Competitive Dynamics: Of Whom Should You Be Aware?

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ABSTRACT

The Awareness-Motivation-Capability (AMC) framework instructs firms to be aware of their rivals, but it offers little guidance on how to develop such awareness. We address this gap by showing which distant, seemingly unrelated, players emerge as direct competitors. Appreciating the concept of *dynamism* in competitive *dynamics* research, we show that a network perspective captures how indirect competitors (the rivals of a one's rivals, and their rivals, etc.) transition to become direct competitors. Studying several networks of direct and indirect competitors in the business software and services industry over six years, we reveal a *competitive distance threshold* below which the odds of indirect competitors turning into direct competitions becomes positive, and thus it warrants increased awareness. Though extant research profiles rivals based on their similar profiles, we show that a firm's greatest awareness must be directed to rivals who are not only dissimilar, but mostly embedded in different network groups, not similar ones. Finally, we nuance the AMC framework by enhancing the scope of awareness from focusing primarily on current competitive intensity in a single space to also addressing the process of *competition formation* across domains.

Keywords: Awareness-Motivation-Capability (AMC), competitive dynamics, network formation

Competitive dynamics research is important because it advances our understanding of what, when, where, why and how firms compete with each other; it is a body of studies that measures, explains and predicts hostile actions, reactions and interactions that firms enact towards each other. To better understand, predict and possibly even avoid hostile engagements, competitive dynamics research has long been complemented by the awareness-motivation-capability (AMC) framework, which offers three core drivers that shape a competitor's actions and responses (Chen, 1996; Grimm, Lee, & Smith, 2006; Smith, Ferrier, & Ndofor, 2001; Yu & Cannella, 2007). That is, firms attack or defend themselves when they are (i) aware of such a need or threat; (ii) motivated to act; and (iii) capable of acting or responding.

Focusing primarily on the Awareness in the AMC framework, we ask how can management science help firms to become more aware to better anticipate impending threats? Enhancing our understanding of awareness antecedents—how firms become aware of threats, especially before hostility ensues—is clearly essential conceptually because it stands to expand competitive dynamics research in general and nuance the AMC framework in particular. Such effort is also critical for closing the theory-practice gap (Kryscynski & Ulrich, 2015). Identifying rivals' threats is hardly a trivial task, even under static market conditions. But now, the complexity and wider span of modern businesses, the formation of new business models, technological innovations, the threat of global and cross-border competition, the blurring span and increased multipoint competition across product and factor markets are but a few examples of recent trends that make a firm's awareness of and ability to distinguish friends from foes even more complex.

Our empirical study uses longitudinal data (2011-2016) from the business software and services industry, and is hoping to make three main contributions. First we offer a more nuanced and better parameterized awareness construct based upon (i) the firm's "closeness" to its rivals (thus awareness is influenced by the degrees of separation between players); and (ii) the density of a firm's competitive ties across its product market(s). The extant literature has focused primarily on direct competition where local network structure is salient (Burt, 2007; Skilton & Bernardes, 2014), but because our study applies a wider network view, it reveals and measures how distant, even seemingly unrelated players impact and eventually become direct competitors. Our network view broadens the traditional perspective of rivalry because it captures rivals' interdependence—it depicts more fully the *dynamism* in competitive *dynamics* research. Put more bluntly, firms that can decipher their position within their dynamic network can preempt would-be rivals, affording them an advantageous position from which to ally, defend or attack.

Second, the AMC framework does not explain how firms become aware of a competitive threat. By explaining and quantifying "how far is far enough to be aware," we help the AMC framework to improve a firm's awareness. Our findings reveal a competitive distance *threshold* above which the odds of indirect competitors turning into direct competitions becomes negative, and thus the costs of awareness would outweigh their benefits. Third, when using awareness, which rivals deserve the most caution? Prior research (including studies using a network view) profiled rivals based on their overlap such as in product commonality and resource similarity (Burt, 1987;1982), but we show that unexpected rivals emerge from different network positions, not similar ones, whether located within or spanning between product markets. Put differently, we nuance the AMC framework by broadening its scope from focusing primarily on competitive intensity in a single space to also addressing *competition formation* across domains.

