	No	No	No.	No	No	No	No	Yes (whether ties involve same or diverse functional bases).	Yes

the results. We conclude by discussing the theoretical and managerial implications of our work.

Theoretical Framework

Buyer–Seller Key Account Teams as Information Gathering and Exchange Networks

We investigate two critical challenges for KAM selling teams: first, we consider the gathering and exchange of information with buyers to uncover their needs; and, second, we consider the processing and use of that information to serve the buyers. Uncovering key account buyer needs is challenging because of the different, and often conflicting, requirements of various stakeholders in the buyer firm (Tuli, Bhardwaj, and Kohli 2010). For example, Ford's buying center includes purchase managers who are sensitive to pricing terms and engineering personnel who are concerned mainly with technical specifications. Seller teams must maintain communication ties with several buying center members to acquire comprehensive information about the buyer's needs and to share information about their own expertise and constraints. Through such connections, the seller also accesses the expertise and resources of the buyer, which can help the seller craft appropriate offerings. Following the social networks literature, we conceptualize this "connectedness" between the buyer and seller teams as a buyer–seller network, which acts as a conduit for information and resource gathering and exchange between buyer and seller firms (Van den Bulte and Wuyts 2007).

A review of social networks theory suggests that network density (Kadushin 2012; Reagans, Zuckerman, and McEvily 2004)—the ratio of number of actual connections present to the maximum number of connections possible in a network—and similar function ties (McPherson, Smith-Lovin, and Cook 2001)—the similarity in the functional backgrounds of network members—are two attributes crucial to information exchange. These network attributes are pertinent to our framework not only because of their role in shaping information flows but also because of their potential to affect KAM outcomes (Ahearne et al. 2013; Borgatti et al. 2009; Slotegraaf and Atuahene-Gima 2011). Increasing density points to greater connections between buyer–seller representatives, which serve as conduits for information exchange (Palmatier 2008), enhance the amount and variety of inputs exchanged, and facilitate attempts to vet the exchanged information (Wang, Gupta, and Grewal 2017). Thus, density pertains to the volume or amount of information exchange. Similar function ties—that is, similarity in the functional backgrounds of the seller and buyer team members (Van den Bulte et al. 2010)—account for the effects of these functional backgrounds on information flows. Similar function ties should facilitate the transfer of complex and rich information across firm boundaries through knowledge overlap and shared expertise (Murtha, Bharadwaj, and Van den Bulte 2014; Rindfleisch and Moorman 2001). Thus, we use similar function ties in the buyer–seller network to reflect the richness of information exchange.

Within-Seller Key Account Teams as Information Processing and Utilization Networks

Beyond exchanging information, the seller team must process and utilize information to generate possible solutions and identify the most promising ones, which typically involves interdepartmental consultations (Jones, Stevens, and Chonko 2005; Ulaga and Reinartz 2011). Griffin and Hauser (1993) describe how original equipment manufacturers leverage connections between their marketing and manufacturing divisions to support product development. Relying on social networks theory, we conceptualize the seller team as a within-seller firm network that processes and utilizes information and resources acquired from the buyer–seller network to develop offerings to serve the buyer's needs.

Following the literature on social networks (Freeman 1992) and selling teams (Jones, Stevens, and Chonko 2005), we identify network density, the role of central actors, and the functional composition of the KAM team as keys to information utilization. As before, greater density represents increasing interconnections and captures increasing capacity for information processing and utilization activities (Houston et al. 2004). Central actors (e.g., key account managers) play an important role in within-team coordination (Moon and Armstrong 1994). Therefore, centralization—the extent to which selling team activities are concentrated around a few central team members—is another network attribute that is salient to information processing and utilization (Bolander et al. 2015).[1] Central actors serve as a "firm's reservoirs of collective insights . . . procedures, and policies" (Johnson, Sohi, and Grewal 2004, p. 22), and can coordinate interactions and harmonize differences that can emerge in intrafirm teams (Mintzberg 1990). Cross-functional ties (i.e., diversity in the functional backgrounds; e.g., sales, engineering) of the selling team members capture the richness of information utilization. Such ties provide dissimilar perspectives and make for richer integration and usage of information (Sethi, Smith, and Park 2001), resulting in offerings that are more appealing to various stakeholders in the buyer firm (Homburg, Schneider, and Fassnacht 2002).

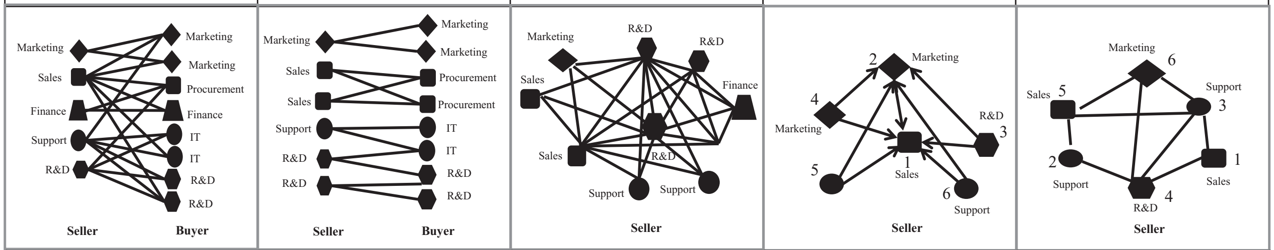
Hypothesis Development

Our conceptualization of key account management involves a buyer–seller network that serves an information gathering and exchange role, and a within-seller network that serves an information processing and utilization role (see Figure 1). As these information exchange and utilization processes are involved in serving the buyer, we posit that interplay between the two networks is critical to KAM outcomes. The specific outcome we focus on is seller account profitability, which is a core metric of

[1] A within-seller network comprises only representatives of the selling firm; it is a single-mode network. A buyer–seller network has two kinds of nodes, so it is a two-mode network. These types differ structurally, and our concept of centralization does not exist for two-mode networks (Wasserman and Faust 1994).

Key Account Management

Buyer–Seller Interfirm Network (Information Exchange)		Within-Seller Intrafirm Network (Information Utilization)		
Network Density (Structural Aspect)	**Similar Function Ties (Functional Composition)**	**Network Density (Structural Aspect)**	**Centralization of Ties (Structural Aspect)**	**Cross-Function Ties (Functional Composition)**
Captures amount of information exchange between buyer and seller.	Captures richness of information exchange through overlap in domain knowledge and expertise.	Captures capacity of information utilization (amount of consultation activity) within the seller team.	Captures presence of integrators who can coordinate and harmonize team efforts for information utilization.	Captures richness of information utilization based on the diversity of perspectives and expertise through cross functional consultation.
The illustration represents buyer–seller network density, where the ties are going from each member of the seller team to many members of the buyer team.	The illustration represents ties between individuals with similar functions in the buyer and seller teams.	The illustration represents a dense within-seller firm network where many consultation ties are going from each member to many other members of the team	The illustration represents a within-seller firm network that is centralized, in which actors 1 and 2 have many consultation ties coming into them. Actor 2 is consulted by 3, 4, 5 and 6, and actor 1 is consulted by 2, 3, 4, 5 and 6, such that all actors in the network consult actor 1.	The illustration represents cross-functional consultation activity in the selling team where ties between 5 and 2, 5 and 6, 5 and 3, 6 and 3, 6 and 4, 3 and 1, 3 and 4, 1 and 4, and 4 and 2 represent cross function ties. Out of the total 9 ties present, all 9 are cross function consultation ties.



Functions: Legend — Marketing — Sales / Procurement — R&D — Support/ IT — Finance

Figure 1. Conceptualization of network aspects in key account management.

successful sales relationships (Mullins et al. 2014; Palmatier, Gopalakrishna, and Houston 2006). To develop our hypotheses, first, we outline the main (baseline) effect of buyer–seller network attributes (density and similar function ties) on seller account profitability. Second, we describe how within-seller network attributes moderate these effects of buyer–seller network attributes. We provide examples of configurations of buyer–seller (interfirm) and within-seller (intrafirm) networks in Figure 1 and depict the hypotheses in Figure 2.

Buyer–Seller Network Attributes and Key Account Profitability

Buyer–seller network density. As more buyer and seller representatives connect with each other, buyer–seller network density increases. Network density is pertinent to information and resource exchange for several reasons. A denser network provides a broader set of exchange points, which should enhance the amount of information the seller has about the buyer's requirements and the information that the buyer has about seller's capabilities and limitations (Levin and Cross 2004). Increasing network density from the increasing number of buyer–seller ties means that a buyer or seller can confirm the information obtained from one tie with that gathered from other ties, which should increase confidence in the acquired information (Wang, Gupta, and Grewal 2017). In denser networks, members are also likely to regard one another as salient exchange partners and to view information sharing as the norm, thereby increasing the likelihood of information exchange. Finally, the denser the network, the more assured parties feel that their shared inputs will not be expropriated by individuals in the partner firm, as doing so would jeopardize many ties (McGraw and Tetlock 2005).

In summary, increasing density should augment the amount of information and resources shared in the buyer–seller network and, in turn, reduce uncertainty in the focal parties' minds regarding each other's needs and constraints (Palmatier, Gopalakrishna, and Houston 2006).[2] As a result, the seller is in a

[2] In KAM settings, different buyer-firm stakeholders can have different needs, so increasing density in the buyer–seller network can help illuminate the requirements of these different stakeholders. Published research also supports the positive impact of interfirm network density on firm performance (e.g., Palmatier 2008). However, we did check for diminishing

