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Seeing What Others Miss: A Competition Network Lens on Product Innovation

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Abstract. How a firm views its competitors affects its performance. We extend the networks literature to examine how a firm's positioning in *competition networks*—networks of perceived competitive relations between firms—relates to a significant organizational outcome, namely, product innovation. We find that when firms position themselves in ways that allow them to see differently than rivals, new product ideas emerge. Simply put, firms with an unusual view of competition are more innovative. We situate our analysis in the U.S. enterprise infrastructure software industry, examining the relationship between the firm's position in competition networks and its innovation over the period of 1995–2012. Using both archival and in-depth field data, we find that two factors—the focal firm's spanning of *structural holes* in the network and the perception of *peripheral firms* as competitors—are positively associated with its product innovation. At the same time, *turnover* in firms perceived as competitors has an unexpected negative association with innovation. Overall, the findings suggest that firms benefit when they see the competitive landscape differently than their competitors. The findings also show that what we know about innovation-enhancing positioning in collaboration networks does not necessarily hold in competition networks.

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Firms do not innovate in isolation. Research in organizational learning suggests that firms can reduce innovation uncertainties by monitoring competitors and then using the information gleaned to guide product development and technical innovation (Huber 1991, Katila and Chen 2008, Bingham and Davis 2012, Giachetti and Dagnino 2014). Yet the question of *which* competitors to pay attention to can be surprisingly difficult to answer. Because firms are limited in their attention (Wilson and Joseph 2015, Katila et al. 2017), they cannot monitor every possible competitor and, instead, must focus on whom they perceive as the most relevant threats. Innovation research further argues that this *selective attention* can result in competitive blind spots, allowing firms to be caught off-guard by competitors, such as firms that were originally in a different industry (Zajac and Bazerman 1991, Rindova and Kotha 2001, McDonald and Eisenhardt 2020). Altogether, research that takes a perceptual view of competition suggests how firms can both benefit from and be limited by their point of view.

Nevertheless, prior work on perception of competition and its potential link to innovation has been limited. First, scholars typically restrict competitors to firms in the same product markets, studying only symmetric dyads in dense clusters (Ferrier et al. 1999, Giachetti and Dagnino 2014). Yet perceptions of competition can extend beyond the firm's closest competitors or its mutual competitors. For example, perceptions may cross traditional market boundaries or may be "one-sided"—that is, not reciprocated—opening up opportunities for differentiation. Second, although several scholars have noted that perceptions aggregate beyond dyads to the network level (Zaheer and Usai 2004, Tsai et al. 2011), prior work often leaves the manner in which firms are embedded within a broader structure of perceived competition networks understudied. Yet a firm's unique positioning in an industry's competition network can be a lever that creates useful differentiation, particularly regarding innovation, and may help explain why seemingly similar firms differ in their innovation outcomes.

In this paper, we bring into sharper focus the *competition network* that emerges when a firm perceives another as a rival. Drawing from Zaheer and Usai (2004), we define a competition network as a relational structure that emerges from aggregation of a firm's perceptions of its relevant competitors, rather than symmetric relationships defined by market overlap.

Importantly, the competition networks we examine differ from the collaboration networks that have been the staple of traditional work in several key aspects.[1] In collaboration networks, two firms agree to collaborate with one another. A collaboration network is objective and results in symmetrical competition: Because the participating firms have explicitly agreed to collaborate, it is not a matter of conjecture or interpretation who is collaborating with whom. In undertaking this collaboration, they have agreed to share private information with each other (Ahuja 2000).

In contrast, competition networks, as we are using the term, are subjective. A firm's competition network—which could also be termed its *perceived competition network*—is the set of firms that it views as rivals. It results from a firm's selective attention (Wilson and Joseph 2015, Joseph and Gaba 2020) to public information about other firms that are perceived as competitors (Zaheer and Usai 2004, Borgatti and Lopez-Kidwall 2011). Because public is not as rich as private information, it creates uncertainty and prompts an additional need for the inquiring firm's search and learning. And because competitive perceptions are idiosyncratic to each firm, they are often asymmetric between a given pair of firms (i.e., within dyads). In other words, "it may well be that firm A perceives firm B to be a competitor while firm B only considers firm C as a competitor" (Zaheer and Usai 2004, p. 74).[2] Because a firm's attention is directed to some competitors and not others, and because that attention may not be reciprocated, the resulting positioning within an industry's competition network is likely to differentiate the firm and be consequential for innovation.

To identify which positioning is likely to matter, we build on research emphasizing that relations between firms are embedded within broader network structures with potential innovation benefits accruing to firms based on their positioning within the network (Granovetter 1985, Gimeno and Woo 1996, Gulati and Gargiulo 1999). Research on interfirm networks has identified three types of embeddedness as particularly consequential: structural, positional, and relational (Gulati and Gargiulo 1999, Polidoro et al. 2011, Ghosh et al. 2016). In competition networks, structural embeddedness means the network structure around the focal firm, positional embeddedness the positions of perceived competitors in the broader network, and relational embeddedness the history of relations between the focal firm and its perceived competitors. Each type of embeddedness is important when firms are looking to differentiate and promote innovation (Granovetter 1985, Rodan and Galunic 2004, Zaheer and Soda 2009, Ahuja et al. 2012).[3]

Paralleling earlier prominent work (Gulati and Gargiulo 1999, Gulati et al. 2000), we identify three central proxies for structural, positional, and relational embeddedness, respectively: structural holes, centrality (versus peripherality) of the firm's perceived competitors, and stability (versus churn) of perceived competitors (Zaheer and Usai 2004, Polidoro et al. 2011, Ahuja et al. 2012). Informational advantages resulting from these dimensions have been a recurrent theme in innovation research. Our aim here is to examine how a key performance indicator for technology-based firms—the ability to introduce new products (Schoonhoven et al. 1990, Kapoor and Adner 2012)—is related to these factors in the firm's competition network. We ask, "how is the firm's position in perceived competition networks associated with its product innovation?"

The key takeaway, elaborated on below, is that seeing competitors differently than other firms can confer a competitive advantage by spurring innovation.

We investigate the research question using a panel of firms in enterprise infrastructure software, which is used to manage and maintain critical information-technology assets in corporations, including cybersecurity and system management. Infrastructure software is a dynamic industry, with firms frequently innovating new products and enterprise customers expecting timely introductions of products for their critical infrastructure needs. Enterprise infrastructure software is a particularly advantageous setting to examine perceived competition's influence on innovation because the industry is intensely competitive; because firms differ widely in their perceptions about relevant competitors; and because weak property rights and malleable projects help enable knowledge gleaned from competitors to influence the firm's own projects (Thatchenkery 2017).

We build a novel, hand-collected data set of 121 public infrastructure software firms, their perceptions of competition, and 8,502 product introductions over an 18-year period from 1995 to 2012. A core strength is our comprehensive coverage of the entire population of U.S. firms that developed infrastructure software during the study's timeframe, including a complete competition network (cross-referenced with *analyst calls* and *fieldwork*) to avoid sample bias. We also compile in-depth hand-collected measures of product introductions. Another strength is our effort to enhance causal inference by careful examination of whether endogeneity is present and the use of a government intervention (the *U.S. v. Microsoft* antitrust case) to *instrument* for positioning in the competition network. We develop an understanding of the mechanisms underlying our quantitative results with the use of *patent data* that tracks the step between competitive perceptions and product innovation, as well as with first-hand *interviews* with 21 industry informants, which further provide insight into how attention to a competitor can influence a new product.

There are three key contributions. First, we find that firms with an unusual view of competition are more innovative. In particular, tracking firms that do not perceive each other as competitors—that is, spanning structural holes—and tracking firms that are peripheral in the network can be significant levers to differentiate a focal firm and are positively associated with product innovation. These effects are then more pronounced when the firm's view stays relatively stable over time, as competitor churn is negatively associated with product innovation. Overall, to find novelty, firms should look to the frontiers of the competition network, not the well-worn middle.

Second, we spotlight perceived competition networks as a significant new concept. Our approach expands a still-emerging stream of research that demonstrates the importance of perceived competitive relations (Zaheer and Usai 2004). This focus allows us to move beyond symmetric dyads within specific markets to consider how each firm's idiosyncratic perceptions of competition aggregate to the network level. Importantly, the competitive relations we examine are directed (i.e., potentially asymmetric) and are not constrained by traditional market boundaries, granting us richer insight into how firms perceive competitive threats. Altogether, our findings indicate that the link between competition and innovation is not simply a matter of *who* the firm names as rival, but how these choices *position* the firm within the wider network of perceived rivals within an industry.

Third, our findings show that the potential innovation influences of positioning in competition networks diverge from those found in collaboration networks. In collaboration networks, there are well-known benefits to being well-connected to the core of the network. In contrast, when it comes to competition networks, we highlight the unexpected benefits of unusual positioning, such as tracking competitors on the periphery of the network or those that do not see each other as rivals. Thus, firms aiming to better position themselves in competition and collaboration networks must understand the key differences between them and between the divergent "optimal" strategies they require.

Research Background

Perceptual View of Competition

Who competes with whom? This seemingly simple question—understanding how to identify a firm's competitors—has been approached from several theoretical perspectives in organization theory, including economic sociology (Burt 1988), categories (Porac et al. 1995, Cattani et al. 2017), and competitive dynamics (Chen 1996, Chen et al. 2007, Kilduff et al. 2010).

For economic sociologists, the question is resolved by looking at an actor's positioning in a market. Competition between firms is defined by their structural equivalence, that is, the degree to which they conduct transactions with the same suppliers and customers (e.g., Burt 1988). For categories researchers (Porac et al. 1995, Burshell and Mitchell 2017, Cattani et al. 2017), organizations in the same category—those similar on central attributes—are defined as competitors. Research on cognitive maps further points out that categories are used as mental shortcuts to define competition even long after the environment has changed (Reger and Palmer 1996). For both of these perspectives, competitive relations are defined as somewhat of an "objective reality," independent of how each firm perceives competition (Zaheer and Usai 2004, p. 73).

Competitive dynamics research, in contrast, defines competitive relations as *perceptual* (rather than objective). "Who competes with whom" is thus subjective and idiosyncratic to each firm, and potentially of strategic consequence. The Awareness-Motivation-Capability perspective, which serves as the "prevailing theoretical framework in recent competitive strategy research" (Kilduff et al. 2010: 946) suggests that organizations vary significantly in whom they perceive as competitors, even within narrowly defined markets. In other words, firms in objectively similar positions can and do differ in their subjective assessments of each other as competitors. These differences in perception are likely to have strategic consequence, for example, increasing the chances that a particular competitor and its actions receive heightened attention to the exclusion of another, ultimately influencing the focal firm's actions. In the world of information overload and boundedly rational decision-makers, such variation in perceptions among otherwise similar firms is likely to be particularly influential.

Competitor Perceptions, Search and Innovation

Literature on organizational learning can help us begin to connect competitor perceptions to innovation. There are three key notions here. The first is that a firm's perception of other firms as competitors *stimulates* the focal firm's search and learning (Sharapov and Ross 2019, Greve and Taylor 2000) because firms focus search efforts and devise solutions based on where their attention resides (Katila and Chen 2008, Eggers and Kaplan 2009, Bingham and Davis 2012, Wilson and Joseph 2015). A key assumption is that organizations, somewhat like physical objects, are inertial entities that remain attached to existing search paths and routines (Helfat 1994) unless an external stimulus prompts them to start searching in new directions (Nelson and Winter 1982, Ahuja and Katila 2004). Greve and Taylor (2000) studied these patterns in radio broadcasting and found, for example, that changes in competitors' choice of radio station format triggered search and market changes in focal firms. Similarly, Clarkson and Toh (2010) found that communications equipment firms redirected search efforts in response to signals of high strategic commitment by rivals.