THEORY DEVELOPMENT AND HYPOTHESES

In their thorough review of competitive dynamics research, Chen & Miller (2012) detail the application of Awareness-Motivation-Capability (AMC) constructs in diverse studies—e.g., in competitive interactions, strategic repertoires, multimarket competition, integrative competitor analysis, and competitive perceptions, to name a few. Our study has implications for competitive dynamics research in general, but because (as noted) prior research and theory offer very little guidance on how firms can become aware of competitive threats, we focus on extending the awareness aspect of the AMC framework in particular. Searching beyond the set of known rivals to consider future rivals requires distinct information that might not be available from merely profiling firms based on the market similarity and resource commonality. Hence, we adopt a network perspective and construct a *competition network*—which is a group of firms connected by their *competitive ties* (or competitive relations) across overlapping product markets (Skilton & Bernardes, 2014; Yao, Ferrier, Yu, & Labianca, 2007). While competitive ties could originate from overlapping resource markets as well (Skilton & Bernardes, 2014; Yao et al., 2007), to remain within reasonable bound we narrow our attention to product market overlap where competitive signals are more explicit.

The literature on infirm networks involving focuses on direct competitive relations (Skilton & Bernardes, 2014) and direct cooperative ties (e.g., Hernandez et al., 2015; Pahnke et al., 2015b). However, we suggest instead that awareness is increased when firms consider a broader set of distant players, chiefly because the accelerating technological complexity and frequent shifts of industry boundaries may turn distant, even seemingly unrelated, players into direct rivals unexpectedly. In this context, a network perspective provides a bird's eye view of not only direct rivals but also distant players, and the changes of competitors' relations. Thus, we suggest that for firms seeking to enhance their awareness and assess the threat from future rivals, a competition network view is an especially useful awareness and assessment tool.

Competition Networks and Early Awareness of Potential Rivalry

The formation process of competitive relations is different from but can be related to that of cooperative relations, and over time competitive relations can turn into a cooperative relations and vice versa. There is ample evidence that cooperative relations present the potential for shared value, such as information exchange and research collaboration influencing innovative output (e.g., Adner & Kapoor, 2010; Ahuja, 2000; Gilsing, Nooteboom, Vanhaverbeke, Duysters, & van den Oord, 2008; Powell, Koput, & Smith-doerr, 1996). Although the maintenance of cooperative relations is not without cost (Hernandez et al., 2015; Pahnke et al., 2015), such relations are essentially a resource (Dyer & Singh, 1998). Competitive relations, on the other hand, are often a cost of doing business. Also, cues of relations often emanate differently as the former happens voluntarily by agreement, while the hostile relations often happen unexpectedly by imposition. The formation of competitive relations is therefore pertinent to the study of market entry (Haveman & Nonnemaker, 2000; Hill, Hwang, & Kim, 1990; Jensen, 2008; Markman & Waldron, 2014; Wu & Knott, 2006), M&A (e.g., Cartwright & Schoenberg, 2006; Haleblian, Devers, McNamara, Carpenter, & Davison, 2009), exists (Girma, Greenaway, & Kneller, 2003), and firm closures (Headd, 2003). Interestingly, management scholars have acknowledged the concept of embeddedness for two decades (Gulati, Nohria, & Zaheer, 2000; Madhavan, Koka, & Prescott, 1998), but the impact of embeddedness upon competitive actions has yet to receive sufficient attention (Bhardwaj, 1997).

Given the differing characteristics of competitive versus cooperative relations and the need for better anticipation of competitive action, we rely on Borgatti & Lopez-Kidwell's (2011) distinction between underlying network models characterizing competition vs. cooperation networks. This distinction was used in explaining the effect of local competition network structure on product market entry (Skilton & Bernardes, 2014), and it can ground our extension from local, indirect competitors to more distant potential rivals embedded within a broader network.