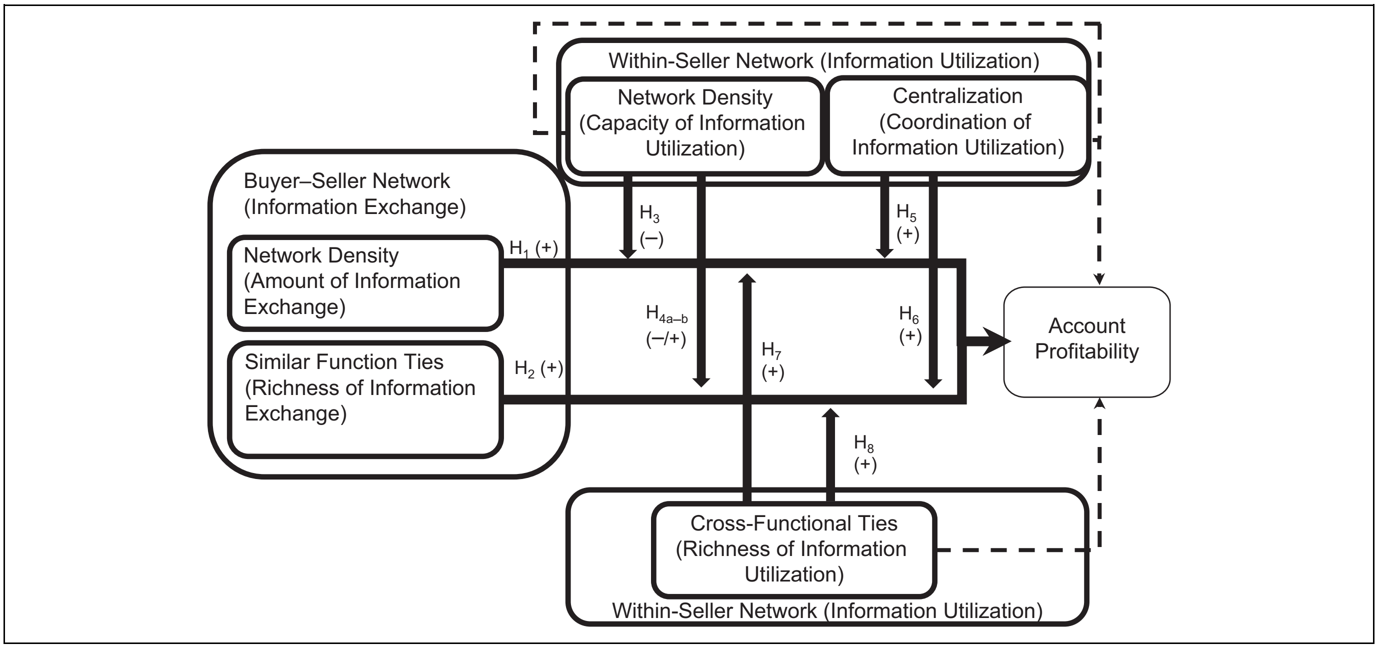


Figure 2. Conceptual framework and hypotheses.
Notes: Dotted arrows represent paths that were estimated but not hypothesized.

superior position to develop the requisite offerings for the buyer, which should increase seller account profitability. Formally,

> **H_1**: Increasing network density in buyer–seller interfirm networks is positively associated with seller account profitability.

Similar function ties. Similar function ties, as reflected by similarity in the functional backgrounds of the seller and buyer team members (Van den Bulte et al. 2010), allows us to account for the richness of information flows. Both marketing and management scholars regard the functional constitution of teams as a significant element influencing team outcomes (e.g., Ahearne et al. 2013; Borgatti et al. 2009; Rothaermel and Boeker 2007). Team members with similar functional backgrounds share overlapping domain knowledge, competency sets, and professional socialization, which can help establish a common understanding and rapport between the parties (Abrams et al. 2003) and facilitate exchange of information (Murtha, Bharadwaj, and Van De Bulte 2014). Shared knowledge bases and worldviews—function-based similarities (McPherson, Smith-Lovin, and Cook 2001)—augment both the partners' willingness to reveal specialized and tacit information (Corsten, Gruen, and Peyinghaus 2011) and the fidelity of complex knowledge transfers between them.

In addition, firm competencies are often "sticky" (Szulanski 1996), so team members with overlapping knowledge bases can better recognize, evaluate, and assimilate information and resources from their matched counterparts (Mallapragada, Grewal, and Lilien 2012). Such exchanges should facilitate better understanding between buyers and sellers, help in the development of appropriate offerings for the buyer, and in turn, increase seller account profitability. Formally,

> **H_2**: Increasing similar function ties in buyer–seller interfirm networks is positively associated with seller account profitability.

Moderating Role of Within-Seller Firm Networks

Within-seller network density. As buyer–seller network density increases, increased seller profitability should result from the greater amount of information exchange in the buyer–seller network (H_1). Increasing buyer–seller network density represents multiple contact points that facilitate exchange and vetting of information (Wang, Gupta, and Grewal 2017). Within-seller network density represents the capacity for information processing and utilization activity within the seller team, such that the capacity increases with increase in density. Increasing capacity to process and utilize information enables seller firms to coordinate complex tasks and make sense of available information (McFayden and Cannella 2004).

Consider how the capacity to process and utilize the information that within-seller network density evinces influences the effect of information gathered and exchanged in the buyer–seller network. As buyer–seller network density increases, there is a corresponding increase in information amount and in the vetting of that information. Therefore, the need for the selling team to "piece together limited

returns by introducing a nonlinear term in our regression but did not find any effects.

information" decreases as volume of vetted information (due to increasing buyer–seller network density) increases (Alvarez and Busenitz 2001, p. 758). In contrast, the capacity to process and utilize the information based on within-seller density in the selling team is more useful when information is scarce (i.e., when there is a greater need to piece together limited information) than when the seller already has abundant information about buyer needs (Choi et al. 2001). In summary, increasing density in the within-seller network[3] will weaken the favorable effect of buyer–seller network density on seller account profitability.[4] Formally,

> **H_3**: The greater the network density in the within-seller firm network, the weaker is the positive association between network density in the buyer–seller interfirm network and seller account profitability.

Similar function ties support specialized, precise, and rich information transfers in the buyer–seller network, which enhances seller account profitability (H_2). Increasing similar function ties implies that team members with similar functions in buying and selling firms connect with each other and, as a result, information richness and diversity increases. Within-seller density, which represents increasing information processing and utilization capacity in the selling team, can influence the relationship between similar function ties and account profitability in two ways.

First, when within-seller density is decreasing, leading to a decrease in the seller's information processing and utilization capacity, the richer information about buyer needs obtained through similar function ties can be critical to compensate for the lower capacity of information processing. Conversely, when information utilization capacity on the seller's part is increasing, the incremental benefits from richer information acquisition is likely lower.

Second, it can be argued that richer information about buyer needs, which follows from increasing similar function buyer–seller ties, will be more valuable as the seller's information processing and utilization capacity increases. To capitalize on the rich information, the seller must be able to assimilate and process the acquired information. Thus, the benefits from similar function ties are likely to be fully realized only when sellers have greater capacity to process and utilize the information (Forgas and George 2001; i.e., for increasing within-seller density). Thus, we propose two alternative hypotheses:

> **H_{4a}**: The greater the network density in the within-seller firm network, the weaker is the positive association between similar function ties in the buyer–seller interfirm network and seller account profitability.

> **H_{4b}**: The greater the network density in the within-seller firm network, the stronger is the positive association between similar function ties in the buyer–seller interfirm network and seller account profitability.

Centralization. Centralization refers to concentrated influence among a limited number of network actors, who possess authority or legitimacy (Ahearne et al. 2013; Hanneman and Riddle 2005). Sometimes called "integrators," these central actors act as linchpins for KAM activities: they coordinate activities, harmonize team efforts, and limit deviations from the overall goal of serving the buyer (Kilduff and Tsai 2003). Selling team members turn to these central actors for official clearances and informal consultations. As we have argued, greater network density in the buyer–seller network represents increasing information and resource flows (H_1), but without an integrator, the seller KAM team might be unable to process these flows (Homburg and Bornemann 2012). In contrast, integrators, given their authority or expertise, can augment the seller's capacity for "sense making" of the information originating in dense buyer–seller network. Because these central actors have a comprehensive view (Balkundi and Harrison 2006) of within-seller KAM activities, they can also channel team efforts toward serving the buyer in an effective and timely manner (Gulati, Mayo, and Nohria 2015). Thus, central actors facilitate the utilization of the inputs obtained from the buyer–seller network, which should enhance seller account profitability. Formally,

> **H_5**: The greater the centralization of ties in the within-seller firm network, the stronger is the positive association between network density in the buyer–seller interfirm network and seller account profitability.

Similar function ties, which support exchange of rich and specialized information in the buyer–seller network, can be especially valuable with increasing centralization in the within-seller network. Given their influence, central actors can integrate information utilization efforts and speed up decision making. That is, with increasing centralization, the seller can more efficiently leverage the rich information obtained from similar function ties in the buyer–seller network to develop appropriate offerings in a timely manner. Formally,

> **H_6**: The greater the centralization of ties in the within-seller firm network, the stronger is the positive association between similar function ties in the buyer–seller interfirm network and seller account profitability.

[3] Another possible explanation for detrimental effects of increasing within-seller density is increasing coordination costs. Increasing within-seller density can also increase internal coordination complexities that might force time-strapped managers to adopt heuristic shortcuts (Thomas, Fugate, and Koukova 2011). Such heuristics might lead to misutilization of the information acquired from the buyer, result in poorer quality of offerings, and even reduce likelihood of the buyer exchanging information (Thomas, Fugate, and Koukova 2011), thus reducing the positive impact of buyer–seller density on profitability. We thank an anonymous reviewer for this suggestion.

[4] Our contention is not that buyer–seller density is irrelevant, but that it contributes to seller performance even when within-seller density is increasing, albeit at progressively lower degrees (i.e., at lower rates).

Cross-functional ties. Cross-functional ties in the within-seller network pool diverse functional expertise in the team (Murtha, Bharadwaj, and Van den Bulte 2014), which should help develop novel offerings that appeal to diverse stakeholders in the buyer firm (Brown and Eisenhardt 1995). Teams with mostly members from the same function instead might develop closed thought-worlds, which could undermine their capacity to develop customer-centric offerings (Gulati 2007). Consistent with this view, cross-functional selling teams have been found to be more adaptive and to perform better, on average, than single-function teams (Cox and Blake 1991; Homburg, Workman, and Jensen 2002). Increasing network density in the buyer–seller network can enhance seller account profitability by increasing the amount of information exchange in the buyer–seller network (H_1); cross-function ties in the within-seller network can augment the seller's ability to harness the information acquired from the buyer–seller network, which should enhance seller account profitability. Formally,

> **H_7**: The greater the cross-functional ties in the within-seller firm network, the stronger is the positive association between network density in the buyer–seller interfirm network and seller account profitability.

Finally, increasing similar function ties in the buyer–seller network increase seller profitability by facilitating the transfer of rich information (H_2). We propose that cross-functional ties in the within-seller network can strengthen this effect, because they enable the superior use of information through the pooling of distinct perspectives and expertise within the team. Consequently, the seller KAM team with increasing cross-function ties can harness the rich information gathered from similar function ties to better serve a varied set of stakeholders in the buyer firm. Formally,

> **H_8**: The greater the cross-functional ties in the within-seller firm network, the stronger is the positive association between similar function ties in the buyer–seller interfirm network and seller account profitability.

Data Collection and Sampling

To test our hypotheses, we sought data from B2B firms that use KAM teams to manage their ongoing buyer–seller relationships. To ensure variation in the buyer–seller and within-seller network characteristics, we targeted a variety of B2B industries that rely on KAM teams; within these industries, we targeted firms with at least 500 employees. We required informants to be knowledgeable about, engaged with, and involved in day-to-day operations of the focal buyer–seller relationship. Therefore, two criteria drove informant selection. First, we targeted only key account managers (with titles such as national account managers, global account managers, or account managers). Second, we excluded informants with fewer than two years of experience as a key account manager to ensure that they had sufficient knowledge about the key accounts.