A related insight is that the *type* of stimulus received by watching particular competitors will further influence the focal firm's search. Repeated, familiar information often provokes a muted or routine response, whereas "vivid" (i.e., more novel or unfamiliar) information creates uncertainty and launches search to improve understanding (Rajagopalan and Spreitzer 1997, Agarwal and Helfat 2009, Li et al. 2013b). For example, observing new types of rivals may create increased uncertainty for the firm's decision-makers, who then engage in search activities such as product engineering or market probes. In a multilevel organization, this renewed attention to new competitors by high-level managers trickles down to product development through resource-allocation decisions—that is, investments in projects that support new directions and de-emphasize old ones. Similarly, a richer array of competitor information is likely to create more uncertainty and increased search in the organization, increasing opportunities for learning and innovation (Huber and Daft 1987, Rindova and Kotha 2001, Katila and Chen 2008). For instance, it is possible that debating the legitimacy of various competitive threats will help dislodge the organization from its habitual patterns and push it to consider a wider range of product features and related projects (Edmondson et al. 2001, Raffaeli et al. 2019, Leatherbee and Katila 2020). Altogether, the key assumption is that new, different types of information about competition can alter innovation of the focal firm through increased stimulation of the firm's own search.

The third insight from the organizational learning literature is the importance of building on raw material that is gained when learning about competitors (Ahuja 2000). Focusing attention on an alter (perceived competitor) also focuses attention on the body of knowledge related to it (Wilson and Joseph 2015, Sharapov and Ross 2019). This knowledge in turn serves as a raw material and launches the firm's own search (Katila and Chen, 2008).[4] If the knowledge differs from what most everyone else is using, it likely differentiates the firm and is more likely to result in search that underlies innovation (Huber 1991, Katila et al. 2017, Katila and Thatchenkery 2014). As Katila and Chen (2008, p. 619) note, "it is not necessarily most advantageous to perform as well as possible in absolute terms; rather, it pays to be different from the opponent." Relatedly, firms are more likely to produce innovation when rivals do not immediately catch up because the focal firm has a head start on access to information. The overall point is that firms are particularly likely to innovate when the search activities differentiate the focal firm from competition.

Beyond Dyadic Competitor Relations

Although competition is clearly at the heart of organizational learning, empirical research in this area is lacking. Extant empirical work lays out a relatively narrow view backed up mostly by evidence from repeat dyadic relations of similar firms (such as leader–follower pairs or peers in the same strategic group). Notably, it leaves broader competition *networks* relatively unstudied. This is significant because dyadic firm relations are embedded within surrounding networks of relations, with potential informational benefits accruing to firms based on their positioning within the network (Gulati and Gargiulo 1999).

Moreover, the handful of studies that have started to examine competition networks have typically viewed firms as competitors if they are in *objectively* similar positions, using structural equivalence to define competition (Tsai et al. 2011, Hsieh and Vermeulen 2014, Downing et al. 2019). These studies have usually inferred structural equivalence from overlap in output markets (i.e., similar geographic markets or product segments). Objective competition is thus simply a matter of who is operating in what markets—not a matter of which firms are on the focal firm's radar, so to speak. For example, Hsieh and Vermeulen (2014) defined two drug producers as competitors if they manufactured active ingredients in the same category, while Tsai et al. (2011) created a competition network for airlines based on route overlap. Downing et al. (2019) similarly looked at 25 firms in customer experience management and formed a network of symmetric competitive relations based on press releases using the word "competition," aggregated by Crunchbase.[5] Empirically, the core result of these studies is that market-based structural equivalence influences the market decisions of firms, such as mimetic entry to the same markets as rivals (Hsieh and Vermeulen 2014) or mimetic investments in similar underperforming corporate initiatives (Hsieh et al. 2015). Despite the insights on objective competition, these studies leave perceptions of competition unexamined.

In contrast, we propose that when networks are defined based on firms' subjective *perceptions* of who is a competitor (Zaheer and Usai 2004), new patterns come to light. Seemingly homogenous rival firms often turn out to track quite different competitors and different information. This variation in positioning within the broader perceived competition network, in turn, is likely to prompt different search behaviors and potentially create innovation advantages for firms with earlier or varied access to information. In particular, the firm's positioning may allow it to capitalize on different forms of network embeddedness (Polidoro et al. 2011). In the hypotheses that follow, we propose links between innovation and positioning in competition networks when firms differ in who they perceive as competitors.

Hypotheses

Using the fundamental characteristics of networks, we propose effects of structural, positional, and relational embeddedness in perceived competition networks, focusing on dimensions that are significantly relevant for innovation. For structural embeddedness, we focus on spanning structural holes (Hypothesis 1); for positional embeddedness, on peripheral competitors that are sparsely identified by others (Hypothesis 2); and for relational embeddedness, on churn (i.e., turnover) of perceived competitors (Hypothesis 3).

Structural Hole Spanning and Product Introductions

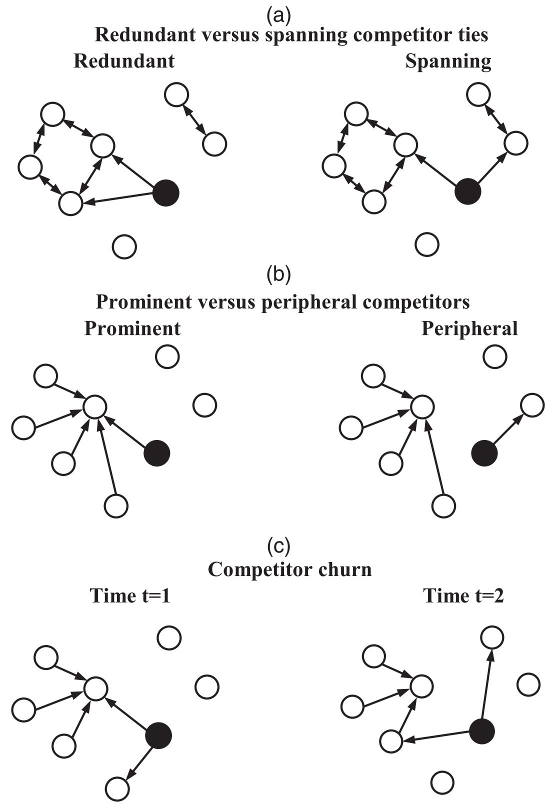
Structural embeddedness captures the impact of the structure of relations surrounding the focal firm, with particular emphasis on relations—or lack thereof—between the focal firm's alters (Gulati and Gargiulo 1999). In Hypothesis 1, we propose implications of the focal firm's spanning of structural holes in the competition network (see Figure 1(a))—that is, paying attention to competitors who ignore each other. Unlike in interfirm collaboration networks, where structural holes have a negative or no relationship with focal firm innovation (Ahuja 2000, Schilling and Phelps 2007, Phelps 2010),[6] we propose that spanning structural holes in competition networks has a positive relationship with innovation. There are several explanations for this positive relationship.

First, spanning structural holes in competition networks can *stimulate* search activities in the focal firm. This is because these positions are likely to unearth knowledge combinations that are unfamiliar or otherwise novel (Cattani and Ferriani 2008). In particular, it is likely that firms bridging structural holes have greater variance in the types of competitor ideas they are exposed to, making the stimulus for search more *vivid* and prompting the firm that is bridging the hole to engage in its own search in order to resolve the resulting uncertainties.

Second, spanning structural holes differentiates the firm's search in terms of *timing*. Brokerage positions provide early awareness of information about competitors in different parts of the network, creating a "vision advantage" that can be particularly relevant in dynamic, technology-based industries (Burt 2004). This vision advantage comes from the fact that a focal actor's alters (in this case, perceived competitors) are ignorant of one another, increasing the chances that observing each alter provides nonredundant information. Spanning structural holes thus provides early awareness of a range of competitive threats and early signals of where competitors are going, which can then give the focal firm a head start in search of innovation (Huber and Daft 1987, Katila and Chen 2008). In contrast, a firm that identifies competitors within a dense local cluster (i.e., tightly connected competitors) may see its efforts move in lockstep with others in the cluster, making it difficult to get a head start on search and innovation relative to other firms.

Third, spanning structural holes may also help differentiate the *content* of information gained from competitors because information gleaned from brokerage positions is more difficult to replicate. As Fleming et al. (2007) point out in their study of creative

Figure 1. Positioning in Competition Networks



Notes. Each node represents a potential competitor, and directed ties indicate that the originating firm identifies the target firm as a competitor. Inward ties to the focal firm are excluded for clarity.

individuals, ideas that originate from structural holes—as opposed to ideas arising from denser networks—are less likely to be reused immediately by others because they are complex (see also Rhee and Leonardi 2018). Firms could thus use ideas gleaned from brokerage positions as material for their own search with less fear of being "scooped" by a competitor. In contrast, if the focal firm is part of a dense cluster where competitors all pay attention to each other, information is more likely to be repetitive and easy to imitate, thereby limiting innovation.

Altogether, spanning structural holes helps the firm put together knowledge from separate parts of the network in new combinations and facilitates product innovation. We propose:

Hypothesis 1. *An increase in the degree to which a firm spans structural holes in perceived competition networks is positively related to product introductions.*

Peripheral Competitors and Product Introductions

Positional embeddedness captures the positions of alters within the overall competition network (Gulati and Gargiulo 1999, Polidoro and Toh 2011, Polidoro et al. 2011). We treat the degree of centrality versus peripherality of the focal firm's competitors as the positional embeddedness attribute that is most relevant for innovation. Specifically, Hypothesis 2 centers on the focal firm's relations with competitors in the *periphery* of the network—in other words, firms that are perceived as competitors by the focal firm, but not by other firms in the focal firm's markets (see Figure 1(b)). Unlike in collaboration networks—where a central partner boosts innovation of the focal firm (Pahnke et al. 2015, Schilling 2015) and peripheral partners would not be helpful (Ahuja 2000)—we propose that the perception of peripheral competitors as worthy of the focal firm's attention has a positive relation with innovation.

First, attention to a peripheral competitor can *stimulate* search activities in the focal firm, launching the firm's own search. A peripheral competitor's "marginal" status in competition networks implies that it is not part of any cohesive network clusters and, thus, likely has different information than firms that are more connected to the rest of the network. Thus, peripheral competitors are more likely to provide a window to *vivid* information than central competitors, stimulating search and innovation. As learning theory suggests, vivid (i.e., novel or unfamiliar) information is likely to attract the searcher's attention and result in increased efforts to resolve the resulting uncertainty. In contrast, repetitive information often stimulates a muted response (Huber and Daft 1987).

Second, because *differentiation* underlies successful organizational learning (Katila and Chen 2008), we propose that observing peripheral firms helps the focal firm spot developments that others are likely to miss. Because fewer firms perceive a peripheral firm as a competitor by definition, fewer firms are using its products or competitive actions (e.g., the customer trends it seems to be following) as models for their own search. Furthermore, the focal firm—if it is one of the first to glean and act on information from a peripheral competitor—will also have a timing advantage (Burt 2004). For these reasons, peripheral competitors are likely to provide an attractive source of differentiated information for the firm to build on, in both substance and timing. Centrally connected competitors, in contrast, represent a less fertile ground because they are less likely to yield insight that others do *not* yet have. In short, to find stimulating novelty, firms should look to the frontiers of the competition network, not the well-worn middle.