Borgatti & Lopez-Kidwell (2011) group common network models into two main models. The first, network flow models, treat ties as conduits for the flow of information and other resource among network members; these models focus mainly on cooperative tie formation so they often mention social capital (Coleman, 1988), weak ties (Granovetter, 1973), small worlds (Milgram, 1967; Watts & Strogatz, 1998), and strutural holes (Burt, 1992). The second, network architecture models, do not represent any direct exchange of information or resources, but the benefits (or costs) still accrue to (deduct from) network members based on their position and adjacecy to specific neighbors, and their neighbors' neighbors, etc. The latter class of network models is arguably less prominent, but it is especially useful for advancing competitive dynamics research—and the awareness construct—since it sheds light on networks in which players generally don't intentionally exchange information or resources with others, but instead, they simply act. For example, the act of market entry often forms new competitive ties that did not exist before, and where players and bystanders observe the action, the shifts in network structure, and their impact on players' positions as a way to assess the severity of the threat or opportunity.

Building upon network architecture models and the formation of competitive ties, we now introduce the concept of indirect competitors, including necessary terminology and notation. Take, for example, a focal firm A with rival firm B. The two firms, A and B, compete in the same product market. We use the notation A-B to represent the competitive tie between them, and we refer to them as 1st order (i.e. direct) competitors, or simply as rivals. This is scenario I in Figure 1. Next, focusing now on scenario II, consider a third firm, C, which is an *indirect competitor* of A (i.e., firm C competes with B but not quite with A). The indirect competitive relationship between firms A and C is denoted by the *competition path* A-B-C. The *competitive distance* (or simply "distance," abbreviated d generally or d_{ij} for a specific dyad) between two firms is the length of the shortest competitive path between them, which is $d = 2$ for A and C. Since there are two ties in the shortest competition path from A to C (A-B-C), these two firms are 2nd order (indirect) competitors. The competition path and corresponding overlap are depicted in Figure 1, scenario II, panel (a).

Place Figure 1 here.

Now consider the market entry of Figure 1, scenario, II panel (b). If firm C enters firm A's market, then a competitive tie forms between A and C, causing two important changes. First, the competition 3-cycle, also commonly known as triad or triple[1] (A,B,C) is introduced, and second, the competitive distance between firms A and C drops from 2 to 1, as their competitive relationship elevates from 2nd order (indirect) competitors to 1st order (direct) competitors.

Extending this one degree of separation, refer next to Figure 1, scenario III. If firm C competes in a separate market with firm D (which does not compete with either A or B), then firm D is a 3rd-order indirect competitor of firm A, signifying a competitive distance of $d = 3$ denoted by the competition path A-B-C-D. The most likely market entry in this case would occur between either A and C or B and D since they are the closest (2nd order) indirect competitors. Essentially, the precedent of a firm already spanning their markets (B spanning the markets of A and C, and C spanning the markets of B and D) increases the likelihood of a similar triad-forming market entry. However, that is not the only possibility. Though less likely, firm D may enter firm A's market,

[1] We avoid a detailed explanation of the triad census (Wasserman & Faust, 1994) used in previous work on triads in interfirm networks (Madhavan, Gnyawali, & He, 2004) for two reasons. First our competition network is undirected, and thus all dyads are symmetric, and second, our focus in this study is on extending the firm's awareness beyond the already commonly considered triad to higher order cycles of competition (i.e., k-cycles of $k \geq 4$).

which would introduce a competition 4-cycle (A,B,C,D) and drop the competitive distance between A and D from $d = 3$ to $d = 1$. This creation of a 4-cycle, shown in Figure 1, scenario III, panel (b), is an example of what we term *unexpected competition formation*, when distant players' market entry creates a competition k-cycle for $k \geq 4$. Extension to arbitrarily distant indirect competition is possible through the same manner, though we expect with decreasing likelihood, which is addressed in the second hypothesis. What merits a firm's attention in this competition network is the potential threat of distant indirect competitors turning into direct competitors, which happens in practice (e.g. smartphones killing point-shoot digital cameras), but has been overlooked by prior research and has important implications for awareness, prevention and yes, even preemption.

With this competition network in mind, we introduce an indicator for the level of required awareness, called *network risk*—a summary statistic of the likelihood of unexpected competition. *Network risk* is influenced by (i) the *density of ties* within and between the firm's local network of competition; and (ii) the firm's "*closeness*" to its rivals' competitors, and to the rivals of those indirect competitors, and so on, through several degrees of separation within the firm's awareness. The first component broadens the awareness regarding the competition scope from direct to the wider community of indirect competitors too. This local competition network, which we call a *competition network group* (CNG), may also include firms that offer substitute products or are likely to enter due to shared competitors. Building on prior research, the CNG closely reflects direct competition but it also captures unexpected competitors by accounting for bridging ties (cf., Blondel, Guillaume, Lambiotte, & Lefebvre, 2008; Newman, 2006).