Pilot Interviews and Instrument Design

For the survey design and validation, we interviewed 35 key account managers and 15 selling team members in nonsales roles (e.g., services, support, product development) across different industries. A typical interview lasted 15–25 minutes, and cumulatively, we gathered more than 10 hours of interviews. Our goal was to understand the workings of KAM selling teams and ascertain the suitability of our approach for studying them. We enquired about informants' knowledge of and involvement in various day-to-day KAM tasks, as well as the roles of KAM teams and team members in decision making and customer interactions.

Virtually every interviewed account manager reported being personally responsible for managing key accounts and vested directly in sales performance outcomes. As an account manager in an information technology (IT) firm put it, "I am the one who is . . . accountable to the customer and also to our top management for managing the account. . . . I am in charge." Approximately 97% of the account managers noted their close involvement in operational and decision-making aspects, and 94% mentioned direct involvement in communication and negotiation with the buyer team as well as in developing offerings and evaluating performance within the selling team. An account manager in a transportation services firm explained that it was incumbent on him to be intimately aware of internal and external KAM team interactions, because "it is, after all, my job to [keep abreast of] . . . what is happening within the team and how the team engages with the customer."

To confirm these insights, we interviewed 15 additional informants from selling teams who were not in a sales role per se. Their views were consistent with the reports from the account managers. For example, a product manager of an industrial equipment firm described an account manager's regular participation in KAM affairs as a key decision maker: "[He is] very participative . . . involved in the team activities. . . . He knows the customer needs very well, and we always seek his input on any changes that we plan for them." A delivery manager for an IT services vendor also portrayed an account manager's deep familiarity with key accounts: "Jack knows which strings to pull, to get work done for [XYZ] account. He is super-informed on what is going on."

These interviews confirm that account managers are closely involved with and understand the interactions in buyer–seller and within-seller KAM networks. As such, key account managers represent qualified informants for our study purposes. We also pretested a preliminary instrument among a small set (ten) of these informants, to gauge the clarity and consistency of the item wording, format, and anchors for our scales. No major issues emerged.

Sample Selection and Data Collection Process

We obtained a list of 1,026 qualified informants from our list of focal B2B industries in the United States from a professional, for-profit, executive panel firm. We emailed initial invites containing a link to our questionnaire to these informants and followed up with a reminder email a week later. We detail the sample demographics in Appendix A.

We instructed each informant to think about a salient key account[5] and answer questions with respect to that account. We asked the informants to list the names (initials, nicknames, designation) of all personnel in the seller team who were involved in supporting the key account over the past six months, irrespective of their function or position (minimum of three names). We also asked them to list the names of all involved representatives from the buyer side. The online setting enabled dynamic updating of questionnaire content, according to the names and number of KAM team members.

For each KAM participant identified by the informants, we first collected information about his or her functional background and role. To construct the within-seller firm network, we followed an iterative process and identified information usage ties within the seller firm. That is, for each member of the selling team, we asked informants to identify the other team members with whom (s)he consults. Repeating this process for every team member yielded the within-seller firm network. To construct the buyer–seller network, we followed a similar iterative process, such that informants completed a matrix to indicate which selling team member interacted with which buying team member, where an interaction was defined as two-way communication exchange through face-to-face meetings, phone calls, emails, videoconferencing, or social platforms. Subsequently, the informants provided data pertaining to performance measures, seller firm characteristics, and their own characteristics. On average, informants took 27 minutes to complete the survey.

Over a two-week period, 539 informants clicked the survey link. These clicks resulted in 247 early responses (within the first week of the initial email), of which 113 were complete, and 292 late responses (within a week of the reminder email), of which 117 were complete.[6] These 230 complete responses represent a 22.4% response rate, similar to that reported by other studies of senior-level sales managers (Homburg, Workman, and Jensen 2002).

To ensure the data quality, we checked each response for consistency and removed 23 responses: 14 that did not meet the data quality checks and 9 that suffered from severe missing data.[7] This procedure resulted in 207 final usable responses. We also checked for sample selection and nonresponse biases, but neither appeared to be a concern.[8]

To address the possibility of common method bias, we computed the measures of our explanatory and moderating variables using network information reported by the informants, not direct measures provided by the informants. For our dependent variable, we used objective performance measures, captured on a percentage scale (as we detail subsequently). Moreover, as recommended by Podsakoff et al. (2003), we varied both the scale format and scale anchors across measures pertaining to seller, buyer, and informant characteristics. Furthermore, we instructed the informants to report (1) performance measures for the current time period and (2) information about the KAM networks for the prior six months. This temporal separation between the explanatory and dependent variables helps mitigate common method bias concerns and reduces the severity of simultaneity issues that may cause endogeneity problems.

Measures

Network Formation

To identify the buyer–seller network, we aggregate bidirectional communication ties reported between all buyer and seller representatives. The resulting two-mode network has two distinct types of actors: buyer and seller representatives. In the within-seller network, the direction of consultation ties to a focal actor indicates that other actors seek out the focal actor for consultation. The result is a directed network, formed by aggregating directed consultation ties reported between all selling team members.

[5] Similar to Homburg, Workman, and Jensen (2002), we defined customer account salience in terms of the account's share of the seller firm's sales, potential for sales growth, relational importance to the seller, and impact on the current and future performance of the seller firm. In our sample, 18% of informants handled a single account, 56% handled 2 to 7 accounts, and 26% handled up to 15 accounts.

[6] Of the 309 excluded responses, 205 failed to meet our selection criteria, and 104 abandoned the survey. Among the 205 informants who did not meet the selection criteria, 28 were part-time employees, 13 were not employed in the sales function, 26 were not involved with key accounts, 35 had been in their position for less than two years, 47 worked for firms with fewer than 500 employees, 22 were not involved in team selling, and 34 did not meet the industry criterion.

[7] We included several questions in multi-item scales that instructed the informant to mark a particular answer. We eliminated nine instances when the informant failed to do so. We also measured informants' confidence about account profitability, ties between buyer–seller representatives, and ties of within-seller team members, as well as their level of knowledge about the key account, on Likert scales. Here, five responses were removed because the informant was not confident or not knowledgeable (score of less than six-on a seven-point scale).

[8] We conducted two tests of nonresponse bias. First, we used a pairwise t-test comparison of mean responses for early and late responses and found no significant differences ($p > .05$). Second, we compared early and late completed responses on variables such as firm annual sales, informant experience, buyer firm annual sales, account profitability, and network characteristics using chi-square tests; again, we found no significant differences ($p > .05$). To check for sample selection bias due to incomplete responses, we applied the Heckman correction procedure, which predicts whether a response will be complete (coded 1) or incomplete (coded 0) and then computed the inverse Mills ratio. This ratio term was not statistically significant in our focal regression ($\rho = .06$, SE $= 1.47$, $p > .1$), which suggests no systematic differences between complete and incomplete responses.

Table 2. Descriptive Statistics and Bivariate Correlation Coefficients.

	M	SD	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Account profitability	7.28	3.20													
2. Seller firm annual sales	4.58	2.38	.09												
3. Buyer firm annual sales	4.20	2.46	.10	.34											
4. Number of accounts handled	2.69	.56	−.02	−.15	−.24										
5. Duration key account (years)	3.03	.86	.08	.04	.14	−.02									
6. Seller team size	7.14	2.41	.02	.18	.24	−.14	.13								
7. Seller function count	3.25	1.38	.00	−.01	.02	−.13	.01	.27							
8. Buyer team size	5.05	1.85	.11	.18	.26	−.22	.15	.35	.16						
9. Buyer function count	2.62	1.24	.04	−.09	−.13	−.16	−.05	.05	.39	.24					
10. Buyer–seller network density (IFDEN)	.39	.17	.01	.14	.05	.08	.05	−.09	−.06	−.14	−.21				
11. Similar function ties (IFFUNCSIM)	.31	.26	.01	−.02	−.08	−.02	.01	−.08	−.20	.03	−.03	−.03			
12. Within-seller network density (SDEN)	.38	.20	.01	.07	−.08	.01	.00	−.16	−.03	−.04	−.13	.30	.02		
13. Centralization (SCENTRAL)	.46	.25	−.01	−.06	−.01	.08	.08	.01	.00	.03	.11	.17	.15	−.36	
14. Cross-functional ties (SCROSSFUNC)	.62	.29	.02	−.09	.00	−.12	−.04	−.04	.38	−.05	.27	.03	−.17	.04	.04

Notes: N = 207. Correlations r > .14 are significant at the .05 level (two-tailed).

Dependent Variable

We capture our dependent variable, the seller's account profitability, with the measure employed by Homburg, Workman, and Jensen (2002) and Workman, Homburg, and Jensen (2003). Consistent with prior research, we define profitability as gross profit minus direct and indirect costs associated with sales and servicing the key account (Bowman and Narayandas 2004; Mullins et al. 2014). Informants had to consider their most recent company archives and categorize their current account profitability into buckets: below 0% (i.e., loss), 0%–2%, 2%–4%, 4%–6%, 6%–8%, 8%–10%, 10%–12%, 12%–14%, 14%–16%, 16%–20%, or 20% and above (see Homburg, Workman, and Jensen 2002; Mullins et al. 2014; Palmatier, Gopalakrishna, and Houston 2006).

Independent and Moderating Variables

Network density in buyer–seller network (IFDEN). Network density is the ratio of the actual number of ties to the maximum possible (Borgatti, Everett, and Freeman 2002). We counted the actual number of ties between buyer and seller representatives (N_A). The maximum number of ties equals $N_S \times N_B$, where N_S and N_B represent the number of selling and buying team members, respectively. The IFDEN measure takes a value between 0 and 1, calculated as $\mathrm{IFDEN} = N_A/(N_S \times N_B)$.

Similar function ties in buyer–seller network (IFFUNCSIM). Each tie between a buyer and a seller representative is coded as 1 if they represent similar functional backgrounds and 0 otherwise. Thus, a tie between finance professionals from both sides or between a salesperson and a buyer procurement person would be coded as 1. A tie between a finance person and a marketing person would be coded as 0. We calculate the similar function ties for the buyer–seller network as ratio of similar function ties (N_{ISF}) to the total count of ties present (N_{IT}) (Borgatti et al. 2009; Tsai and Ghoshal 1998), or $\mathrm{IFFUNCSIM} = N_{ISF}/N_{IT}$.

Network density in within-seller network (SDEN). We calculate density as the ratio of the number of actual ties (N_A) to the maximum number of possible ties (Wasserman and Faust 1994), or $\mathrm{SDEN} = (2 \times N_A)/[N_S \times (N_s - 1)]$, where N_S is the number of selling team members.