Hypothesis 2. *An increase in the degree to which a firm pays attention to peripheral (rather than central) competitors in perceived competition networks is positively related to product introductions.*

Competitor Churn and Product Introductions

Relational embeddedness captures the history of relations between particular actors within a network (Gulati and Gargiulo 1999). In competition networks, turnover of competitors is particularly relevant for innovation. Which firms a focal firm perceives itself to be in competition with changes over time. Drawing from studies on network churn (Kumar and Zaheer 2019)[7] and cognitive competitor maps (Reger and Palmer 1996), we focus on year-to-year turnover in perceived competitors, including both additions of new competitors and pruning of existing ones (see Figure 1(c)). Unlike in collaborative relationships, where stability can help the collaborating firms by enabling the build-up of trust and deepening of relationships, we argue for a positive relationship between churn and innovation in competition networks. Shaking things up in the network would seem to be good for bringing new ideas.

First, churn can *stimulate* search activities by creating instability. The addition of new firms that are now perceived as competitors, as with the withdrawal of their predecessors, reduces the focal firm's certainty about its competitive environment, thus providing an opportunity and stimulus for search (Huber and Daft 1987). Even if new competitors share some characteristics with existing competitors, they will have unique histories of observable competitive actions and search behaviors from which the focal firm can learn (Tsai et al. 2011). In particular, because the focal firm has less experience observing their ideas, they are more likely to be "vivid" and attract attention, stimulating search and innovation (Li et al. 2013b). Similarly, the removal of old competitors further threatens instability, creating more vivid stimulus.

Second, we propose that turnover in competitors can *differentiate* the firm's search. The addition of new competitors and removal of past ones is likely to continually refresh the firm's attention to knowledge (Ahuja et al. 2012), which is likely difficult for other competitors to immediately follow. Prior work also suggests that firms' competitor perceptions are rather stable over time (Reger and Palmer 1996), such that any churn of perceived competitors (both adding new competitors and removing old competitors) can in and of itself differentiate the focal firm from others. Thus, we propose:

Hypothesis 3. *An increase in a firm's competitor churn in perceived competition networks is positively related to product introductions.*

Competition and Innovation in Enterprise Infrastructure Software

Before proceeding quantitatively to test the hypotheses, we conducted fieldwork to gain deeper understanding of competition dynamics in our empirical setting. We interviewed 21 individuals in the software industry (both enterprise and consumer software) in order to understand how perception of competitors is related with firm behavior. The interviews lasted between 35 minutes and 1.5 hours. They were unstructured, but all featured the following open-ended questions: "What does the product development process look like in your firm? Who is involved (functions, hierarchical levels)? How do you find out about new competitors? Tell me about a competitor that you wish you had stopped paying attention to." We refrained from asking leading questions that would either support or negate our theory.

The interviewees included former and current chief executive officers (CEOs) of leading firms in the industry, other key executives (chief operating officer, chief technology officer (CTO), Director of Business Development, Vice President of Sales) in both leading and more niche firms, venture capitalists, and industry consultants. We also included interviews with product managers, two software engineers, and a marketing executive to gain understanding of how decisions about the firm's competitive field trickled down to influence how products were developed and marketed.

Overall, the interviews provided field-level understanding of competition in enterprise software. They also helped us understand how the firms turned insights from perceptions into innovation in the form of product development and product introductions. Insights from the interviews, as described below, helped ground our theory in our empirical setting and provide a foundation for the measures that we present in the next section.

First, careful analysis of the written material about the industry and subsequent confirmation by industry experts suggested that enterprise software is a *competition-focused* industry. Rivalry was ubiquitous and intense (Campbell-Kelly 2003). Instead of spending their time on crafting collaborative agreements, executives were intensely focused on "beating [a particular rival]." In marked contrast to coopetitive logics in some industries, then, our setting is representative of technology-intensive industries in which competition is dominant. We also learned that most firms in infrastructure software operate in limited markets (one to two markets on average), which puts competition rather than multimarket forbearance (Gimeno 2004) in focus.

The interviews also confirmed that competition was *idiosyncratic* to each firm, with firms differing significantly in their perceptions. The question about "the firm's competitors" did not produce a laundry list of all firms in overlapping markets, but, rather, was determined by perceptions of each firm's top executives. For example, we learned of several examples of projects that were initiated because the top team was personally invested in beating a particular competitor or because they became intrigued by a "new kid on the block." A product manager we interviewed traced the origins of her project as follows:

> "The CEO and a couple other top executives at our company looked at [a new competitor] and were like, 'Dude why don't we have this, we could totally do this.' . . .Not because this was something we were already doing, or, like, something we needed to do. I think he saw [the new competitor] and thought we could just swoop in and grab most of the market."

Often, it was not immediately obvious to executives whether a firm was worth following or not. Consistent with this idiosyncratic quality of perceptions, the industry was neither too concentrated (few competitors, easily tracked) nor too fragmented (too many competitors to track, treated as interchangeable). This balance between concentration and fragmentation (Campbell-Kelly 2003) provided rich, but tractable, variation.

We also learned that the setting was particularly relevant because learning from competitors was facilitated by relatively weak intellectual property protection in software (Cohen and Lemley 2001). Our interviewees gave several examples of how their firms learned from and reacted to competitors by introducing new products. Product-development projects were also relatively malleable and generally lacked long development cycles, again supporting the idea that competitor tracking can meaningfully influence product innovation.

Another recurring theme throughout our interviews was that identifying the relevant competition was a key strategic task of executives. An experienced executive explained that "how [executives] respond...once they figured out that there is a competitive issue" was crucial for the firm to decide. "What kind of strategic moves do they make? Is it building up their product offerings? Their product portfolio. Or is it a matter of cutting their prices so they're the cheapest ones out there to buy from?" Interviewees also mentioned that competition discussions were front and central in executive roundtables. These discussions often pulled attention to a new competitor and away from an existing one.

Our interviews also helped establish the link between the process of identifying competitors and product development. An interviewee said that top executives in her company often debated which competitors posed the most potent threats, which "led us to consider a richer set of product features and capabilities." Several others described how competition trickled down to product development through resource-allocation decisions. As one product manager explained: "[Our product] was the CEO's pet project because he wanted to compete with [a particular competitor]...We got our own design team, our own engineering team, and everyone else had to share." Enterprise software is also an advantageous setting in which to study these linkages, because public software firms are relatively young and small, making the decision-making paths between organizational levels potentially less complicated and shorter than in public companies in many other industries.

We also asked our interviewees how they "watched" competitors. A CTO whom we interviewed illustrated: "One of our marketing people puts together a few competitive feeds every week. Like a competitive digest. What competitors have been up to. He shares it with product and engineering and with the top people." When asked whether there was any connection between the feeds and the firm's technology, he said that the idea to apply machine learning to a specific area of web interfaces (the company's second product) could be attributed to exposure to different ideas from the two communities.

We also asked what mistakes our interviewees had made regarding competitors. A board member recounted the time his company had lost a major deal with an enterprise customer. The customer offered to walk the focal firm through a "side-by-side comparison" of the firm's and the competitor's product "that caused us to start spending a lot more money on the user interface. And that was a redirection of the R&D organization." When asked why the firm didn't modify the product sooner, he replied, "we were very dismissive of [other firm] as a competitor. We missed the fact that, even though they had fewer features, the [customer's] CFO's office could get [the product] up and running with very little training."

Finally, interviewees also noted that because rivalry was intense and there were many competitors, top executives needed to be selective with their attention and prioritize. "You would drive yourself nuts trying to develop against the entire field," said a former CEO. Another interviewee offered that identifying the "wrong" competitors rapidly undermines the firm's strategy: "You may spend a lot of time looking at the competition but you do not have a good way of filtering or of prioritizing your competition... So if you keep focusing on the wrong thing, you're missing the market."

Method

Sample

We tested the hypotheses on a novel, hand-collected data set of 121 public U.S. firms in the enterprise infrastructure software industry between 1995 and 2012. Infrastructure software products form the backbone of enterprise computing and are used to manage and maintain complex information technology (IT) assets for corporations. By the start of our study's timeframe, infrastructure software was well established within the enterprise software ecosystem, alongside enterprise applications (i.e., user-facing applications) and enterprise server operating systems (i.e. platforms). Although prior research on competitor relations in software has focused on relatively narrow market niches and few firms (e.g., Downing et al. 2019 on 25 customer-experience management firms), infrastructure software covers a comprehensive range of critically important functions for enterprise clients, including data backup, antivirus, and system performance. Prototypical examples of firms in this industry include Computer Associates (network and system management), Symantec (security), and Forte Software (developer tools).

We began our sample in 1995 to coincide with the transition from centralized to distributed (i.e., "networked") computing. This transition marked a fundamental shift in the architecture of enterprise IT and created the need for more sophisticated infrastructure tools. We ended the sample at a time when the industry underwent its next major technology shift, the advent of cloud computing in 2012. The core strength of our data is its comprehensive coverage of the entire population of public U.S. firms that developed software in the five enterprise infrastructure software markets, as defined by standard industry source Gartner

Research: *developer tools*, *integration & middleware*, *database management*, *network & system management*, *and security*. Comprehensive data on the full population is particularly important for accurately documenting the competition network and for avoiding sampling bias. The five markets are defined by technical function and correspond to five major functionalities that are all required to run an enterprise IT system. The firms in our sample also served all major server operating systems in our sample timeframe.

Sample Construction. Because infrastructure software is not distinguished from other types of software in standard industrial classifications, we took several steps (outlined below) to identify the firms that operated in the industry. We also took care to triangulate between multiple sources to improve the coverage and to create a comprehensive data set.

We started by compiling a list of all public software firms in the United States. Consistent with prior work (Lavie 2007), we defined a "software firm" as any firm with either a primary or secondary[8] classification under the Standard Industrial Classification (SIC) code of "prepackaged software," 7372. Between 1995 and 2012, there were 1,206 public software firms in the United States. After excluding the 390 firms that developed products only for consumers (to focus on enterprise software), we compared each firm's product portfolio with the list of Gartner Research's *IT Glossary* (a standard industry source), which provides a comprehensive list of infrastructure software product categories. Gartner Research's list has been found to provide a detailed and accurate description of the industry (Pontikes 2012, Thatchenkery 2017). We classified a firm as an infrastructure software company if the majority of its product portfolio matched the Gartner keywords.[9] We triangulated this information with *The Software Catalog* (an annual listing of software products) to ensure a comprehensive sample. We also went to two industry experts for suggestions of companies to include. Cross-validation of these sources yielded a final sample that consists of 121 firms and 823 firm-year observations between 1995 and 2012. Our sample firms exhibited patterns of regional concentration typical of software, with 31% of the sample firms headquartered in the San Francisco Bay area, 11% headquartered in the Los Angeles area, and 9% headquartered in the Boston area.

Data Sources

Product Introductions. We used several sources to build the data set. For *product introductions*, we assembled data using a "literature-based innovation output indicator" method (Coombs et al. 1996); specifically, we did a careful examination of *company press releases*. Press releases are the most common way in which enterprise software firms announce new products and are the standard source for product data in the industry (Thatchenkery 2017). We searched LexisNexis using the combination of the names of our sample firms and product-related keywords (e.g., new product, announce, launch, release, version) to identify potentially relevant announcements (Li et al. 2013b). Our initial search returned more than 118,000 press releases. Next, we used text analysis coded in Python to filter out duplicates (e.g., the same press release issued to multiple newswires), as well as announcements about unrelated topics, such as new executive hires or international expansions. This automatic text analysis returned roughly 42,000 unique press releases with possibly relevant information about new products.