The second component of unexpected competition incorporates the distance between (or "closeness" to) indirect competitors. The logic here, as noted, is that since 2nd-order competitors

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share at least one common rival there is already precedent for a firm to compete in overlapping markets, and it would therefore be less surprising for an additional firm from the one market to enter the other. Competition between 3rd-order competitors is less likely; however, if one of those firms introduces a new product into one of the intermediary markets, then at that point the firms become 2nd-order competitors and the likelihood of becoming direct competitors increases. In the same manner, the formation of direct competition between 4th-order indirect competitors is less likely, though one would reasonably surmise that it is more likely than competition between 5th-order indirect competitors since the latter is one additional degree of separation (or one more triad-forming market entry away) from becoming direct competitors.

In theory, the possibility that indirect competitors become direct competitors is always there, but our "closeness" indicator suggests that the likelihood of this occurrence is diminished with increased interfirm distance. There is thus a logical, negative association between competitive distance and the risk of direct competition formation: The closer (farther) a pair of indirect competitors the more (less) likely they are to become direct competitors. Generalizing this rule for one focal firm to the whole competition network (within a given search scope of the focal firm's d^{th}-order indirect competitors), the closer a firm is to all indirect competitors the more likely it is to face more direct competition on average. We proxy this concept with network closeness centrality (Freeman, 1978), a measure of network centrality equal to the sum of inverse distance to all reachable competitors.

Incorporating these two components of structure and position in the competition network, the *network risk* concept represents a firm's potential to encounter direct competition originating from any of its indirect competitors. The proposed construct is functionally a market-density-weighted sum of a focal firm's closeness to all indirect competitors, and thus conceptually it could serve as a competition awareness heuristic. With this interpretation in mind, we offer a baseline hypothesis, mostly to ground the rest of the theory development regarding competition networks and embedded competition:

> *H1: An increase in network risk (i.e., market-density-weighted closeness to indirect competitors) is associated with an increased likelihood that indirect competitors will become direct competitors.*

Indirect Competition and Awareness of Unexpected Competition

We are finally ready to answer the "how far is far enough to be aware?" question, which is our main contribution to the construct of awareness of unexpected rivals. As research shows, networks tend to have a similar structure (e.g., triads, higher k-cycles, k-stars, etc.), but the mechanisms or processes that underlie competition networks differ fundamentally from those of cooperation networks. Of particular importance for enhancing the awareness construct are the mechanism(s) that 'transition' indirect competitors into direct competitors and one of the best contexts to appreciate this transition in action is of course new market entry (Zachary et al., 2015)—once a firm enters a new market, it often encounters new networks and new competitors (Basole, 2009; Eisenmann, Parker, & Van Alstyne, 2011).

Research suggests that shorter competition network distances decrease uncertainty for a new market entry, thereby often making such entries more appealing and that as competition network distance increases, the likelihood of successful market entry declines (Galunic & Rodan, 1998; Kogut & Zander, 1992; Whittington, Owen-Smith, & Powell, 2009). We therefore posit that there is an 'optimal' range of network distance within which unexpected market entry may occur—that is, far enough to be unexpected but not so far as to be infeasible—and of course market entries across shorter competitive distances within that range remain more likely.

Having discussed, albeit briefly, why and how market entry transitions distant indirect competitors into direct competitor, here we also posit that an increase in the number of competition paths of short to moderate length make this transition into direct competition more likely. This is because indirect competitors at minimal degrees of separation operate in markets that are similar in terms of required resources and capabilities, which means that entry into an adjacent market is more predictable and thus less risky to the entrants. Naturally, an increase in the number of competition paths of greater lengths makes the occurrence of direct competition less likely. That is, too many degrees of separation mean significant differences in market context, and cumulatively these differences present growing barriers to entry. For the same set of firms in a competition network, a network structure with more distant paths acts to suppress the occurrence of distant market entry and thus decreases the likelihood of unexpected competition formation, and this, of course, narrows the required scope of competitor awareness. On the other hand, a network structure of dense interconnectedness, or similarly a small world structure (Milgram, 1967; Watts & Strogatz, 1998) of local clustering with a certain proportion of distant spanning ties promotes the occurrence of distant market entry and therefore increases the likelihood of unexpected competition formation. Such a network structure in turn widens the firm's required scope of awareness for their potential competitors, which informs the following related hypotheses:

> *H2a: There is a significant positive relationship between indirect competition and direct competition.*

> *H2b: The positive relationship between indirect competition and direct competition is negatively moderated by the competitive distance. Below a threshold distance, more competition paths of a given length* increase *the likelihood of direct competition formation; whereas above the threshold distance, more paths of a given length* decrease *the likelihood of direct competition formation.*

Network Structural Similarity and Competition Formation

Finally, we address which potential rivals deserve particular attention. Generalizing from the burgeoning stream of interorganizational network literature for this particular purpose requires proceeding with caution because most interfirm network literature has focused on cooperative ties (e.g., Baum, Calabrese, & Silverman, 2000; Goerzen & Beamish, 2005; Phelps, 2010; Schilling & Phelps, 2007; Polidoro, F., Ahuja, G., & Mitchell, 2011) concerning the identification of opportunities for collaboration with mutually beneficial partners (Gulati & Gargiulo, 1999). However, competitive ties, the focus of this study, are formed without bilateral agreement; they are instead manifest through the conflicting interests of firms to generate rents from the same group of consumers. Shedding light on the issue of which potential rivals require cautious attention, therefore, presents a challenge that requires a different, competitive frame of reference. This is an issue involving competitive interdependence and the firm's local network structure, since the CNG accounts for the bulk of the firm's attention and motivation to expend resources in attacking or defending its market territory from rivals.

The existing literature emphasizes the importance of network position and the effects it has upon various outcomes, including innovation (Galuni and Rodan, 1998; Burt, 1987; Tsai, 2003) and performance (Powell, Koput, Smith-Doerr, & Owen-Smith, 1999; Zaheer & Bell, 2005), which persist above and beyond exogenous factors such as geographic proximity (Whittington et al., 2009). Local network structure can be used to assess a firm's position as either constrained within or spanning between product markets in terms of observed competition, which has obvious implications for the narrowness or breadth of strategic focus (Burt, Guilarte, Raider, & Yasuda, 2002). For firms sizing up potential rivals, it is the similarity or dissimilarity of their network structures that is of particular importance, since structurally similar network members tend to have similar roles by interacting with similar others in similar ways and have access to relatively similar

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resource profiles (Gynawali and Madhavan, 2001). This role similarity implies a notion of network position (Borgatti & Everett, 1992) representing firm position within or spanning between product markets, termed *structural similarity*[2] in this study.

Structural similarity, as defined above, has differing effects depending upon the type of interfirm relation. Similarity of a firm's local network structural relative to that of another firm increases the likelihood of alliance formation if viewed within a network of cooperative ties, but it decreases the likelihood of competition formation when viewed amidst a network of competitive ties (Gulati and Gargioulou, 1999). While information and resource flow-based network studies (i.e. those involving cooperative ties) also find that structurally equivalent actors can be more competitive to each other than other actors in the network (Burt, 1987), the competitive dynamics literature regards resource asymmetry as an importance indicator of competitive behavior (Chen, 1996), as well as mutual coordination among firms with similar resource endowments to avoid initiating direct conflict (Caves & Porter, 1977; Smith, Grimm, Young, & Wally, 1997). From this context, Gnyawali and Madhavan (2001) offer the proposition that structural equivalence decreases the likelihood of a competitive action or response. As their proposition has yet to be tested, we intend to examine it empirically from a different view that pertains to pre-awareness in the AMC framework, namely that competitive structural similarity actually increases the formation of competitive relations. For this investigation, the outcome is not competitive intensity (or timing) but the formation of competition, and the concept of network similarity as a contributing factor is

[2] Strictly speaking, we build upon the concept of regular structural equivalence, meaning that actors with similar network structures have a similar pattern of relations with other actors in the network (Rice & Aydin, 1991; Wasserman & Faust, 1994). This is an abstraction of the original structural equivalence (Lorrain & White, 1971) from measuring the number of identical shared partners to measuring the similarity of the "roles" that the pair of actors play within the network (Burt, 1990). As this role similarity implies a notion of network position, it is itself closest to our intended focus of firm position in the competition network.

not shared partner structural equivalence but role equivalence connoting similar positions within or spanning between product markets.