Centralization in within-seller network (SCENTRAL). The centralization index reflects the dispersion of actors' centrality in the network relative to the greatest actor centrality value. Similar to Freeman (1992), we compute centralization as $\mathrm{SCENTRAL} = \{\sum_{i=1}^{N_s}[C_D(n^*) - C_D(n_i)]\}/[(N_S - 1)\times(N_S - 2)]$, such that the centrality $C_D(n_i)$ for each actor (where n_i is indicator of actor i) is the sum of the number of ties for actor i, $C_D(n^*)$ is the greatest actor-level centrality, and N_S is the number of selling team members. Our centralization measure is based on in-degree centrality for all actors, to account for the directionality of the consultation ties (Wasserman and Faust 1994).

Cross-functional ties in within-seller network (SCROSSFUNC). Following a process similar to that we applied for buyer–seller similar function ties, we coded the ties among selling team members from the same functional background as 0, and 1 otherwise. For example, a tie between two salespeople was coded as 0; a tie between a finance and a marketing person was coded as 1 (i.e., cross-function tie). We calculated within-seller cross-functional ties as the ratio of cross-functional ties (N_{WCF}) to the total ties in the within-seller network (N_{WT}) (Borgatti et al. 2009; Tsai and Ghoshal 1998), or $\mathrm{SCROSSFUNC} = N_{WCF}/N_{WT}$.

We present the descriptive statistics and correlation matrix for our measures in Table 2.

Model Development

We seek a model specification that is appropriate for testing our hypotheses. The nature of the dependent variable (account profitability, measured in ordered categories) suggests a nonlinear model, such as an ordered logit specification, but a linear model with interactions is more appropriate, because the marginal effects are easier to interpret. Using a linear model to test hypotheses, even if a nonlinear model might be appropriate, is common (e.g., Goldfarb and Tucker 2011; Nair, Manchanda, and Bhatia 2010). Thus, we report the results from a linear model and use an ordered logit model specification as a robustness check. Specifically,

$$\begin{aligned}\mathrm{PERF_f} = {} & \alpha_0 + \beta_1\mathrm{IFDEN_f} + \beta_2\mathrm{IFFUNCSIM_f} + \beta_3\mathrm{SDEN_f} \\ & + \beta_4\mathrm{SCENTRAL_f} + \beta_5\mathrm{SCROSSFUNC_f} \\ & + \beta_6\mathrm{IFDEN_f}^2 + \beta_7\mathrm{SDEN_f}^2 + \beta_8\mathrm{SCENTRAL_f}^2 \\ & + \beta_9(\mathrm{IFDEN_f} \times \mathrm{SDEN_f}) + \beta_{10}(\mathrm{IFFUNCSIM_f} \\ & \times \mathrm{SDEN_f}) + \beta_{11}(\mathrm{IFDEN_f} \times \mathrm{SCENTRAL_f}) \\ & + \beta_{12}(\mathrm{IFFUNCSIM_f} \times \mathrm{SCENTRAL_f}) \\ & + \beta_{13}(\mathrm{IFDEN_f} \times \mathrm{SCROSSFUNC_f}) \\ & + \beta_{14}(\mathrm{IFFUNCSIM_f} \times \mathrm{SCROSSFUNC_f}) + \varepsilon_f,\end{aligned} \tag{1}$$

where the subscript f indicates the firm; PERF represents seller account profitability; IFDEN, IFFUNCSIM, SDEN, SCENTRAL, and SCROSSFUNC indicate buyer–seller network density, buyer–seller similar function ties, within-seller network density, within-seller centralization, and within-seller cross-functional ties, respectively; IFDEN^2, SDEN^2, and $\mathrm{SCENTRAL}^2$ represent the squared terms for nonlinear effects[9]; α_0 is the intercept term; β indicates regression coefficients for main and interaction effects; and ε_f denotes the error term. The coefficients β_1 and β_2 map to H_1 and H_2, and the coefficients β_9, β_{10}, β_{11}, β_{12}, β_{13}, and β_{14} refer to H_3, H_{4a-b}, H_5, H_6, H_7, and H_8, respectively.

Observed and Unobserved Heterogeneity

To account for observed heterogeneity, we incorporate several covariates that could influence the seller's account performance. First, we include buyer and seller firm sizes (captured as annual sales) as proxies of availability of resources; these are used extensively as controls in prior B2B research (Mithas, Krishnan, and Fornell 2005; Palmatier 2008; Shah et al. 2012). Second, we note the number of accounts handled by the informant, which can influence allocations of time and effort and thereby affect seller account performance. Third, we incorporate the duration of the key account relationship (in years) to capture relationship age, shown in prior research to affect buyer–seller outcomes (Palmatier 2008). Fourth, we use the sizes of the seller team and buyer team, because team size indicates the importance of the relationship on both sides and should correlate with seller account performance. Fifth, we include the number (count) of different functions (e.g., sales, support, engineering) involved from the seller and the buyer sides to account for the breadth of functional representation in the KAM teams.

Beyond these observed covariates, unobserved factors (e.g., firm culture) could influence seller key account performance. Failure to account for such unobserved factors can lead to statistically biased, inconsistent parameter estimates. We use a semiparametric approach to represent the intercept term and the error variance with a finite number of support points (Chintagunta 2001; Wang, Saboo, and Grewal 2015). Thus, we can specify our model as follows:

$$\begin{aligned}\mathrm{PERF_f} = {} & \textstyle\sum_{(k=0)}^{K} \pi_k\alpha_k + \beta_1\mathrm{IFDEN_f} + \beta_2\mathrm{IFFUNCSIM_f} \\ & + \beta_3\mathrm{SDEN_f} + \beta_4\mathrm{SCENTRAL_f} \\ & + \beta_5\mathrm{SCROSSFUNC_f} + \beta_6\mathrm{IFDEN_f}^2 \\ & + \beta_7\mathrm{SDEN_f}^2 + \beta_8\mathrm{SCENTRAL_f}^2 + \beta_9(\mathrm{IFDEN_f} \\ & \times \mathrm{SDEN_f}) + \beta_{10}(\mathrm{IFFUNCSIM_f} \times \mathrm{SDEN_f}) \\ & + \beta_{11}(\mathrm{IFDEN_f} \times \mathrm{SCENTRAL_f}) \\ & + \beta_{12}(\mathrm{IFFUNCSIM_f} \times \mathrm{SCENTRAL_f}) \\ & + \beta_{13}(\mathrm{IFDEN_f} \times \mathrm{SCROSSFUNC_f}) \\ & + \beta_{14}(\mathrm{IFFUNCSIM_f} \times \mathrm{SCROSSFUNC_f}) \\ & + \gamma_j\mathrm{Controls_{f,j}} + \textstyle\sum_{(k=0)}^{K} \varepsilon_{f,k},\end{aligned} \tag{2}$$

where CONTROLS is a vector of covariates to account for observed heterogeneity, represents latent support points for the intercept, γ indicates regression coefficients for the control variables; denotes the error term with k support points; and the value of K is empirically determined on the basis of model fit (e.g., Wedel and Kamakura 2001).

Endogeneity

Buyer–seller network density. A seller might increase the number of relationship ties with a buyer in anticipation of future performance (e.g., increased orders). Similarly, a buyer might engage a larger number of seller representatives to gain more insights from it. Such private intentions are unobservable, but they might correlate with the seller's account profitability, which suggests potential endogeneity in buyer–seller network density.

Buyer–seller similar function ties. Endogeneity can arise due to unobserved factors, such as the strategic intent of the seller or buyer. For example, the seller might design its KAM team purposefully to overrepresent employees from operations as opposed to marketing, which might facilitate the solution

[9] These squared terms represent nonlinear effects and account for the possibility of diminishing returns in the relevant variables. For example, increasing buyer–seller network density (IFDEN) might be beneficial initially, whereas beyond a threshold, it could create information overload, which then might reduce seller account profitability. Similarly, centralization (SCENTRAL) could facilitate KAM project execution, but increasing centralization might overwhelm the central actor, slow down the project (Cross and Parker 2004), and lower seller account profitability. We thank an anonymous reviewer for this suggestion.

development process and also could affect seller account profitability.

Within-seller network density. Increasing within-seller network density represents increasing consultation activity among selling team members. Such activity might result from formal or informal team management tactics deployed by the seller firm, which are unobserved by the researcher and could result in potential endogeneity concerns.

Within-seller centralization. Centralization represents the prominence of few central actors who are consulted by many selling team members. Such consultation efforts might be prompted by the formal authority of the central actor or by standard operating procedures in the seller firm. Underlying mechanisms such as these are unobserved but might influence account performance and thereby give rise to endogeneity concerns.

Within-seller cross-functional ties. Within-seller firm cross-functional ties might be driven by a firm culture that promotes cross-functional coordination and team-oriented processes. Such aspects of organizational culture are typically unobserved and create endogeneity concerns.

Potential endogeneity often can be corrected using instrumental variables (IVs). However, in practice and strategy research, it can be challenging to find valid instruments. As an alternative, we adopt the latent instrumental variable (LIV) approach (Ebbes et al. 2005), as adopted by marketing literature (e.g., Grewal, Chandrashekaran, and Citrin 2010; Rutz, Bucklin, and Sonnier 2012; Zhang, Wedel, and Pieters 2009). It introduces a discrete, unobserved, latent IV that has m categories and partitions the variance of the endogenous regressor into an exogenous (uncorrelated with error term) part and an endogenous (possibly correlated with error term) part, such that

$$X_f = \theta_l \widehat{Z}_f + \zeta_f, \tag{3}$$

where f indicates the firm; X_f denotes the endogenous regressor; θ_l represents the (m $\times$ 1) vector of category means; $\widehat{Z}_f$ is the unobserved discrete instrument that partitions the sample into m groups (where m $>$ 1), such that $\widehat{Z}_f$ is uncorrelated with ε_f and ζ_f; and ζ_f refers to the error residual that may correlate with the error term ε_f. To correct for each possible endogenous variable, we compute $\widehat{Z}_f$ and ζ_f and introduce them into Equation 2.