We then engaged in a painstaking manual review of the 42,000 unique releases. The first author categorized all articles, and a team of trained coders conducted a second, independent review of the entire sample. We first read through the headlines only, identifying about 9,000 as relevant to our firms' product introductions. We then reviewed those articles in more detail and, for those that were about product releases, recorded each product's release date, name, version number, and a brief description. Infrastructure software products were distinguished from other software products (e.g., services or applications) by comparing product descriptions with Gartner keywords. Interrater reliability was 92%, indicating very high agreement and accuracy of coding. Disagreements were resolved through discussion between coders. Overall, our careful content analysis of over 118,000 press releases yielded data on 8,502 unique infrastructure software products.

Networks of Competitors. Building on and extending prior work, we used *10-K filings* as a source for *perceived competition* (Lewellen 2013, Li et al. 2013a, Hoberg and Phillips 2016), verifying the accuracy of this source using analyst calls and fieldwork, as described in detail below. All public U.S. firms must file a yearly 10-K report that updates shareholders on the company's strategy, structure, and performance. We examined the mandatory "competition" section in Item 1, in which the firm describes the competitive conditions it faces, including specifically naming competitors.

There are several reasons why 10-Ks are an appropriate source for data on competitors. The 10-K listings are (1) comprehensive records (due to their mandatory nature and incentives tied to Securities and Exchange Commission (SEC) filings); (2) shown to more accurately capture managerial perceptions of competition than do more traditional SIC-based measures; and (3) particularly relevant in software, as discussed in detail below.

First, SEC filings are high-stakes documents for a public firm, so there are strong incentives for firms to accurately and comprehensively document the range of firms that they identify as competitors in their 10-K filings. Because 10-K filings are carefully inspected by stakeholders, including investors, it is critical for firms to not leave the impression that they do not understand the competitive environment. Research also confirms that the qualitative descriptions of the firm and its business in the SEC filings are consequential. Investors respond to changes in the textual portions of the 10-K, even after controlling for changes in financial results (Brown and Tucker 2011). Moreover, Li et al. (2013a, p. 402) note that 10-K filings capture competition from "many different sources that are hard to identify empirically [otherwise], such as. . .potential new entrants." The regulation governing the 10-K filing also requires that firms *not* include names of competitors that would be "misleading" to investors, reducing the likelihood that firms would include irrelevant competitors.

Second, research confirms that 10-Ks create valid measures of how managers perceive competition, consistently surpassing the traditionally used measures. Hoberg and Phillips (2016, p. 1448) note that 10-Ks show what "managers themselves perceive to actually be rivals." Research in finance and accounting has similarly found that measures of competition based on text analysis of SEC filings are more accurate measures of competition than more traditionally used SIC code-based measures (Lewellen 2013, Li et al. 2013a, Hoberg and Phillips 2016, Kim et al. 2016). For example, Rauh and Sufi (2012) found that listed competitors in the firm's SEC filings provided a 40% improvement in explanatory power over more traditional SIC-based measures. Another case in point is Dedman and Lennox's (2009) survey of managers in a cross-industry sample of firms that found little relation between managers' perceptions of their competitive environment and traditional economic measures of competition, such as industry concentration or numbers of firms in a market.

10-Ks as Data Source in Enterprise Software. Next, we carefully verified that the competitor listings in the 10-Ks were an appropriate source for our industry setting—namely, infrastructure software. The first step was comparison with *analyst calls*. For 32 sample firms, we compared the competitors that the executives—typically the CEO—mentioned in quarterly analyst calls versus those listed in the corresponding year's 10-K. We found that the competitors mentioned by executives were consistently found listed in the firm's 10-K, providing independent confirmation of 10-Ks as a comprehensive data source. See the online appendix (Cross-Validation of Competitors in 10-Ks vs. Analyst Calls and Table A1) for details.

As another step, we validated the use of 10-Ks by *interviewing* current and former executives in enterprise software. During interviews, we showed each executive a list of firms in enterprise software and asked the executive to rate each firm on a scale of one (not a competitor) to 10 (intense competitor). We also asked if there were any competitors that were not mentioned but were relevant to that particular firm. Comparison of these interviews with each firm's 10-K filings confirmed that executives viewed the competitors listed in the 10-K as significant threats; there were no instances of relevant competitors that were omitted from the 10-K.

Our expert interviews and examination of the 10-Ks also indicated that naming competitors is the norm in infrastructure software. Firms in our sample listed a minimum of one competitor and an average of six to seven competitors in the 10-K.[10] These numbers are highly consistent with survey research on perceptions of competition, which finds that managers focus on between two and nine competitors (Porac et al. 1995, Clark and Montgomery 1999). Interviewees also confirmed that competitive analysis in public firms that we study was typically done "across a 12-month timeframe," matching the frequency of 10-K reports that we observe.

Finally, we verified that our results were robust to including or excluding ties that were simultaneously competitive and collaborative. Our interview data indicated that because of the nature of enterprise software, it was more typical to collaborate with partners that were complements, rather than direct competitors. For example, Symantec, a leading security software firm, entered into partnerships with a database-management firm, Informix; platform owner IBM; telecommunications firm AT&T; and professional-services firm KPMG. Regardless, we checked, and our results were robust to including or excluding ties that were simultaneously competitive and collaborative. Overall, the evidence that we gathered showed that *within infrastructure software*, the 10-Ks' lists of competitors were accurate representations of the firm's perceptions of its competition.

Data Sources for Control Variables. Finally, we collected data on *executive team characteristics* with a comprehensive search and triangulation of several sources: LexisNexis, Thomson ONE, Compustat, SEC filings, and LinkedIn (Smith et al. 1994).[11] To identify executives, we used triangulation of multiple sources (including proxy statements and Compustat) because this has been shown to provide an accurate list (Hambrick et al. 2015). We also collected data on *firm and competitor financial indicators*, including *S&P index membership*, *firm size*, *financial performance*, *R&D expenditures*, and *acquisition activity* from Compustat, Thomson ONE, CapitalIQ, and SDC Platinum.

Measures

Dependent Variable. We measured *product introductions* by new infrastructure software products introduced and subsequently shipped by each firm yearly, collected from press releases (roughly 8,500 unique sources). To qualify as new, a product had to be *brand-new only* (i.e., 1.0). Extensions of existing products (e.g., 1.1 or 2.0) or ports of existing products to new operating systems were excluded.[12] To determine what qualifies as an infrastructure product, we carefully cross-referenced product descriptions with keywords from the Gartner IT Glossary, as described above, excluding all consumer and all enterprise application and server operating-systems products.[13] We only included products that were confirmed to have shipped (i.e., we excluded planned releases that never materialized).

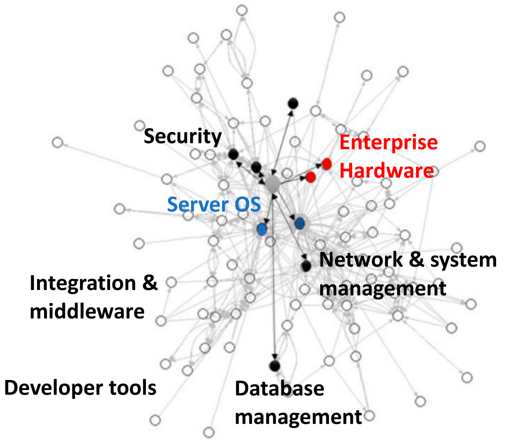
New products are a particularly important outcome in infrastructure software for several reasons. Software firms frequently innovate with new products, and introduction of a brand-new product is a major innovation and product-development effort (Thatchenkery 2017). Information technology and software is also generally recognized as a fast-moving industry where timely introduction of new products matters (Eisenhardt 1989, Holmberg and Mathiassen 2001). Each product introduction is also closely watched by sophisticated enterprise clients (IT departments), putting further emphasis on speed in introducing new products. The sample firms introduce, on average, only up to two or three brand-new products yearly, and the enterprise customers expect top-of-the line performance for their critical infrastructure needs. Consistent with this observation, research has shown that new product introductions boost software firms' financial performance (Zahra and Bogner 2000, Ndofor et al. 2013). As one of our interviewees noted, "If you're a public company, you need to keep growing, and the way to do that is to...create new products."

Independent Variables. We used 10-K filings to measure attributes of competition networks, as noted above. Like Braha et al. (2011), we defined a competition network as a *directed network graph* where a unilateral competitor relation between a focal firm A and a firm B was coded each year A listed B as a competitor in its 10-K. Ties are directed because firms may list competitors that do not list them in return. For illustration, Figure 2 shows an annual snapshot of a network graph centered on Internet Security Systems (ISS), a security software firm.[14] The graph includes ISS, its 10-K-listed competitors, and additional degrees of listed competitors (i.e., competitors' competitors). As shown in the figure, ISS attends to a relatively small subset of potential competitors (nine in total), but these competitors span various segments of infrastructure software, as well as other parts of the enterprise software ecosystem (i.e., server operating systems) and even more distant markets (i.e., hardware) (see also Figure 3). It is also interesting to note that some of the competitors are peripheral, whereas others are more central. Moreover, ISS' perceived competitors vary in whom *they* perceive as competitors, spanning all five infrastructure software markets.

To construct our independent-variable measures, we focused on *public competitors* in 10-Ks. This was important so that variation across organizations reflects differing perceptions of which particular competitors are relevant, not differences in how easy they are to notice in the first place (Miller and Chen 1994). Although the correlation between the measures based on all competitors versus public competitors is high ($\rho = 0.88$), in a sensitivity analysis, we also assessed the impact of all competitors (public and private listed in the 10-K to capture any emerging firms), with similar results.

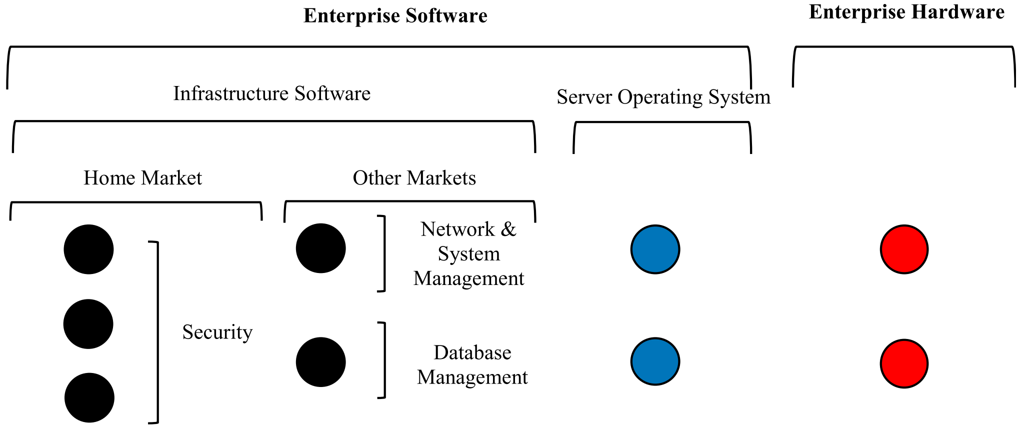
We measured *spanning structural holes* by the extent to which a focal firm identifies competitors that do not identify each other as competitors, presenting a bridging opportunity for the focal firm. We used Burt's (1992) constraint measure of structural holes[15] and reverse-coded it by multiplying by negative one in order to examine the effects of less constrained positions—that is, spanning structural holes.

Figure 2. (Color online) Annual Snapshot of the Perception-Based Competition Network for ISS Inc.