To assess local structural similarity, we employ Burt's (1992) measure of constraint. Although this was designed for use in network flow models of asymmetric access to information and control of resources, we suggest that is it equally fitting for assessing local network structure in an architectural model of adaptation and anti-coordination among competitors (Borgatti & Lopez-Kidwell, 2011), such as this study's competition network. Burt introduced constraint as a summary index of brokerage opportunities that comprises the firm's local network size, density, and hierarchy (Burt, 1998, 1992). Analogously, size (number of firms in the market), density (proportion of possible ties in the firm's CNG), and hierarchy (extent to which firms focus their attention on a flagship rival) all pertain to local structure in competition networks as well. We utilize constraint to measure the proportion of the firm's resources and attention that are focused on rivals (or "expected" potential rivals) within their local network, which is analogous to the concept of a CNG introduced above. Firms with less network constraint occupy brokerage positions, which implies that they are multiproduct firms and require managerial ambidexterity for maintaining a broader focus and balancing the explore-exploit tradeoff across multiple product markets (Raisch, Birkinshaw, Probst, & Tushman, 2009). Firms with more constraint exhibit more closure in their local network, implying that they are more likely to be single product firms located within their network group and maintaining a narrow strategic focus for expending resources and directing awareness. Following the network architecture model and competitive dynamics literature, we expect that local network structural similarity induces competitive tie formation. Stated another way, structural dissimilarity suppresses competitive ties, which leads us to posit the following hypothesis:

H3: Similar local network structure (i.e., less absolute difference of constraint) increases the likelihood of competition.

As an endnote to the hypothesis development, we remark on the dynamics of competitive *dynamics*. It is easy to overlook the fact that each mechanism contributing to competition network formation in the above hypotheses is actually a dynamic process. We therefore emphasize here and depict in Figure 2, that our study to expand the awareness of firms in assessing potential rival formation is inherently dynamic. In any model of network formation, the interplay between structure an action is the core phenomenon from which all effects emerge (Gulati & Gargiulo, 1999), but this is particularly poignant from a competitive dynamics perspective, as it is a research tradition that is “quintessentially longitudinal” (Chen & Miller, 2012:2). The choice to enter or exit a product market (or when a firm makes an acquisition or goes out of business) changes the structure of the competition network; however, as we have argued in the above hypotheses and will show in the following empirical analysis, that structure is a valuable source of information about the determinants of change in the future competition network structure. We represent this endogenous effect conceptually with the dashed line in Figure 2 and functionally with a lagged depend variable in our network regression models to capture the persistence or stability, as referred to as tie memory (Cranmer, Heinrich, & Desmarais, 2014), of competitive relations apart from new competition formation over time.

Place Figure 2 here.

METHODS

Network Inference – Temporal ERGM

The empirical study of interfirm network formation has recently risen to prominence in the strategic management literature (Kim, Howard, Pahnke, & Boeker, 2016). Borrowing the experience of social network analysis scholars, Kim *et al.* (2016) address the computational advantages of a particular class of network models, exponential random graph models (ERGM) (Frank & Strauss, 1986; Snijders, Pattison, Robins, Handcock, & Pattisorf, 2006; Wasserman & Pattison, 1996), that account for network-based dependence between dyadic (i.e., pairs of firms) observations, and they detail how these advantages may be realizable as well for strategic management scholars whose unit of observation is the interfirm dyad or network. It may help to think of this network model for inference purposes as being like a logistic regression for situations when the data are *not* independent and identically distributed (i.i.d).