Model Specification

The corrected variables $\mathrm{IF\widehat{DEN}}_f$, $\mathrm{IFF\widehat{UNC}SIM}_f$, $\mathrm{S\widehat{DEN}}_f$, $\mathrm{SCE\widehat{NTR}AL}_f$, and $\mathrm{SCRO\widehat{SSF}UNC}_f$ represent the predicted values from the LIV correction (Equation 3), uncorrelated with the error terms for the actual regressors; they are introduced in the main regression model with the additional error (residual) terms from the LIV correction step, that is, $\zeta_{f,1}$, $\zeta_{f,2}$, $\zeta_{f,3}$, $\zeta_{f,4}$, and $\zeta_{f,5}$. The final regression equation, after correcting for endogeneity, is thus:

$$\begin{aligned}
\mathrm{PERF}_f = {} & \sum_{k=0}^{K} \pi_k \alpha_k + \beta_1 \mathrm{IF\widehat{DEN}}_f + \beta_2 \mathrm{IFF\widehat{UNC}SIM}_f \\
& + \beta_3 \mathrm{S\widehat{DEN}}_f + \beta_4 \mathrm{SCE\widehat{NTR}AL}_f \\
& + \beta_5 \mathrm{SCRO\widehat{SSF}UNC}_f + \beta_6 \mathrm{IF\widehat{DEN}}_f{}^2 \\
& + \beta_7 \mathrm{S\widehat{DEN}}_f{}^2 + \beta_8 \mathrm{SCE\widehat{NTR}AL}_f{}^2 \\
& + \beta_9 (\mathrm{IF\widehat{DEN}}_f \times \mathrm{S\widehat{DEN}}_f) + \beta_{10} (\mathrm{IFF\widehat{UNC}SIM}_f \\
& \times \mathrm{S\widehat{DEN}}_f) + \beta_{11} (\mathrm{IF\widehat{DEN}}_f \times \mathrm{SCE\widehat{NTR}AL}_f) \\
& + \beta_{12} (\mathrm{IFF\widehat{UNC}SIM}_f \times \mathrm{SCE\widehat{NTR}AL}_f) \\
& + \beta_{13} (\mathrm{IF\widehat{DEN}}_f \times \mathrm{SC\widehat{ROSSF}UNC}_f) \\
& + \beta_{14} (\mathrm{IFF\widehat{UNC}SIM}_f \times \mathrm{SCRO\widehat{SSF}UNC}_f) \\
& + \gamma_j \mathrm{Controls}_{f,j} + \beta_{12} \zeta_{f,1} + \beta_{13} \zeta_{f,2} + \beta_{14} \zeta_{f,3} \\
& + \beta_{15} \zeta_{f,4} + \beta_{16} \zeta_{f,5} + \sum_{k=0}^{K} \varepsilon_{f,k}
\end{aligned} \tag{4}$$

Estimation

In line with extant research (e.g., Wedel and Kamakura 2001), we estimated Equations 3 and 4 by maximizing the log-likelihood function using the expectation–maximization algorithm. We mean-centered all explanatory variables. The low variance inflation factor (<3.01) and condition index (<8.5) suggested that multicollinearity was not an issue. Moreover, the sequential model-building process, such that we introduced the control variables first, then the main effect terms, and finally the interaction terms, did not inflate the standard errors, which mitigates multicollinearity concerns.

Results

Model Selection

We first estimated Equation 3 to calculate the correction term for the endogenous variables. To determine the number of support points, we relied on the Akaike information criterion (AIC3) (Andrews and Currim 2003), which suggested, respectively, two-, six-, four-, five-, and five-support point solutions for buyer–seller density (IFDEN), buyer–seller similar function ties (IFFUNCSIM), within-seller density (SDEN), within-seller centralization (SCENTRAL), and within-seller cross-functional ties (SCROSSFUNC). Before estimating the final specification in Equation 4, we incorporated the support points to account for unobserved heterogeneity. The AIC3 criterion supports a three–support point solution for the final corrected model (one point: 1,108.12, two points: 958.51, three points: 952.20, four points: 956.88, five points: 989.09).

Hypothesis Testing

In Table 3 we present the results from a series of nested models, which include the main effects only; hypothesized interactions; interactions and nonlinear terms; interactions with the LIV correction; and finally, all interactions, nonlinear terms, and LIV corrections (FINALLIV MODEL). The results are consistent in statistical significance across models, so we discuss the results of the final model. The LIV error term is significant for buyer–seller density ($\beta = -.664$, $p < .05$), which suggests the importance of accounting for endogeneity.

At the buyer–seller (interfirm) network level, we find support for the positive main effect of buyer–seller network density ($\beta = .868$, $p < .05$), as predicted by H_1. We do not find support for H_2, however: the coefficient for similar function ties is not statistically significant. (Because we include interactions and mean-center the interacting variables, we interpret the main effects only at the mean value of the moderator variable).

Regarding the moderating effects of within-seller network density (SDEN), we find mixed support. In line with H_3, SDEN negatively moderates the positive effect of buyer–seller network density (IFDEN) on seller account profitability ($\beta = -3.809$, $p < .05$). However, the joint effect of buyer–seller similar function ties (IFFUNCSIM) and SDEN is insignificant ($\beta = -.107$, $p > .10$), such that neither H_{4a} nor H_{4b} are supported. To investigate H_3 further, we conducted slope analyses (Aiken, West, and Reno 1991) by computing the effect of buyer–seller density (main effect variable) on seller account profitability at five levels of within-seller density (moderator variable): two and one standard deviations below the mean (−2 SD and −1 SD), at the mean, and one and two standad deviations above the mean (+1 SD and +2 SD). We plot these slopes in Figure 3.

In Panel A of Figure 3, buyer–seller density (IFDEN) increases seller account profitability at a decreasing rate over the range of the within-seller density (SDEN) moderator. Statistically, this effect captures the slope (first derivative) between buyer–seller density and seller account profitability (δPERF/δIFDEN) at different levels of the moderator. Buyer–seller density increases account profitability at low levels (−2 SD) of within-seller density ($\beta_{-2\ SD} = 2.056$, $p < .01$), but this effect weakens progressively ($\beta_{-1\ SD} = 1.639$, $p < .01$; $\beta_{mean} = .868$, $p < .05$), and vanishes above the mean ($\beta_{+1\ SD} = .096$, $p > .10$; $\beta_{+2\ SD} = -1.485$, $p > .10$).

Regarding the moderating effects of within-seller centralization (SCENTRAL), we find support for both our predictions. That is, as we anticipated in H_5, SCENTRAL positively moderates the positive effect of buyer–seller network density (IFDEN) on seller account profitability ($\beta = .872$, $p < .10$). The slope plot for this interaction (Figure 3, Panel B) reveals that buyer–seller density increases account profitability consistently at or above –1 SD of within-seller centralization: The effect of buyer–seller density on account profitability is insignificant at very low levels of within-seller centralization ($\beta_{-2\ SD} = .463$, $p > .10$). Then it is significantly positive at or beyond −1 SD of within-seller centralization ($\beta_{mean} = .868$, $p < .05$; $\beta_{+1\ SD} = 1.087$, $p < .05$), in support of H_5.

Consistent with H_6, within-seller centralization (SCENTRAL) also positively moderates the positive effect of buyer–seller similar function ties (IFFUNCSIM) on seller account profitability ($\beta = 1.521$, $p < .05$). The slope plot in Figure 3, Panel C, reveals the profitability impacts, such that buyer–seller similar function ties are insignificant at or below the mean of within-seller centralization ($\beta_{-2\ SD} = -.301$, $p > .10$; $\beta_{mean} = .404$, $p > .10$), but their effect becomes significantly positive at higher levels ($\beta_{+1\ SD} = .787$, $p < .05$; $\beta_{+2\ SD} = 1.219$, $p < .01$).

We find mixed support for the predicted moderating effects of within-seller cross-functional ties (SCROSSSFUNC). The results in Table 3 indicate no moderation of the positive effect of buyer–seller density (IFDEN) on seller account profitability by SCROSSFUNC ($\beta = .03$, $p > .10$), so we must reject H_7. However, in line with H_8, we find a positive joint effect of buyer–seller similar function ties (IFFUNCSIM) and SCROSSFUNC ($\beta = 1.503$, $p < .01$). To explore H_8 further, we again use Aiken, West, and Reno's (1991) methodology and plot the slopes between seller account profitability and IFFUNCSIM over the range of SCROSSFUNC. In Figure 3, Panel D, IFFUNCSIM has a positive overall effect on account profitability, but at low levels of within-seller cross-functional ties, the relationship is not significant ($\beta_{-2\ SD} = -.521$, $p > .10$; $\beta_{mean} = .404$, $p > .10$). The effect becomes significantly positive only beyond the mean level of the moderator ($\beta_{+1\ SD} = .846$, $p < .05$). This pattern of effects further supports H_8.

Post Hoc Analysis

In our model specification, we considered the possibility that certain network attributes such as within-seller density (SDEN) might exhibit diminishing returns by incorporating the relevant quadratic terms (e.g., $SDEN^2$). As Table 3 shows, we find negative nonlinear effects for SDEN ($\beta = -.916$, $p < .10$) and centralization (SCENTRAL; $\beta = -2.441$, $p < .01$) but not for buyer–seller density (IFDEN; $\beta = 1.488$, $p > .10$). We also explored whether $SDEN^2$ and $SCENTRAL^2$ might further negatively moderate the impact of buyer–seller network attributes on account profitability. As such, we reestimated our regression model (Table 3) after accounting for the relevant quadratic terms (e.g., $SDEN^2$) and their three-way products with buyer–seller density (IFDEN) and similar function ties (IFFUNCSIM) (i.e., we included $SDEN^2 \times$ IFDEN and $SDEN^2 \times$ IFFUNCSIM. While all hypothesized effects remained similar to those reported in Table 3, we found support for the $SDEN^2 \times$ IFDEN interaction ($\beta = -4.117$, $p < .10$), but not for $SDEN^2 \times$ IFFUNCSIM ($\beta = -3.476$, $p > .10$). These findings are consistent with prior research that shows a negative effect of dense interactions in intrafirm teams (Rowley, Behrens, and Karckhardt 2000) but not in interfirm settings (Palmatier 2008). Following a similar procedure as before, we also tested for three-way interactions involving the quadratic term for within-seller centralization ($SCENTRAL^2$), but

Table 3. Effect of Buyer–Seller Interfirm Network and Within-Seller Firm Network on Seller Account Profitability.