Notes. Graph provides an aerial visualization of the security firm Internet Security Systems Inc. (gray circle), the nine firms it perceives as competitors (colored nodes), and the second-degree competitors (i.e., competitors' perceived competitors; white nodes). The nine firms that ISS perceives as first-degree competitors traverse market segment boundaries: Three of the firms are in security (home segment), two in other infrastructure software segments (network and systems management, database management), two outside infrastructure software (server operating systems), and two outside enterprise software (i.e., hardware). In the figure, five infrastructure software markets are denoted in black type. The two noninfrastructure markets, i.e., server operating systems and hardware, are colored differently (see Figure 3).

Figure 3. (Color online) Breakdown of ISS Inc. Listed Competitors from Figure 2 by Market Segment



We measured *peripheral competitors* by examining whether the competitor listed in the focal firm's 10-K was also listed by other firms in the focal firm's market(s) and used lack of listing by other firms to construct the measure. In line with Greve and Taylor (2000) and prior work's measure of "outlier" competitors (Reger and Huff 1993), we calculated peripheral competitors as: $\sum \frac{1}{d_j}$ where d_j is the number of firms in the focal firm's markets that listed competitor j in their 10-K, aggregated across all competitors listed by the focal firm.[16] For our main measure, it was important to limit peripheral competitors to competitors in the focal firm's markets. This allows us to focus on competitors that have a "marginal" status within the firm's own market and excludes the possibility that peripherality simply reflects a difference in how easy a competitor is to notice in the first place. However, our results are robust to excluding or including different-market competitors (see Table A4 in the online appendix).

Following prior work, we measured *competitor churn* as the proportion of the focal firm's listed competitors that are added or dropped from the previous year (Kumar and Zaheer 2019). Specifically, we add the number of newly listed competitors (competitors listed in year t that were not listed in year $t-1$) to the number of dropped competitors (competitors listed in year $t-1$ but not listed in year t) and divide the sum by the total number of competitors listed in years $t-1$ and t.

To test the robustness of our main results, we also tested alternative measures for many variables, including our dependent variable, hypothesized variables, and controls. Details about these robustness checks can be found in the online appendix.

Controls. We included several controls. Because diversification in multiple enterprise software markets may influence product introductions by creating internal opportunities for cross-pollination (Ahuja and Katila 2001), or simply more potential firms to follow and more potential opportunities to introduce products, we controlled for *firm diversification*, measured as the number of infrastructure software markets in which the focal firm developed products each year.

We controlled for *firm performance,* measured as return on sales annually (Young et al. 1996), because firms with declining performance may be less likely to innovate—or perhaps more likely to do so because performance may increase urgency to out-compete rivals. Because investment in R&D is likely to influence new products, we also controlled for firm *R&D intensity,* measured by dividing R&D expenditure by total sales annually.

We controlled for top *executive team turnover* because research has tied top management-team composition to innovation (Virany et al. 1992). We measured turnover by the number of executives who joined or departed the executive team yearly. We counted joining and departing as separate events because team size and roles were not fixed, and not all executives who departed were replaced.

Because attention to competitors across market boundaries may influence product development separately from the firm's competition network positioning, we control for *different market competitors*, measured as the proportion of the firm's perceived competitors that did not compete in the focal firm's infrastructure software markets.

Because competitive pressures within each enterprise software market may differ, we included controls to account for the level of "objective" competitive pressure the firm faces. The level of objective competition should be distinguished from the *perceived* competition networks that are the focus of this study. Objective competition is simply a matter of who is operating in what markets—not a matter of which firms are on the focal firm's radar, so to speak.

We controlled for *number of objective competitors* as the total number of firms annually that developed products in the focal firm's infrastructure software market(s). Competitors that overlapped with the firm in more than one market were only counted once.

We also controlled for any unobserved market effects with five *market segments* in which our sample firms operated. We included controls for five standard enterprise infrastructure markets based on Gartner's IT Glossary—developer tools, integration and middleware, database management, security, and network and system management—setting each binary variable to one if the firm had at least one product in that market in a year and zero otherwise.

We also controlled for three geographic *regions* with high numbers of enterprise software firms—San Francisco, Boston, and Los Angeles—because knowledge spillovers within a region can enhance product development (Owen-Smith and Powell 2004). Region effects drop out from the fixed-effects Poisson regressions that we report in the tables, but are included in sensitivity analyses (e.g., random effects or negative binomial regressions). We also controlled for time periods: 1995–1999 and 2000–2008, with 2009–2012 as the omitted category. We chose these periods because they coincide with major macroeconomic shifts that can have significant influences on innovation.

Lastly, we included a two-year *lagged dependent variable* (i.e., new products in year $t - 2$) to control for time-variant firm heterogeneity and to further enhance causal inference (Heckman and Borjas 1980). The use of a two-year rather than one-year lag helps reduce the potential bias on standard errors. Because standard errors can be inaccurately reduced in models with a lagged dependent variable, we also ran a model excluding the lagged dependent variable, with consistent results. Standard errors were highly consistent across models with or without the lagged dependent variable.

Statistical Method

Because our dependent variable is a count variable, our main analysis used *fixed-effects Poisson models*. Fixed-effects models help control for any baseline (i.e., time-invariant) heterogeneity between firms and were preferred over random effects by the Hausman test (Hausman 1978). We also ran several alternative specifications as robustness checks. Because fixed-effects models drop any firms with two or fewer observations or firms that do not exhibit variation in the dependent variable over time, we also report *random-effects Poisson* results. Because our dependent variable exhibits signs of overdispersion, we also ran *fixed-effects negative binomial* regressions, with consistent results. Although most firms introduce at least one new product each year, a few firms introduce none, and so we also verified our results with *zero-inflated Poisson models*, which produced consistent results.

Causal Inference

Although we controlled for as many relevant factors as possible in our models, there may be unobservable variables, such as firm quality, that also influence new products and, thus, could bias our results. We attempt to reduce potential bias in several ways. As noted above, we included *firm fixed effects* in all models, to control for unobserved, time-invariant variation between firms. We also included several variables to control for time-variant firm characteristics and a lagged dependent variable, as described above. To further account for unobserved firm heterogeneity, we ran a model in which we included a *presample products* variable (Blundell et al. 1995)—that is, we controlled for products introduced by the firm three years prior to the sample period. Because it is plausible that firms that have been active in product development in the past will continue to be so, the presample variable accounts for such unobserved heterogeneity that may otherwise influence the results (Heckman and Borjas 1980). To further facilitate causal inference, we also *lagged* all independent and control variables by one year and tested several alternative explanations for our findings (detailed in sensitivity analyses).

We also ran a *falsification test* (Chatterji and Toffel 2010). In the falsification test, we used measures of *future* peripheral competitors, structural hole spanning, and churn (e.g., values in year t+2 or in year t+3) to predict current product introductions (i.e., product introductions in year t). A significant result would suggest reverse causality or omitted variable bias. Measures of our explanatory variables in future years (t+2 or t+3) do *not* predict new products in year t, adding further credence to our analysis.

Finally, we ran an *instrumental-variables analysis*, detailed in Results. As part of that analysis, we examined the extent to which potential endogeneity exists by running *Durbin and Wu-Hausman tests* (Durbin 1954, Wu 1973, Hausman 1978). The tests do not raise significant concerns that endogeneity is present, but we still report instrumental-variables results out of an abundance of caution.

Results

Table 1 reports descriptive statistics and correlations. In general, 60% of perceived competitors—that is, competitors listed in the sample firms'10-Ks—are in infrastructure software (51% in focal firm's market segments and 9% in other segments). Another roughly 30% are in noninfrastructure software (17% in server operating systems and 10% in enterprise applications). Finally, roughly 10% of the competitors

Table 1. Descriptive Statistics and Correlations

	Variable	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13
1	New product introductions	2.72	3.20													
2	Spanning structural holes[a] (Hypothesis 1)	−0.31	0.17	0.24												
3	Peripheral competitors (Hypothesis 2)	0.60	0.76	0.23	0.27											
4	Competitor churn (Hypothesis 3)	0.19	0.22	−0.03	−0.05	−0.02										
5	Different market competitors	0.49	0.25	0.02	0.10	−0.31	0.11									
6	Firm diversification	1.58	0.79	0.27	0.14	0.21	−0.05	−0.19								
7	Firm performance	−0.46	3.23	0.06	0.14	0.06	−0.01	−0.03	0.04							
8	R&D intensity	0.43	3.20	−0.03	−0.06	−0.05	−0.01	−0.02	−0.04	0.09						
9	Executive team turnover	0.38	0.31	−0.06	−0.03	−0.05	0.14	−0.05	−0.14	−0.05	0.02					
10	Number of objective competitors	35.83	17.34	0.25	0.16	0.15	0.10	−0.19	0.48	0.002	0.02	0.003				
11	Developer tools	0.28	0.45	0.05	−0.07	0.02	−0.01	−0.12	0.44	−0.04	−0.01	0.003	0.12			
12	Integration and middleware	0.31	0.46	−0.07	−0.05	0.06	0.01	−0.18	0.43	−0.04	−0.02	−0.06	0.23	0.25		
13	Database management	0.25	0.43	0.14	0.10	0.16	−0.06	−0.18	0.50	0.05	−0.02	−0.08	0.11	0.19	0.08	
14	Security	0.25	0.43	0.15	0.14	0.14	0.05	0.16	0.01	0.03	−0.03	0.001	−0.20	−0.32	−0.36	−0.17

Notes. Data are for 121 firms, 823 firm-years. Correlations above 0.07 are significant at $p < 0.05$.
[a]Burt's constraint measure, multiplied by −1

are not in software at all—they are hardware firms. As expected, spanning structural holes is relatively uncommon (constraint measure is 0.32), which indicates that an average firm watches clusters of competitors that are moderately connected rather than completely disconnected. Of the firms that the focal firm perceives as a competitor, on average 14% are "peripheral," or mostly ignored by other firms in the same markets.[17] Average yearly competitor churn is 19%. Finally, the average firm that we study releases two to three new products per year and develops products in one to two markets.

All three measures of perceived competition exhibit high variation. Among explanatory variables that are included in regression models simultaneously, correlations are mostly low to moderate. Variance inflation factors (VIFs) for most independent variables (Menard 2001), including our hypothesized variables of spanning structural holes, peripheral competitors, and competitor churn, were less than the recommended cut-off value of 5.0.[18] The only exceptions were controls (firm performance, R&D intensity, and competitive density). We tested the results with and without these controls, with consistent results.

Regression Analysis

Firm Fixed-Effects Analysis. We first ran a Hausman test to determine whether fixed-effects or random-effects models were more appropriate (Hausman 1978). The Hausman specification test revealed systematic differences in coefficients when estimating fixed versus random effects, indicating that fixed effects were appropriate. Fixed-effects Poisson panel regression results are reported in Table 2, models 1–6 and random effects in model 7. Results for control variables (model 1) are in line with expectations. More diversified, higher-performing, and more R&D-intensive firms also have more new products.

Hypothesis 1 predicted that spanning structural holes is positively related to product introductions. The coefficient of spanning structural holes is positive and significant across models, supporting Hypothesis 1. An increase of one standard deviation from the mean, which roughly equates to one additional structural hole, yields around one additional product per year (0.9 products).

Hypothesis 2 predicted that focus on peripheral competitors is positively related to product introductions. The coefficient of peripheral competitors is positive and significant in Table 2, supporting the hypothesis. A one standard deviation increase from the mean, which roughly equates to adding two competitors that no other firm has identified as a competitor, increases product introductions by half a product per year (0.5 products), or one additional product every two years.