Dealing with network cross-sections over time, our dynamic competition network requires an alteration to the ERGM specification, called temporal ERGM (TERM), that can account for the trend of factors driving competition formation and persistence (Hanneke, Fu, & Xing, 2010). For the purposes of estimation, Cranmer & Desmarais (2012) express the probability of the network at time t as a function of the observed q preceding time periods: $\mathbb{P}\left(\mathbf{Y}^t = \mathbf{y}^t | \{\mathbf{Y}\}_{t-q}^{t-1}, \{\mathbf{X}\}_{t-q}^{t}, \boldsymbol{\theta}\right) = \frac{1}{Z(\boldsymbol{\theta}, \mathbf{Y}^{t-1})} \exp\left\{\boldsymbol{\theta}' \boldsymbol{g}\left(\{\mathbf{y}\}_{t-q}^{t}, \{\mathbf{x}\}_{t-q}^{t}\right)\right\}$. $\mathbf{Y}$ is a random network (i.e., adjacency matrix) with realization $\mathbf{y}$ and elements $y_{ij} \in \{0,1\}$, taking on the value 1 if a tie exists between dyad (ij) and 0 if a tie does not exist. The firm and relation covariates are represented as a random array $\mathbf{X}$ with realization $\mathbf{x}$**.** The network sufficient statistics term $\boldsymbol{g} = g_1, g_2, \ldots, g_p$ is a vector of functions on the space of graphs, where each element $g_i(\cdot)$ yields a sufficient statistic for the graph; $\boldsymbol{\theta} = \theta_1,\ \theta_2,\ \ldots, \theta_p$ is the vector of coefficients to be inferred for their corresponding network statistics, and $Z(\cdot)$ is the normalizing constant.[3]

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[3] To deal with the computationally expensive normalization term, exponential random graph models utilize change statistics affecting the conditional log-odds for a single node pair: logit $\mathbb{P}\left(Y_{ij}^t = 1 \middle| \boldsymbol{Y}_{-ij}^t, \mathbf{X}^t, \boldsymbol{\theta}\right) = \ln \frac{\mathbb{P}\left(Y_{ij}^t = 1 | \boldsymbol{Y}_{-ij}^t, \mathbf{X}^t, \boldsymbol{\theta}\right)}{\mathbb{P}\left(Y_{ij}^t = 0 | \boldsymbol{Y}_{-ij}^t, \mathbf{X}^t, \boldsymbol{\theta}\right)} = \boldsymbol{\theta}' \delta\left(\boldsymbol{g}\left(y_{ij}^t, \mathbf{y}_{-ij}^t, \mathbf{x}^t\right)\right)$, where $\mathbf{y}_{-ij}^t$ is the complement to y_{ij}^t, i.e., all other dyads excluding

We perform estimation of the TERGM coefficients via by bootstrapped maximum pseudo-likelihood (MPLE) (B. A. Desmarais & Cranmer, 2012), which estimates the conditional probability of a competitive relation by iteratively maximizing a form of the likelihood over all time periods $t = \{1, \dots, T\}$ in the observed network cross-section. MPLE has been shown to be a consistent estimator (Strauss & Ikeda, 1990). This is implemented in the R statistical computing language (R Core Team, 2016) package *xergm* (Leifeld, Cranmer, & Desmarais, 2016a), and depends on *ergm* and *network*, also utilizing *texreg* (Butts, 2008; Hunter, Handcock, et al., 2008; Leifeld, 2013).

Measures

To capture the dependence of each competitive tie between firm i and j (y_{ij}^t) on the rest of the network ($\mathbf{y}_{-ij}^t$), the network sufficient statistics ($\boldsymbol{g}$) used in the TERGM are computed by summing the product of the covariate and the competitive tie over all dyads in the network (Cranmer et al., 2014; Leifeld, Cranmer, & Desmarais, 2016b). In this way, each of the following network statistics takes on the value of the covariate when the tie exists or 0 otherwise, and the tie probability captures dependence by carrying information from every other dyad.

Network risk. The network statistic for the network risk measure g_R is:

$$g_R(\mathbf{y}^t) = \sum_{i=1}^{n} \sum_{j=1}^{n} y_{ij}^t \cdot R_i^t \,, \quad \forall j \neq i \tag{1}$$

where firm i's individual network risk at time t (R_i^t) is a modified form of closeness centrality (Freeman, 1978):