	Without Endogeneity Correction			With Endogeneity Correction			
Predictors	Controls and Main Effects Only Coeff. (SE)	Model with Interactions Coeff. (SE)	Final Model: Interactions + Nonlinear Effects Coeff. (SE)	Controls and Main Effects Only Coeff. (SE)	Model with Interactions + LIV Coeff. (SE)	FINALLIV Model: Interactions + LIV + Nonlinear Effects Coeff. (SE)	
Controls							
Seller firm annual sales	.014	.009	.001	.004	.008	.012	
	(.021)	(.03)	(.022)	(.024)	(.023)	(.021)	
Buyer firm annual sales	.032	.042	.053**	.038	.035*	.061***	
	(.021)	(.027)	(.023)	(.025)	(.020)	(.021)	
Number of accounts handled	.039	.044	.045	.038	.041	.052	
	(.066)	(.029)	(.035)	(.028)	(.037)	(.034)	
Duration key account (years)	−.007	−.027	−.012	−.022	−.019	−.008	
	(.027)	(.031)	(.028)	(.03)	(.032)	(.027)	
Buyer team size	.041*	.019	.060	.029	.106*	.056	
	(.024)	(.039)	(.042)	(.039)	(.056)	(.036)	
Buyer function count	.095*	.111***	.127**	.073	.073	.098	
	(.052)	(.063)	(.058)	(.063)	(.058)	(.075)	
Seller team size	−.047*	−.015	−.072*	−.021	−.062**	−.077**	
	(.025)	(.034)	(.037)	(.034)	(.028)	(.031)	
Seller function count	.221***	.065	.011	.117	.103	.013	
	(.064)	(.070)	(.063)	(.078)	(.081)	(.058)	
Buyer–Seller Interfirm Network							
Buyer–seller interfirm density (IFDEN)	.676+++	.866++	1.123+++	.873++	.771++	.868++	H_1 supported
	(.24)	(.406)	(.407)	(.396)	(.421)	(.403)	
Similar function ties (IFFUNCSIM)	.527++	.012	.180	.952+++	.316	.404	H_2 not supported
	(.23)	(.286)	(.239)	(.378)	(.318)	(.379)	
Within-Seller Firm Network							
Network density (SDEN)	−.522*	−.891**	−.673	−.812	−.527	−.697	
	(.29)	(.353)	(1.018)	(.612)	(.49)	(.515)	
Centralization (SCENTRAL)	.516**	.413*	.781***	.552**	.49*	.701*	
	(.233)	(.218)	(.299)	(.233)	(.264)	(.363)	
Cross-functional ties (SCROSSFUNC)	.474	.080	.166	.763	.739	.759	
	(.31)	(.306)	(.762)	(.819)	(.736)	(.669)	
Nonlinear							
IFDEN × IFDEN			1.531			1.488	
			(1.325)			(1.254)	
SDEN × SDEN			−1.186*			−.916*	
			(.670)			(.493)	
SCENTRAL × SCENTRAL			−2.117**			−2.441***	
			(.883)			(.852)	
Interactions							
IFDEN × SDEN (H_3)		−3.244++	−3.162++		−2.324++	−3.809++	H_3 supported
		(1.592)	(1.817)		(1.217)	(2.180)	
IFFUNCSIM × SDEN ($H_{4a,\ b}$)		−.026	−.137		−.061	−.107	H_4 not supported
		(1.121)	(1.088)		(1.268)	(1.032)	
IFDEN × SCENTRAL (H_5)		.446++	.782+		.928+	.872+	H_5 supported

(continued)

Table 3. (continued)

Predictors	Without Endogeneity Correction: Controls and Main Effects Only Coeff. (SE)	Without Endogeneity Correction: Model with Interactions Coeff. (SE)	Without Endogeneity Correction: Final Model: Interactions + Nonlinear Effects Coeff. (SE)	With Endogeneity Correction: Controls and Main Effects Only Coeff. (SE)	With Endogeneity Correction: Model with Interactions + LIV Coeff. (SE)	With Endogeneity Correction: FINALLIV Model: Interactions + LIV + Nonlinear Effects Coeff. (SE)	
		(.266)	(.494)		(.589)	(.541)	
IFFUNCSIM × SCENTRAL		.574^{++}	.508^{++}		.954^{+++}	1.521^{++}	H_6 supported
(H_6)		(.295)	(.249)		(.362)	(.699)	
IFDEN × SCROSSFUNC		.748	.077		.931	.030	H_7 not supported
(H_7)		(.942)	(.916)		(.952)	(.921)	
IFFUNCSIM ×		1.072^{++}	1.238^{+++}		1.068^{++}	1.503^{+++}	H_8 supported
SCROSSFUNC (H_8)		(.473)	(.516)		(.514)	(.527)	
LIV Correction Terms							
IFDEN_Error				−.274**	−.373*	−.664**	
				(.133)	(.210)	(.311)	
IFFUNCSIM_Error				−2.903**	−1.447	−1.525	
				(1.900)	(1.834)	(.956)	
SDEN_Error				−1.282	−1.353	−1.323	
				(1.105)	(1.697)	(1.384)	
SCENTRAL_Error				−.275	−.359	−.729	
				(.717)	(.859)	(.851)	
SCROSSFUNC_Error				−.315	−.861	−.172	
				(.685)	(.837)	(.684)	
Support Point Intercepts							
Class 1	.276*	.292**	.130	.269*	.156	.130	
	(.144)	(.128)	(.098)	(.140)	(.237)	(.096)	
Class 2	.225	.237	−.061	.250	.035	−.046	
	(.186)	(.173)	(.205)	(.181)	(.108)	(.182)	
Class 3	.013	.003	−.070	−.034	−.191	−.085	
	(.244)	(.212)	(.198)	(.235)	(.254)	(.180)	
Class 4	−.513**	−.532***		−.485**			
	(.234)	(.198)		(.217)			
R^2	.967	.964	.943	.964	.963	.943	

$^{+}p < .10$ (one-tailed for hypothesized effects).
$^{++}p < .05$ (one-tailed for hypothesized effects).
$^{+++}p < .01$ (one-tailed for hypothesized effects).
*$p < .10$ (two-tailed for nonhypothesized effects).
**$p < .05$ (two-tailed for nonhypothesized effects).
***$p < .01$ (two-tailed for nonhypothesized effects).
Notes: Standard errors of the estimates are in parentheses.

neither effect was significant (SCENTRAL^2 × IFDEN: $\beta = 1.896$, $p > .10$; SCENTRAL^2 × IFFUNCSIM: $\beta = -1.046$, $p > .10$); this effect pattern suggests that significant diminishing returns are a feature of only within-seller density. We report these results in Appendix B and detail their implications in "Discussion" section.

Robustness Tests

To test for the robustness of our conclusions to alternative model specifications and operationalizations, we ran several additional models. We detail these models in the following subsections.

Ordered logit model specification. We treated our dependent variable (account profitability) as continuous, with 11 closely spaced levels; we checked the robustness of the results by using an ordered logit model specification. The results in Appendix B reveal no substantive differences from those obtained with the linear regression model (Table 3).

Interactions between attributes in the same network. Given our hypothesized interactions involving cross-network attributes, we also checked for interactions among attributes within a given network. We reran our regression model (Table 3) after incorporating interactions between IFDEN and

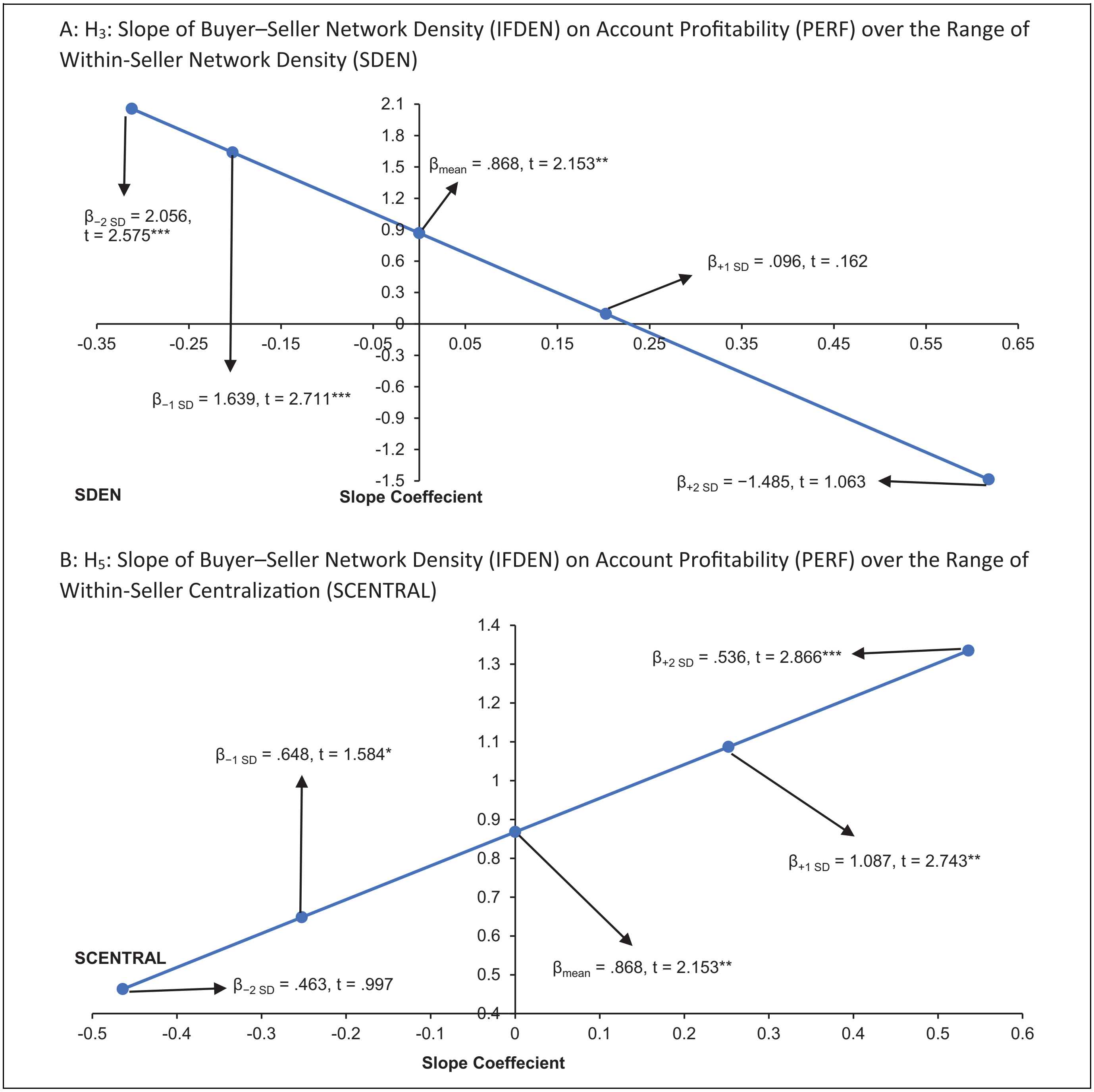


Figure 3. Slope analyses for buyer–seller interfirm network and within-seller firm network interactions.
*$p < .10$.
**$p < .05$.
***$p < .01$.
Notes: One-tailed tests of significance. Panel A depicts a negative slope between buyer–seller density and account profitability over the range of within-seller density (H_3). Panel B depicts a positive slope between buyer–seller density and account profitability over the range of within-seller centralization (H_5). Panel C depicts a positive slope between buyer–seller similar function ties and account profitability over the range of within-seller centralization (H_6). Panel D depicts a positive slope between buyer–seller similar function ties and account profitability over the range of within-seller cross function ties (H_8).