Hypothesis 3 predicted that competitor churn is positively related to product introductions. In contrast to our prediction, the coefficient on churn is negative in Table 2. An increase of one standard deviation from the mean in competitor churn (additional 22% churn) *reduces* product introductions by roughly half a product per year (0.4 products). We return to this unexpected result in the Discussion. Random-effects regressions are consistent with our fixed-effects results, as are fixed-effects models excluding the lagged dependent variable (see Table 2).

Table 2. Fixed-Effects Poisson Models Predicting Number of Product Introductions

Dependent variable (DV): Product introductions	1	2	3	4	5	No lagged DV	Random effects
Spanning structural holes (Hypothesis 1)		0.76**			0.66*	0.60*	0.90***
		(0.28)			(0.29)	(0.28)	(0.26)
Peripheral competitors (Hypothesis 2)			0.11*		0.09*	0.10*	0.13**
			(0.05)		(0.05)	(0.04)	(0.04)
Competitor churn (Hypothesis 3)				−0.32*	−0.34*	−0.29*	−0.39**
				(0.14)	(0.14)	(0.14)	(0.14)
Controls							
Firm controls							
Firm diversification	0.50**	0.46**	0.41*	0.49**	0.39*	0.24***	0.19†
	(0.16)	(0.16)	(0.16)	(0.16)	(0.17)	(0.08)	(0.11)
Firm performance	0.15*	0.16**	0.16**	0.16**	0.17**	0.19***	0.11*
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.05)
R&D intensity	0.64**	0.68**	0.65**	0.64**	0.68**	0.80***	0.31†
	(0.25)	(0.24)	(0.25)	(0.25)	(0.25)	(0.25)	(0.20)
Executive team turnover	0.12	0.14	0.12	0.15	0.17	0.18	0.10
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)
Different market competitors	−0.02	−0.06	0.06	−0.05	−0.03	−0.02	0.10
	(0.17)	(0.17)	(0.17)	(0.17)	(0.18)	(0.17)	(0.16)
Market controls							
Number of objective competitors	0.01***	0.01***	0.01***	0.01***	0.01***	0.02***	0.01***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Developer tools	−1.22***	−1.17***	−1.11***	−1.19***	−1.05***	−0.95**	−0.11
	(0.32)	(0.31)	(0.32)	(0.32)	(0.32)	(0.30)	(0.16)
Integration and middleware	−0.71*	−0.62†	−0.58	−0.73*	−0.54	−0.26	−0.21
	(0.36)	(0.36)	(0.37)	(0.36)	(0.37)	(0.29)	(0.16)
Database management	−0.95***	−0.92***	−0.88***	−0.96***	−0.88***	−0.58***	−0.40*
	(0.25)	(0.25)	(0.25)	(0.25)	(0.25)	(0.18)	(0.16)
Security	−0.27	−0.22	−0.24	−0.26	−0.20	0.15	0.06
	(0.22)	(0.21)	(0.21)	(0.22)	(0.21)	(0.18)	(0.15)
Chi-squared	114.5	121.0	120.5	119.2	130.1	136.0	131.8

Notes. Standard errors are in parentheses. Data are for 121 firms and 823 firm-years. All models include firm and time period effects and two-year lagged dependent variable unless otherwise noted.
†$p < 0.10$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$ (two-tailed significance tests).

Instrumental-Variables Analysis

To further facilitate causal inference, we used *instrumental-variables* analysis to attempt to control for unobserved factors that are simultaneously related to firm's perception of competition and to new products. For instance, "high-quality" firms may more selectively pay attention to particular competitors and introduce more products. Running a two-stage instrumental-variables analysis allows us to provide more assurance for our original results.

We first examined whether it was appropriate to treat our explanatory variables as endogenous. As noted above, we ran Durbin and Wu–Hausman tests for both variables (Durbin 1954, Wu 1973, Hausman 1978). The null hypothesis for both tests is that the explanatory variables may be treated as exogenous and, if not rejected, indicates that using observed data are more efficient than instrumental variables. For peripheral competitors, the Durbin chi-squared statistic is 0.23 ($p = 0.88$), and the Wu–Hausman F statistic is 0.22 ($p = 0.88$). For structural holes, the Durbin chi-squared statistic is 0.26 ($p = 0.61$), and the Wu–Hausman F statistic is 0.25 ($p = 0.62$). For competitor churn, the Durbin chi-squared statistic is 1.35 ($p = 0.24$), and the Wu–Hausman F statistic is 1.32 ($p = 0.25$). We therefore *cannot* reject the null hypothesis that our explanatory variables may be treated as exogenous. However, for comprehensiveness, we proceed with the instrumental-variables analysis.

Identification Strategy. The instrument we use is an interaction between a major regulatory antitrust event and firm visibility. The regulatory event is the landmark *United States v. Microsoft Corp* antitrust case, in which Microsoft was found to have obstructed competition in software. Like Toh and Kim (2013), we first document details of the regulatory event and then explain in detail how our instrument relates to each of the hypothesized variables.

U.S. v. Microsoft was the first major regulatory action taken against a software firm. It was a sharp departure from the past, leading to immediate concern over increased enforcement around competition in the future (Liebeler 2002). In particular, many software firms engaged in the same practices—such as product bundling—that had drawn regulatory attention. The Association for Competitive Technology noted that while Microsoft was scrutinized for "integrating its products, [other developers], too, are vying to bring integrated products [to market]" (Association for Competitive Technology 2002). Altogether, the Microsoft case and its implications were highly salient to software firms at the time (Thatchenkery and Katila 2021), indicating its potential to serve as an instrument.

However, it was apparent from field evidence that more visible firms felt more vulnerable to increased antitrust enforcement. We reasoned that greater attention to a firm's stock draws greater attention to the firm itself, increasing vulnerability. Because inclusion in a Standard & Poor's (S&P) index draws increased attention from investors and other stakeholders (Aghion et al. 2013), we followed Aghion et al. (2013) and Clay (2002) and measured visibility with a firm's membership in one of the major Standard & Poor's stock indices: S&P LargeCap 500, S&P MidCap 400, and S&P SmallCap 600 (together, informally referred to as the "S&P 1500"). We measured *visible firm* as a binary variable set to one if the firm is a member of the S&P 1500. S&P index membership provides a particularly good candidate for an instrument: It tracks a firm's visibility, but is unlikely to be correlated with product introductions because inclusion is based not on expectations of future performance, but, rather, on the extent to which a stock contributes to a balanced representation of the overall economy (Standard & Poor's 2013).

Because we expected visibility to be related to how competition is perceived by the firm in the years following the initial Microsoft antitrust case, we instrument our explanatory variables with an interaction between the focal firm's visibility and the resolution of the initial Microsoft case in 2001 (*Post-Microsoft* case measured as a binary variable set to one if the year is after 2001). Thus, the interaction of these variables (which serves as the instrument) takes a value of one when the year is after the case and the firm is a member of an S&P 1500 index (i.e., the firm is visible).

Relevance of the Instrument. A valid instrument needs to be *relevant*: It must trigger changes in our explanatory variables. We establish relevance in several ways, including interviews, text analysis of management's discussion in 10-Ks, and statistical tests, as detailed below.

General Relevance. Our field interviews and archival research support the relevance of the Microsoft antitrust case for enterprise software. To avoid antitrust scrutiny, our interviewees noted that if you were a prominent firm, competition was "top of mind" because "they may be targeted next." This increased urgency to pay attention to competition helps provide face validity for the instrument. Further examination of the data revealed that firms were 50% more likely to add new competitors after the Microsoft antitrust case.[19] Table 3 further reports descriptive comparisons of competitor perceptions for the treatment (visible) and control (nonvisible) firms in the three years before and after the Microsoft case.

Relevance to Each Hypothesized Variable. To obtain evidence of the relevance of our instrument for each hypothesized variable, we followed the approach of Flammer (2015) and conducted a text analysis of the 10-K filings to see whether the Microsoft case triggered a change in competitor perceptions among visible firms. We *excluded* the lists of competitors used to construct our quantitative measures and instead qualitatively examined how competition was discussed throughout the 10-K. We compared the qualitative descriptions of the competitive environment in the two years prior to the case with the two years after the case for a randomly selected sample of 10 visible and 10 nonvisible firms.

With respect to *structural holes*, we tracked data on the number of distinct, self-defined "categories" of competitors that our sample firms discussed in 10-Ks. Similar to structural holes where a firm's attention spans disparate clusters of competitors in the competition network, self-defined categories of competitors listed in 10-Ks indicate attention that is spread across disparate groups. We found that visible firms discussed an average of 2.5 categories of competitors prior to the Microsoft case versus an average of 4.5

Table 3. Average Number of Listed Competitors Pretrial vs. Posttrial

Time	Treated (S&P index members)	Control (Not S&P Members)
Pretrial	6.1	6.9
Posttrial	7.2	6.6

Note. Comparisons are for the three years before and after the Microsoft trial.

categories of competitors after the case. For nonvisible firms there was no change (3.3 categories prior versus 3.5 categories after the case). Thus, visible firms were more inclined to look across clusters of competitors after the Microsoft case, bolstering the relevance of the instrument for the structural-holes hypothesis (Hypothesis 1).

With respect to *peripheral* competitors, we compared the frequency with which the management discussion pointed to a potential threat posed by peripheral competitors as a group. We found that, although both visible and nonvisible firms frequently mentioned the threat posed by "large" or "powerful" competitors (consistent with prior work, e.g., Porac et al. 1995), visible firms were more likely to make note of more peripheral threats after the Microsoft case. For example, database-management firm Sybase first made note of "smaller firms" that could grow to be more relevant after the case in 2001. Overall, four out of 10 visible firms discussed the threat posed by peripheral firms after the case, whereas none of the nonvisible firms did, supporting the relevance of the instrument for Hypothesis 2.

With respect to competitor *churn*, we compared the frequency and nature of comments regarding changes in the competitive landscape to support the relevance of the instrument. Again, the evidence strengthened the relevance: Potential changes in competition were discussed by seven out of 10 visible firms prior to the case and nine out of 10 visible firms after the case, whereas there was no significant change in discussion by nonvisible firms (six precase versus five postcase). Furthermore, after the case, visible firms explained the sources of potential change in more detail. For example, in 1998, BMC Software made no specific mention of changes in competition. However, in 2002, it noted that "...many new technological advancements and competing products entered the marketplace. The distributed systems and application management markets in which we operate are far more crowded and competitive."

Finally, we statistically tested the relevance of our instrument for each of the hypothesized variables using a Stock–Yogo test (Stock and Yogo 2005), which involves comparing an F-statistic to Cragg and Donald (1993) minimum eigenvalue statistics to determine the relative bias of the two-stage least squares (2SLS) estimator compared with an ordinary least squares (OLS) estimator. The F-statistic is 9.12 for *peripheral* competitors, 5.10 for *structural-holes* competitors, and 4.26 for competitor *churn*, suggesting a bias of 10% (peripheral), 30% (structural holes), and 35% (churn) relative to the bias of an OLS estimation.[20] This indicates that our instruments are somewhat weak (a typical challenge in organizations research) and that instrumental-variables results should be interpreted with caution.

Exogeneity of the Instrument. A valid instrument must also be *exogenous* with respect to our dependent variable, product introductions. Given the timing of the Microsoft case in 2001, an obvious concern with the instrument is the influence of macroeconomic trends. It is noteworthy that the downturn in the U.S. economy in 2000 *reduced* product introductions for both the treated and the control groups (32% versus 20% decrease in Table 4), making our estimates more conservative. Thus, the data in Table 4 potentially reduce the concern that changes in the economy, independent of the antitrust case, would be confounding.

We also statistically examined whether the instrument was exogenous using Hansen's J-statistic for nonlinear models for each of the hypothesized variables (Hansen and Singleton 1982). The null hypothesis of this test is that the instruments are not correlated with the structural error, which indicates that the two-stage model is correctly specified. Failure to reject the null hypothesis can thus be interpreted as evidence that the instrument is valid. The test statistic for *structural-holes* spanning is 1.65 ($p = 0.20$), the test statistic for *peripheral* competitors is 2.58 ($p = 0.11$), and the test statistic for competitor *churn* is 15.97 ($p = 0.001$), indicating that our instrument is likely valid for structural holes and peripheral competitors, but *not* valid for competitor churn. For robustness, we ran the instrumental-variables analysis for all three variables, but the results for churn should be interpreted with caution.

Instrumental-Variables Results. Results from our *instrumental-variables regressions* are reported in Table 5. The first stage uses the instrumental variables and control variables to predict the potentially endogenous variables using a linear OLS model. The second stage uses the predicted values of the endogenous variables to predict counts of new products, using a Poisson model in models 4–6 and using standard two-stage least squares in models 7–9.

Models 1–3 report results from first-stage linear regressions. As noted above, we instrument each explanatory variable separately with an interaction between the Microsoft case and firm visibility. As expected, the coefficients on the interaction terms between Post-Microsoft case and firm visibility are positive and significant. Models 4–9 report second-stage Poisson and OLS results, with the instrumented values for structural holes, peripheral competitors,

Table 4. Average Number of New Product Introductions Pretrial vs. Posttrial

Time	Treated (S&P index members)	Control (Not S&P Members)
Pretrial	6.0	3.0
Posttrial	4.1	2.4

Note. Comparisons are for the three years before and after the Microsoft trial.

and competitor churn. The coefficients on structural holes and peripheral competitors are positive and significant, lending further support for Hypotheses 1 and 2. The coefficient on competitor churn is negative, albeit not significant ($p = 0.17$), in the Poisson model and is weakly significant in the OLS model. Altogether, although the tests reported above (Durbin 1954, Wu 1973, Hausman 1978) do not indicate that endogeneity is a concern, our additional instrumental-variables analyses provide further confidence in our main findings.

Sensitivity Analyses

We include a detailed online appendix with several additional robustness checks. A few particularly important tests are explained below.

Uncovering the Underlying Mechanisms. We used patent data from the National Bureau of Economic Research (NBER) (Hall et al. 2001) to tease out the in-between steps that connect aspects of perception-based competition networks to our dependent variable, product innovation.[21]

First, to test the idea that attending to competitors (measured by listing them in the 10-K) is related to using information about competitors for innovation, we examined *patent citations*. The data were strongly supportive, showing that a firm was *more likely to cite* other firms that had been on its 10-K competitor list in the previous year. Specifically, we found that firms are more than 18 times more likely to cite a patent from a firm that was listed in its 10-K compared with a firm that operates in the same product markets, but that was not listed (72.4% for listed competitors versus 3.9% for nonlisted). The propensity to cite patents from listed competitors adds another point of confidence in our data and our proposed search and learning mechanisms.

Second, in seeking the specific mechanisms through which each type of embeddedness in competition networks is translated into products, we expected attention to competitors that are *peripheral* to grant firms access to more *original* information (and, thereby, ultimately increase innovation). We also expected spanning *structural holes* to be tied to the *breadth* of information that was pulled together, consistent with the underlying mechanisms related to brokerage. We investigated these possible links using patent data that included measures of patent originality and patent generality.[22] The results (Table A2 in the online appendix) show that firms that track peripheral competitors were indeed drawing from more original patents, whereas firms that spanned structural holes had more general patents. Both of these findings provide support for the underlying steps we hypothesized.

We also examined the in-between steps by using patent counts as an alternative dependent variable.[23] Ideas that result from churn and peripheral positions are more likely to be already patented than are ideas resulting from structural holes (because spanning holes yields combinations of knowledge in new ways that are less likely to have already been patented, by definition). Therefore, we expected structural holes to yield more new patents. This is indeed the case (model 4, Table A3 in the online appendix).

We also modified the dependent variable by exploiting variation in software products. As noted above, because spanning structural holes is a more complex network positioning than the others, we expected it to have less impact on incremental products—that is, new generations (e.g., 2.0 or 3.0) and intragenerational upgrades (e.g., 2.1 or 2.2)—and more impact on brand-new products (version 1.0). Again, these sensitivity tests provided another point of support for the in-between mechanisms that we had proposed to translate competition to innovation (see models 1–3, Table A3 in the online appendix).

To further probe the possible learning mechanisms at play, we also recognized that our perceived competition network includes competitors both within *and* outside the focal firm's markets. We split our different-market competitors control in *moderately different* market competitors and *highly different* market competitors. Competitors in other enterprise infrastructure software markets (outside the focal firm's infrastructure markets) were classified as moderately different, whereas competitors in other enterprise software (i.e., applications) or enterprise hardware markets were classified as highly different (Gartner 2011). If attention to competitors primarily influences product introductions through learning, we would expect that competitors in moderately different markets would be more useful than those in highly different markets, in keeping with absorptive capacity arguments in the learning literature (Cohen and Levinthal 1990). Indeed, moderately different competitors are positively associated with innovation, whereas highly

Table 5. Two-Stage Instrumental-Variables Models Predicting Number of Product Introductions

	First-stage OLS			Second-stage Poisson			Second-stage OLS		
	Peripheral competitors	Structural holes	Network churn	Number of product introductions			Number of product introductions		
Variable	1	2	3	4	5	6	7	8	9
Instruments									
Post-Microsoft case × Visible firm	1.11***	0.15**	0.09*						
	(0.32)	(0.05)	(0.04)						
Post-Microsoft case	−0.75***	−0.14***	−0.06*						
	(0.20)	(0.04)	(0.03)						
Visible firm	−0.45	−0.04	−0.07						
	(0.26)	(0.05)	(0.03)						
Instrumented explanatory variable									
Spanning structural holes (Hypothesis 1)				3.10***			7.60*		
				(0.94)			(3.02)		
Peripheral competitors (Hypothesis 2)					0.42**			0.87*	
					(0.15)			(0.41)	
Competitor churn (Hypothesis 3)						−0.93			−1.62†
						(1.75)			(9.56)
Controls									
Firm controls									
Firm diversification	−0.12	0.04	−0.03	−0.02	0.13	0.05	0.43	0.68†	−0.33
	(0.16)	(0.03)	(0.02)	(0.11)	(0.11)	(0.11)	(0.35)	(0.35)	(0.58)
Firm performance	0.005	0.03*	−0.01	−0.09	0.01	−0.01	−0.05	0.05	0.08
	(0.07)	(0.02)	(0.01)	(0.08)	(0.06)	(0.06)	(0.08)	(0.03)	(0.25)
R&D intensity	−0.14	0.05	−0.03	−0.26	−0.03	−0.18	0.03	−0.002	−0.12
	(0.23)	(0.06)	(0.05)	(0.29)	(0.25)	(0.25)	(0.04)	(0.02)	(0.86)
Executive team turnover	−0.40*	−0.01	0.08*	−0.22	−0.02	−0.06	−0.05	0.07	0.81
	(0.20)	(0.05)	(0.03)	(0.19)	(0.17)	(0.23)	(0.46)	(0.41)	(1.19)
Different market competitors	−2.59***	−0.10*	−0.03	0.67**	1.43***	0.17	0.70	2.42*	−0.51
	(0.23)	(0.05)	(0.03)	(0.22)	(0.45)	(0.16)	(0.71)	(1.23)	(0.92)
Market controls									
Number of objective competitors	−0.01*	0.001	0.002†	0.01*	0.02***	0.02***	0.02	0.05***	0.07**
	(0.01)	(0.001)	(0.001)	(0.004)	(0.005)	(0.005)	(0.02)	(0.02)	(0.02)
Developer tools	−0.07	−0.06	0.02	0.36*	0.23†	0.20	0.56	0.14	0.58
	(0.18)	(0.04)	(0.03)	(0.17)	(0.14)	(0.13)	(0.66)	(0.56)	(0.61)
Integration and middleware	0.70***	0.004	0.04†	−0.26*	−0.50**	−0.15	−0.87†	−1.40**	0.01
	(0.17)	(0.03)	(0.02)	(0.13)	(0.17)	(0.13)	(0.50)	(0.48)	(0.66)
Database management	1.07***	0.09**	0.02	−0.31†	−0.44*	0.01	−0.23	−0.27	0.97
	(0.19)	(0.03)	(0.02)	(0.16)	(0.22)	(0.12)	(0.61)	(0.81)	(0.75)
Security	0.93***	0.10**	0.08***	−0.02	−0.03	0.45*	0.40	0.63	2.78**
	(0.21)	(0.04)	(0.02)	(0.18)	(0.22)	(0.18)	(0.81)	(0.89)	(0.99)

Notes. Standard errors are in parentheses. Data are for 121 firms and 823 firm-years. All models include firm and time-period effects. Because the *Post-Microsoft case* and *Visible firm* indicators are correlated with time period and firm fixed effects, respectively, we test the robustness of our results to dropping those variables. Results are consistent.

†$p < 0.10$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$ (two-tailed significance tests).

different competitors are not (model 4, Table A6 in the online appendix), again providing confidence in the underlying learning arguments as we had proposed.

Finally, we further probed the mechanisms behind our results on peripheral competitors by distinguishing between changes in how the firm perceives competition (i.e., adding a new competitor that is peripheral) and changes in the nature of competition (i.e., an existing competitor becoming peripheral within the network).[24] Is it better to seek out new competitors on the periphery of the network or to "hold on" to existing competitors, even as they become more marginal? Our results (Table A5 in the online appendix) indicate innovation benefits from adding peripheral competitors, but not from holding on to increasingly peripheral existing competitors. Newly added peripheral competitors provide both vivid stimulus and differentiation, whereas newly peripheral existing competitors most likely only provide the latter. These results should be interpreted with caution because newly peripheral competitors are rare in our data (i.e., it is rare that a firm holds on to an increasingly peripheral competitor). However, they do suggest that our results are driven by the firm's perception of competition and that firms benefit from actively searching for new competitors that may be worth learning from.

Robustness Checks. One alternative explanation is that our findings are simply driven by plans for expansion. Firms may be more likely to change the competitors they track, and they may be more likely to introduce new products when they *diversify to new markets*. However, new market entry is rare our data and the majority of firms only develop products in one to two markets overall. Nevertheless, we tested the robustness of our results to dropping years prior to firm entries into new infrastructure software markets. Results are consistent, indicating that the observed effects are probably not simply driven by plans for expansion (models 1 and 2, Table A4 in the online appendix).

A related question is whether firms *strategically underidentify* certain competitors as they consider a significant strategic move such as a market entry, so as not to reveal their intentions. However, because such underidentification would make it harder for us to find results, this is not a likely alternative explanation. In contrast, might some firms *strategically overidentify* lower-performing firms to appear relatively stronger to their investors? In this scenario, low performance of competitors, rather than network position, would potentially explain the results on peripherality. Again, this seems an unlikely explanation. The correlation between peripherality and financial performance is very low, indicating that peripheral firms are not necessarily low performers. In fact, in parallel with the observation (from our first-stage models predicting peripheral competitors) that higher-performing rather than lower-performing firms are more likely to perceive peripheral competitors, these additional analyses pose interesting questions for future work: Who are the peripheral firms, and are they newcomers to the network?