IFFUNCSIM in the buyer–seller network. We did not find any support for this interaction ($\beta = 1.454$, $p > .10$), though all other results remained same as those reported in Table 3. We similarly checked for potential interactions in the within-seller network: between SDEN and SCROSSFUNC ($\beta = -1.196$, $p > .10$); between SDEN and SCENTRAL ($\beta = .988$, $p > .10$); and between SCROSSFUNC and SCENTRAL ($\beta = -1.046$, $p > .10$). None of these

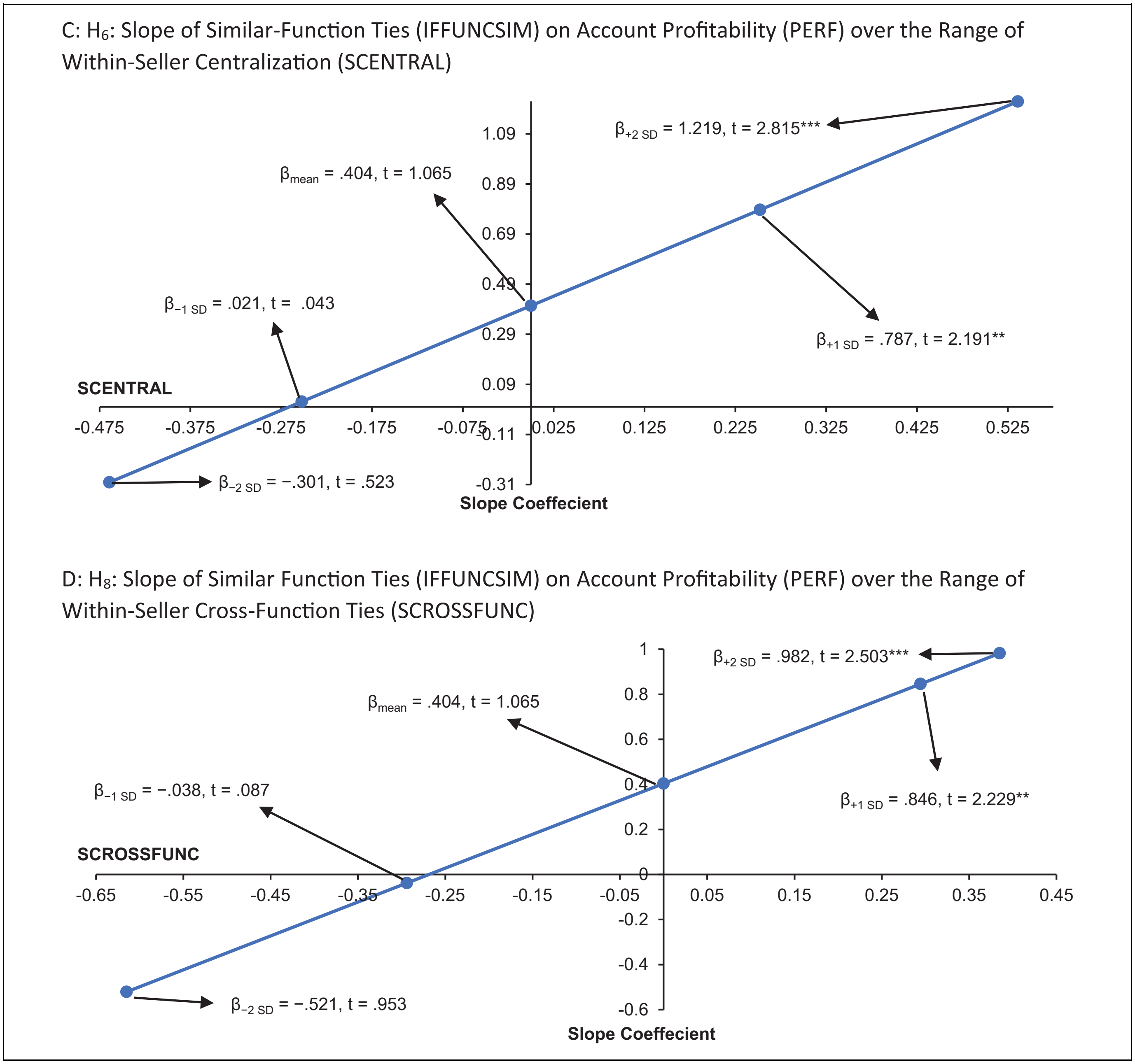


Figure 3. (continued).

interactions were significant, and all focal results remained the same as in Table 3.

Fixed industry effects. Informants across different industries might possess different notions or definitions of account profitability. Cross-industry variations in the levels of account profitability might also influence our results. We tackled these issues in several ways. First, in the survey questionnaire, we clearly defined profitability as gross profit minus direct and indirect costs for selling and servicing the key account (Bowman and Narayandas 2004; Mullins et al. 2014). This unambiguous, explicit definition should limit the scope of differences in informants' understanding of account profitability. Second, we purposely employed a latent class regression framework to account for any unobserved heterogeneity resulting from differences in industry-level profitability. Thus, as opposed to assuming one overall intercept in our regression or one intercept for every industry (as in industry fixed effects specification), we allow the data to determine the number of intercepts. As a result, the latent class analysis allows for the possibility that intercept could be the same across industries or vary within an industry.

Nevertheless, we reran our hypothesized model after incorporating industry fixed effects to account for cross-industry differences. Specifically, we introduced seven dummy terms to account for the eight industries represented in our sample and dropped the latent intercepts to limit potential overfitting or power issues. As reported in Appendix B, we find significant fixed industry effects for two industries (business services and pharmaceutical); still, the results remain largely similar to those reported in Table 3. Thus, our inferences appear robust to potential interindustry and interinformant differences in the account profitability measure.

Contextual effects. Our research goal was to examine interactions across network attributes, but a host of other contextual influences could temper the observed effects. For example, as seller KAM team size increases, the coordination difficulties associated with greater within-seller density worsen (H_3), with negative impacts on account profitability (SDEN $\times$ seller team size: $\beta = -.168$, $p < .05$). The two-way effect of buyer–seller similar function ties $\times$ cross-functional ties in the within-seller network (H_8) also might vary with the level of centralization in the within-seller network, which suggests a potential three-way effect; however, this was not significant in our data (IFFUNCSIM $\times$ SCROSSFUNC $\times$ SCENTRAL: $\beta = 2.256$, $p > .10$). Such three-way interactions are beyond the scope of our study, but they offer pertinent avenues for future KAM research.

Network analysis considerations. We made several specific choices regarding the data collection and analyses stages. For example, we relied on an egocentric (vs. sociometric) data collection approach, included account managers as informants, and demarcated network boundaries according to informants. Appendix C contains a detailed discussion of the trade-offs associated with these choices, as well as the theoretical rationales that guided our choices.

Discussion

We conceptualize the KAM process as a set of information gathering and exchange, and information processing and utilization activities that occur across two intermeshing networks: the buyer–seller (interfirm) network and the within-seller (intrafirm) network. We have argued that key account profitability is shaped by interplays across these networks. Thus, it is necessary to consider the specific attributes of these networks jointly to accurately assess their impact on key account profitability.

Theoretical Implications

Most prior research in the KAM and sales areas has adopted either an individual or a dyadic perspective (see Table 1). Where networks have been considered, the focus has been on either inter- or intrafirm networks in isolation (Ahearne, Lam, and Kraus 2014; Ronchetto, Hutt, and Reingen 1989; see Table 1). We extend KAM research by introducing a network perspective, wherein the buyer–seller and within-seller KAM teams are viewed as intersecting networks, which have both direct and interactive influences on key account profitability. By introducing a network perspective, we extend the level of analysis in KAM research, which marketing scholars have long called for (Bradford et al. 2010; Hartmann, Weiland, and Vargo 2018). Our study is also the first to identify the *specific* ways in which cross-network interplays support or undermine account profitability. Our findings suggest that extant models that focus only on individual salespeople or on single networks might be incomplete and even misspecified. Finally, we examine account-level profitability as opposed to individual salesperson performance, which has been the focus of prior social network research (e.g., Ustuner and Iacobucci 2012; see Table 1). While valuable, insights regarding individual outcomes might not apply directly to key accounts or team level issues.

Beyond considering different networks, we also examine distinct network attributes, in which certain attributes such as network density represent structural aspects, others such as cross-function ties represent functional composition aspects of KAM teams (Hanneman and Riddle 2005). Extant research has frequently considered the former but has largely ignored the latter (see Table 1). Using similar function ties and cross-function ties, we measure participation of KAM team members from different functional backgrounds on the basis of the reported ties and go beyond measuring just the presence (or absence) of members from different functions on the team. By doing so, we heed calls to build richer models of sales relationships that reflect their "network-level endowments" (Ahearne et al. 2013; Bolander et al. 2015, p. 5) and account for individual-level characteristics.

Consider some specific insights that follow from our model. First, in the buyer–seller network itself, density exhibits a positive main effect as well as a series of insignificant or even negative interaction effects (H_3, H_7). In contrast, similar function ties have an insignificant main effect but enhance profitability under a variety of conditions (H_6, H_8). As such, while density by itself can be beneficial (H_1), it is the similar function ties that appear to be more relevant across a wider range of circumstances (H_6, H_8). Thus, overall, the richness of information about buyer needs—as facilitated by similar function ties—may be more important than simply the amount, which density facilitates. Thus, functional constitution of teams enriches models of KAM that emphasize interaction frequency as a measure of relationship quality with external customers (Palmatier 2008).

Our analyses also reveal important differences between the density attributes in the two networks. Unlike buyer–seller density, within-seller density fails to show a positive main effect and, in fact, exhibits diminishing returns (Table 3). These effects align with our conception of the distinct information roles of these networks: Buyer–seller density helps clarify buyer needs to the seller team, so increasing density by itself can help surface those needs incrementally. However, the within-seller network processes and utilizes information to develop offerings; here, increasing internal density serves a facilitating role only for those buyer–seller networks that possess limited ability to exchange information with the buyer. These nuanced effects shed light on conflicting findings in prior research in which density has been argued to both support and undermine performance (Rowley, Behrens, and Karckhardt 2000) and suggest that whether buyer–seller density is desirable or not depends on the within-seller network context and the specific information process (exchange vs. utilization) at hand.

Within-seller density presents an interesting contingency pattern. Increasing density in the within-seller network is *less* beneficial as buyer–seller density increases (H_3); thus, the two network densities are mutually substitutive. As such, teams that are able to gather and exchange more information may not need to invest in copious information processing and utilization capacity in internal networks. However, for increasing similar function ties, the capacity of internal processing and utilization in the seller team appears to be immaterial (H_4). As such, similar function ties—or the fine-grained information they channel—serve as a buffer against limitations in information utilization capacity of seller teams. More broadly, these results speak to how KAM teams can resolve the "tension between density . . . within their group and connections to other groups" (Bradford et al. 2010, p. 249).

Extant research has suggested that centralization has a negative effect on firm performance, especially for nonroutine tasks (Ruekert, Walker, and Roering 1985). However, our findings run counter to this position, because among the within-seller network attributes we study, only centralization positively moderates the effects for both buyer–seller density and similar function ties (H_5, H_6). Our findings address the boundary-spanning role of KAM team members, who need to exchange information but, at the same time, need to coordinate the utilization of that information internally. Because central actors facilitate both information exchange and utilization tasks by coordinating the effort, firms should be particularly mindful of incorporating such roles in the design of KAM teams.