Another alternative explanation for our findings is that executives may be more aware of competitors that are peripheral or from disparate clusters (structural holes) when they are interested in *acquiring* those firms. Then, perceived competitors and product introductions would go hand in hand because firms watch acquisition targets, and acquisitions boost product introductions (Ahuja and Katila 2001). We tested for this alternative explanation by removing competitors that the focal firm later acquired (within one year, within two years, or at any later point). Results were again consistent (model 3, Table A4 in the online appendix).

It is also possible that more *diversified firms* may be more likely to track different kinds of competitors and to span structural holes (i.e., attend to competitors more broadly), while also being more likely to introduce new products. Diversification in our sample is low (the average firm competes in only one to two markets), and we partially control for this potentially confounding effect with our measure of firm diversification. Finally, because more diverse firms may identify more diverse competitors, we also controlled for *competitor diversity*, measured as an H-index based on the concentration of the firm's listed competitors across different markets, with consistent results (model 6, Table A6 in the online appendix).

Discussion

Perception is powerful. Informed by an analysis of enterprise infrastructure software, we sought to understand the link between *perceived competition networks* (i.e., "competition networks") and innovation. The decision to focus attention on some competitors over others is idiosyncratic to a firm and its managers, with the firm's attention limited and not always reciprocated. These differences in perception are consequential for innovation: By tracing the aggregation of competitive perceptions to the network level, we show that when firms position themselves in ways that potentially allow them to see differently than rivals, new product ideas are encouraged. In other words, firms benefit when they can see what others miss.

Key Contributions

Drawing on a longitudinal analysis of 121 enterprise infrastructure software firms from 1995 to 2012, we find that competition networks are consequential for innovation. Simply put, firms with an unusual view of competition are more innovative. Controlling for intensity of competition in the firm's markets and for firm heterogeneity, we find that positional, structural, and relational embeddedness all matter. The firm's ability to innovate is increased by spanning structural holes and by attending to peripheral firms, but is reduced with higher levels of churn as specific firms that are named as competitors change.

Effect sizes are substantial. For example, adding one additional structural hole is related to one additional product per year, while adding a peripheral competitor is related to roughly one product every two years, in a context where the average firm only introduces two to three products per year.

Altogether, our findings indicate that firms with an unusual view of competition can generate a series of competitive advantages through innovation. Tracking firms that do not perceive each other as competitors—that is, spanning structural holes—and tracking firms that are peripheral in the network can be significant levers to differentiate a focal firm and foster innovation. We also spotlight perceived competition networks as a significant new concept. Our findings indicate that competition is both a matter of who the firm names as a rival and how those choices position the firm within the wider network of perceived competitors across an industry.

Competitive Dynamics. There are several contributions. First, we highlight the importance of perceptions of competition. Introducing 10-K filings as a data source for perceived competition, we show that innovation is driven by how competition is perceived by the firm's managers, not simply the objective competition that outside observers might designate. "There is never definitive data about competition," as one industry informant noted, "just a lot of built-in assumptions." Our key finding is that firms with an unusual perception of competition are more innovative. In particular, it is beneficial to attend to peripheral firms and firms that do not see each other as rivals. This unusual view allows for asymmetric competition—that is, the focal firm may view another firm as a rival, but not vice-versa. The focal firm may also identify rivals from several different markets. Further, such a view of competition tends to be rather stable over time. Altogether, viewing competition in a creative and unusual way allows firms to better innovate.

An exemplar case is two similar security-software firms in our data: Axent Technologies and Cyberguard. Although both faced the same objective competitors in their product markets, Axent had a unique view of competition that spanned structural holes and stretched to the periphery of the competition network, whereas Cyberguard had a more conventional view that positioned it in a denser and more central part of the network. Being different paid off for Axent, as it introduced new products at a fast pace, whereas Cyberguard struggled to launch products and grew more slowly. Altogether, our findings indicate that firms seeking to innovate should broaden their thinking about competition and look to the fringes of the competition network, not the tightly monitored center.

Second, we introduce perceived competition networks to the literature on rivalry. By aggregating a firm's dyadic perceptions of competition into a broader competition network, we highlight different forms of network embeddedness (structural, positional, and relational) and show how varied positioning in the competition network enables varied opportunities for search, learning, and, ultimately, innovation. The link between perceptions of competition and innovation is not simply a matter of who the firm views as a rival, but how these choices position the firm within the wider network of perceived competitive relations within an industry. The firm's unique positioning in the competition network can facilitate useful differentiation and in turn explain why otherwise similar firms differ in their innovation outcomes.

Contrary to expectations, we find that high-performing firms' views of competition are stable over time. Perhaps this finding is explained by the fact that competitors do not actively share information in competition networks (unlike in collaboration networks). Without active information sharing, information gained about competitors is less vetted and potentially less reliable. As a result, firms that move too quickly to new competitors do not have time to build up the experience that enables them to fully interpret and utilize information gained from tracking a specific one. Firms with a more stable view may therefore generate a sustainable series of competitive advantages through time. In fact, stability may be key to building an understanding of particular competitors and how to best learn from them.

Third, we show that optimal positioning strategies are not the same for competition networks as they are for the more familiar collaboration networks. Although research on collaboration networks emphasizes the benefits of being connected to the network core, we find that firms in competition networks benefit from more atypical connections to peripheral and loosely connected competitors. A CEO we interviewed told us about a peripheral firm whose product strategy was "very new and seemed strange back then," noting that, at the time his firm "did not recognize the [relevance]" of this new competitor. Being among the first to watch these off-the-radar firms can be particularly crucial for innovation.

Conclusion

Perception shapes reality for firms in significant ways. A firm's perceptions about competition are an unexpected lever for innovation. Managers can encourage innovation by paying attention to what others miss—by adopting an unusual view of competition that differentiates the firm from its rivals. Objective analysis of competitors based on metrics such as product-market overlap is not enough. Firms with an unusual view on competition can gain an innovative edge.

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Endnotes

[1] At first, network concepts seem to have been neutral, applicable to both collaborative (friends) and competitive (enemies) relations (Burt 2010), but subsequent work has almost exclusively focused on collaborative ones.

[2] As noted below, some research defines competition networks based on objective relations between firms. In this view, firms in the same industry or in the same product market are, by definition, symmetric (i.e. mutual) competitors. We control for these "objective" competitive relations in our analysis, but focus on perceptual relations as the core contribution of our study.

[3] Consistent with these fundamental properties of networks, Zaheer and Soda (2009, p. 54) write "…a source of opportunities that help network actors arrive at favorable outcomes… are related not only to the network's structural characteristics but also to its content..." In collaboration networks, structure corresponds to structural and positional embeddedness (i.e., configuration) of an actor's network of relations and content to relational embeddedness (i.e., quality) of those relations.

[4] Thank you to our reviewers for pushing us to clarify how tracking competitors helps learning and distinct search.

[5] These studies treat competition as symmetric between two firms. Consistent with the symmetric view, individual firm's perceptions are not isolated, and competition relations are instead based on product and market overlaps.

[6] In collaboration networks, it is commonly found that network closure—that is, having partners that are connected to each other and *not* brokered—increases innovation. Because collaborations are two-way relations, authors reason, spanning structural holes potentially leaks the firm's own private knowledge to remote firms. Consistent with this theoretical argument, most empirical studies find the negative effects to trump positive ones (Ahuja 2000, Schilling and Phelps 2007, Phelps 2010), yielding a negative relation with innovation.

[7] There is no empirical consensus of the implications of churn in collaboration partners. Research finds a positive (Moorman et al. 1992, Baum et al. 2000, Kumar and Zaheer 2019), negative (Lorenzoni and Lipparini 1999), or no (Vandaie and Zaheer 2014) relationship with innovation of the focal firm.

[8] The most common primary classifications for infrastructure software firms with 7372 as a secondary classification were 7371 (programming services) and 7373 (integrated computer systems).

[9] We primarily relied on the 2012 version of the glossary, but cross-referenced against descriptions of infrastructure software categories found in older Gartner reports and found them to be consistent.

[10] The number of direct competitors that could have been potentially listed for an average firm is 36. One of our expert interviewees noted that industries differ to the extent that competitors are listed in 10-Ks, but the norm in infrastructure software is to provide an accurate list of specific competitors.

[11] The SEC requires that public firms disclose their principal executive officers, including "any other officer who performs a policy making function," in major filings (Securities Act of 1933, Rule 501(f), 17 C.F.R. § 230.501(f)). Prior work has used SEC filings as a source of individuals at a firm who are making executive-level decisions, including about competition strategy.

[12] During the sample timeframe, there were three major enterprise server operating systems (Windows, Linux, and UNIX). Multihoming—that is, releasing a version of each product for every platform—is typical for our sample firms.

[13] Note that when we constructed the competition network, as described below, perceived competitors were included independent of their product focus. Thank you to an anonymous reviewer for helping us clarify this point.

[14] Because we have a more comprehensive and, thus, larger sample of firms (121 in total) than previous studies on competition networks, we chose to focus on a focal firm for visualization clarity. A full network graph is available from the authors.

[15] Constraint is measured as $C_i = \sum_j \left(p_{ij} + \sum_{q \neq i \neq j} p_{iq}p_{jq}\right)^2$, where C_i is the constraint of firm i, p_{ij} is the proportion of firm i's total ties invested in competitor j, and p_{iq} and p_{qj} are defined analogously for competitors j and q. The lower end of the theoretical range approaches, but does not reach, zero when every identified competitor is disconnected from every other identified competitor. The upper end of the theoretical range exceeds one in dense networks. Although this is not a concern in our sparse networks, we test an alternate measure that standardizes constraint (i.e., divides by the maximum possible value) (Burt 2004) with consistent results.

[16] If the focal firm is the only firm to list competitor j, d_j takes a value of one. The upper end of the theoretical range is m, where m is the total number of competitors identified by the focal firm, which would only occur if every identified competitor was not identified by anyone else in the focal firm's markets. The lower end of the theoretical range approaches, but does not reach, zero when all identified competitors are prominent—that is, identified by a high number of other firms.

[17] There is no pattern of peripheral firms identifying other peripheral firms (i.e., dyads of isolates are not common).

[18] VIFs for structural hole spanning and peripheral competitors are 3.73 and 3.47, respectively, indicating the collinearity is unlikely to affect our results. Moreover, our results are robust to a stricter measure of spanning structural holes that specifically excludes ties between peripheral competitors (Burt 2010).

[19] In the two years prior to the case, on average, 26% of a firm's perceived competitors were new—that is, they had not been perceived as a competitor before. In the two years after the case, the average yearly percentage of new perceived competitors increased to 39%.

[20] In more concrete terms, a relative bias of 30% for structural holes indicates that if the OLS estimate for structural holes was biased by 50%, the 2SLS estimate will be biased by 15% (i.e., 30% of 50%).

[21] Thank you to our editor and reviewers for suggesting that we further probe the mechanisms behind our hypotheses.

[22] Patent originality measures the breadth of *backward* citations of the patent, and patent generality measures the breadth of *forward* citations to the patent (see Hall et al. 2001).

[23] Many studies on collaboration networks have used patents (a measure of technical innovation; Ahuja 2000, Schilling and Phelps 2007, Schilling 2015, Kumar and Zaheer 2019) as an outcome measure, so it was also important to test this alternative outcome.

[24] Thank you to our editor and reviewers for suggesting we further examine and clarify these mechanisms.

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