Within-seller cross-function ties enhance profitability in conjunction with similar function ties (H_8) but not with buyer–seller density (H_7). As noted previously, similar function ties stimulate expert knowledge sharing, and the diversity of perspectives based on cross-functional ties seems to help the seller cope with this specialized knowledge. This finding suggests that use of cross-functional teams, representing collaboration and overcoming of functional silos, is more valuable the greater the functional expertise alignment between buyer and seller representatives. However, the same cross-functional collaboration is not as valuable when the seller team is inundated with voluminous information from dense buyer–seller interactions. These mixed findings suggest that rather than viewing cross-functional teams as a panacea (Gulati 2007), firms should assess their external relationships before implementing cross-functionality internally.

Managerial Implications

Firms often view KAM as an individual responsibility of an account manager who normally works for the sales department (Macdonald, Kleinaltenkamp, and Wilson 2016). Our findings instead suggest that firms should view KAM as an initiative that cuts across multiple functional areas. Even among firms that have incorporated different function-based stakeholders in their KAM, teams often appear aligned according to an exclusively internal focus that fails to consider the external (buyer–seller) ties (Woodburn 2009). We recommend that practitioners address the design of both internal and external KAM teams jointly, for each key account.

We propose some actionable possibilities for KAM team design. First, at the relationship initiation stage, selling firms can design their internal teams to correspond with the network attributes of the key account. Second, as the relationship evolves, the selling firm can audit and modify, as needed, both networks to improve alignment. In the Siemens example, the firm failed to benefit from cross-functional practices it had instituted internally, partly because managers had trouble understanding how the firm's offerings could serve the buyer's requirements without the proper information exchange with the buyers. Our findings suggest that aligning these internal practices with external buyer–seller network attributes at each account level—for instance, by developing high-quality similar function ties to better match the buyer's needs to the firm's cross-functional expertise—would have been more effective.

In Figure 4, we depict a template for KAM team design decisions. We examine four interaction scenarios at high (+2 SD) versus low (–2 SD) values of the interacting variables, to create the 2×2 design decision matrix in Figure 4. In Panel A, when both buyer–seller and within-seller densities are high, this leads to lower seller profitability. However, given high buyer–seller density, low within-seller density enhances profitability (gray cells in each panel). In practice, a selling team could achieve low internal density by separating the role responsibilities of the team members; this should reduce role ambiguity and reduce excessive consultation (Zablah et al. 2012). For example, the firm ABB thus has created specialized bridging roles through which communications with key accounts are channeled to "ensure effective collection and distribution of account information" (Vänskä 2017, p. 25). When density is low in both networks, profitability again drops, so cultivating dense ties with customers, such as through interfirm socialization (Ouchi 1980), can augment profitability, as Day (2006) describes with reference to IBM and General Electric.

Alignment across KAM networks can be achieved by other means as well. As Figure 4, Panel B, reveals, low density in the buyer–seller network leads to lower profitability when centralization in the within-seller network is low. These sellers therefore should work to increase centralization to improve information utilization by identifying team members with informal influence or by appointing selected members with decision-making authority. In fact, Xerox appoints so-called focus executives who, because of their "experience and organizational position," can "make things happen" for the key account (Capon 2002, p. 413). Cultivating dense ties in the buyer–seller network is another viable action. Across within-seller network attributes, centralization positively interacts with both buyer–seller density and similar function ties. These

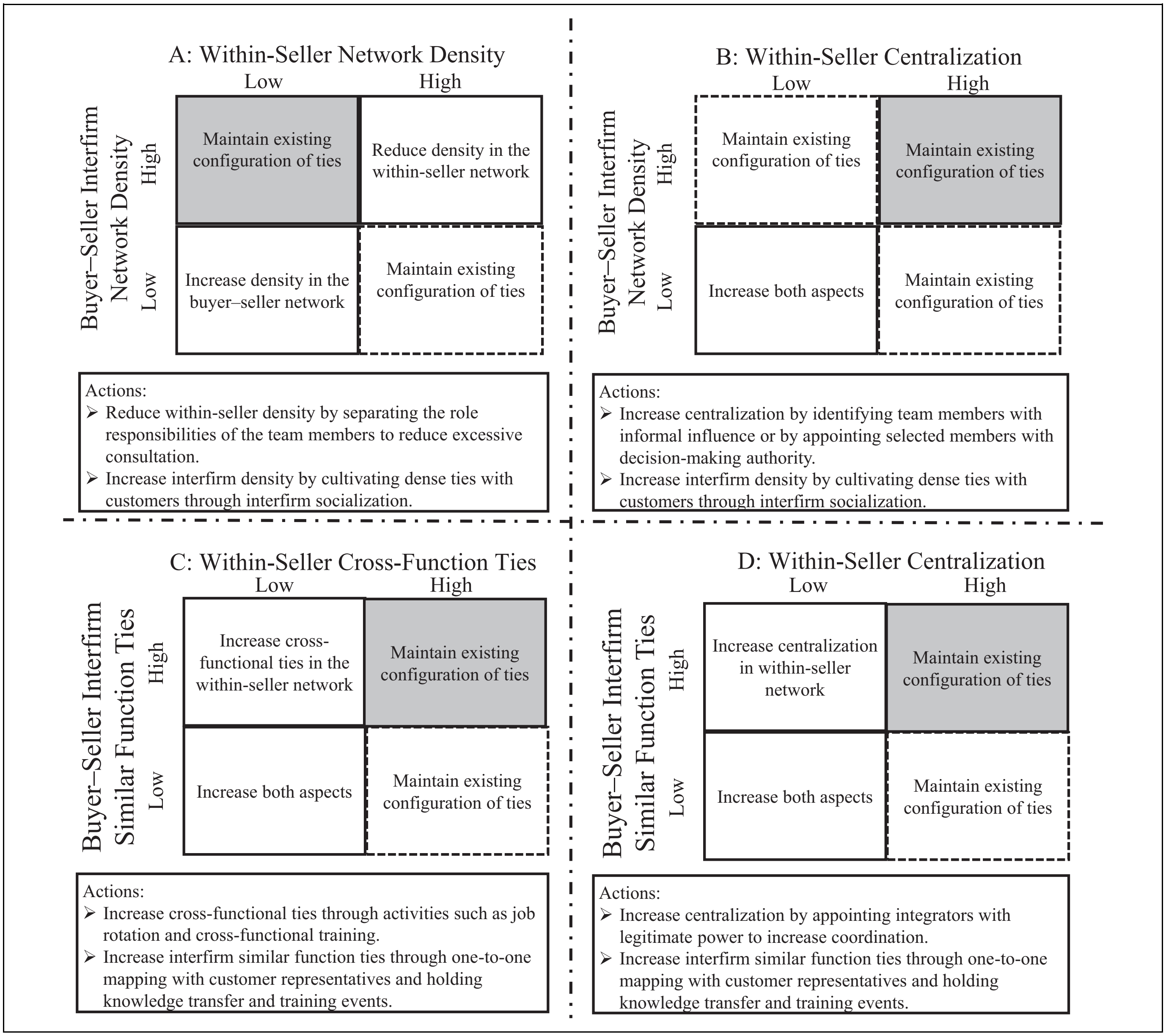


Figure 4. Managing KAM network relationships: A managerial template.

Notes: The KAM design actions apply to the seller firm. High and low levels signify ± 2 SD from the sample mean and are specific to our sample. The gray shaded cells in each panel represent the configuration that achieves profitability greater than baseline (mean) profitability for our sample. Dashed-line cells indicate a configuration that has no impact on account profitability, relative to the baseline profitability for our sample.

results suggest that centralization of KAM teams is a viable option to improve profitability.

Given high levels of cross-functional ties in the within-seller network, firms can benefit from cultivating a high level of similar function ties with the customer (Figure 4, Panel C), aligning richer information exchange with richer utilization of information for improving profitability. Thus, P&G, which has a cross-functional structure internally, builds marketing teams staffed jointly with its and Walmart's personnel, even colocating the team at Walmart offices (Ellison, Zimmerman, and Forelle 2005). Such teams are critical for in-depth understanding of the product and packaging issues facing the buyer, which feeds into the creation of next-generation products. Conversely, high similar function ties in the buyer–seller network, when paired with low levels of cross-functional ties in the within-seller network, reduce profitability. Such a seller should create cohesive, cross-functional teams in-house, through activities such as job rotation and cross-functional training. For example, Daimler routinely employs cross-functional teams, responsible for product engineering, development, and regulatory compliance, to sell automotive components to buyers such as Mercedes-Benz.

Finally, the combination of high similar function ties in a buyer–seller network with low centralization in the within-seller network reduces profitability (Figure 4, Panel D). To avoid this situation, a seller could turn to integrators to increase the level of centralization in-house, as brands such as Gillette and Electrolux have done (Bartlett and Ghoshal 2003). Combining a high centralized within-seller network with a buyer–seller network with high similar function ties increases profitability. Johnson Controls, for instance, staffs its account teams with highly knowledgeable engineers (central actors) who act as coordinators and interact fluently with Ford's (client's) research-and-development personnel.

In summary, the combinations across the two networks that can help KAM practitioners improve profitability are (1) aligning high within-seller centralization with either high buyer–seller density or high similar function ties and (2) aligning high similar function ties with high cross-functional ties. Firms should avoid simultaneous high density in both the networks because it hurts profitability.

Limitations, Further Research, and Conclusion

Our data portray buyer–seller and within-seller KAM networks that had not yet been examined together. However, our cross-sectional design is a limitation. Longitudinal data could reveal changes in the KAM networks and their performance over time, leading to stronger causal inferences. Newer theoretical lenses, such as social affiliation theories, can be brought to bear on this data, too. We collected the network data from individual account managers, but future studies could gather full sociometric data from selling team members to provide a basis for triangulating the account managers' responses. The single informants in our study are qualified, given their knowledge and involvement in KAM decisions, but relying on single informants always raises common method concerns. We proactively limited this bias in several ways, but future researchers might gather firsthand access to company records and profitability data, as well as obtain network data from multiple informants, to increase the reliability.

In addition, we focus on buyer–seller and within-seller KAM networks, but a third type of network also exists: the within-buyer intrafirm network. We did not include it, because in practice, selling firms lack direct knowledge of interactions within the buyer firm. However, including the within-buyer network could produce a more complete view of the KAM process.

Finally, we focused on two-way interactions across network attributes; additional two- and three-way interactions involving these and various other contextual attributes are also plausible. We conducted a post hoc analysis to specifically explore a few such higher-order interactions and find limited support. Presence of such higher-order interactions represents a fruitful avenue for future scholarship in the larger area of sales, KAM, and CRM literature streams.

Our networks theory–based model explains variations in account profitability across KAM teams. We show that the network attributes across buyer–seller (interfirm) and within-seller (intrafirm) KAM networks interact to influence the seller's account profitability. We also find that a purposive alignment of these networks can improve KAM performance. We thus hope our study proves useful for KAM managers and provides an impetus for continued network-based research in the B2B sales domain.

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