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y_{ij}^t in the observed network $\mathbf{y}^{\boldsymbol{t}}$. The "change statistics" $\delta\left(\boldsymbol{g}(y_{ij}^t, \mathbf{y}_{-ij}^{\boldsymbol{t}}, \mathbf{x}^t)\right) = \boldsymbol{g}(y_{ij}^t = 1, \mathbf{y}_{-ij}^t, \mathbf{x}^t) - \boldsymbol{g}(y_{ij}^t = 0, \mathbf{y}_{-ij}^t, \mathbf{x}^t)$ are the difference of the network statistics, when the value of node pair (ij), is changed from 0 (a network comprised of $\mathbf{y}_{-ij}^t$ and $y_{ij}^t = 0$) to 1 (a network comprised of $\mathbf{y}_{-ij}^t$ and $y_{ij}^t = 1$). Refer to Wasserman & Pattison (1996) for details.

$$Network\ Risk \equiv R_i^t = \left(\frac{n-1}{\sum_{j=1}^{n} w_{ij}^t}\right), \quad \forall j \neq i \tag{2}$$

which takes the sum of inverse of competitive distance between firms i and j (d_{ij}), down-weighted by the CNG density[4] $D(G_i^t)$ or CNG cross-density $D\left(G_i^t, G_j^t\right)$ for the firms' network groups G_i^t and G_j^t:

$$w_{ij}^t = \begin{cases} d_{ij}^t\left(2 - D(G_i^t)\right), & G_i^t = G_j^t \\ d_{ij}^t\left(2 - D\left(G_i^t, G_j^t\right)\right), & G_i^t \neq G_j^t \end{cases} \tag{3}$$

Larger values of density (or cross-density) yield smaller values of w_{ij}^t and contribute more to the risk of direct competition formation (larger values of R_i^t). If the CNG is completely dense (i.e., a network clique), then w_{ij}^t reduces to its minimum value of 1.0, which is controlled by the use of the constant 2 in $\left(2 - D(\cdot)\right)$. The density-weighted closeness ($1/\left(\sum_{j=1,i\neq j}^{n} w_{ij}^t\right)$) is then scaled by the number of firms (minus the focal firm) for comparison across networks of different sizes (e.g., different time periods or scopes of awareness).

***k*-Cycles.** The network statistic for the count of network cycles of length k, denoted g_{C_k}, is a generalization from the number of triangles (3-cycles) following the notation of Desmarais & Cranmer, (2012):

$$\text{Cycles} \equiv g_{\mathrm{C_k}}(\mathbf{y}^t) = \sum_{i=1}^{n}\sum_{j=1}^{n} \dots \sum_{k=1}^{n} y_{ij}^t \cdot y_{jl}^t \cdot \dots \cdot y_{ik}^t\,, \qquad \forall k \neq \cdots \neq j \neq i \tag{4}$$

This measure adds one whenever all the competitive ties ($y_{ij}^t, \dots, y_{ik}^t$) are present during the same time period, forming a cycle.

[4] The CNG density at time t is the ratio of observed intra-group ties to possible ties: $D(G_i^t) = \sum_{i,j \in G_i^t; i \neq j} \left\{\frac{y_{ij}^t}{|G_i^t|(|G_i^t|-1)/2}\right\}$, and the cross- density is: $D\left(G_i^t, G_j^t\right) = \sum_{i \in G_i^t} \sum_{j \in G_j^t; i \neq j} \left\{\frac{y_{ij}^t}{|G_i^t| \cdot |G_j^t|}\right\}$. Here the operator $|\cdot|$ denotes the cardinality (count) of the set.

***Structural Similarity*.** The network statistic for the structural similarity measure g_S is:

$$g_S(\mathbf{y}^{\mathrm{t}}) = \sum_{i=1}^{n}\sum_{j=1}^{n} y_{ij}^t \cdot S_{ij}^t \quad \forall j \neq i \tag{5}$$

where S_{ij}^t is the absolute difference of constraint (Burt, 1992), the summary index of the lack of structural holes in an actor's local network:

$$\text{Structural Similarity} \equiv S_{ij}^t = \left|C_i^t - C_j^t\right| \tag{6}$$

Here we denote constraint $C_i^t = \sum_{j \in V_i}\left[\left(p_{ij}^t + \sum_{l \in V_i} p_{il}^t p_{lj}^t\right)^2\right], \forall j \neq l \neq i$, and while p_{ij}^t represents the proportion of time or resources devoted by actor i to alter j, in our undirected, unweighted competition network this simplifies to $p_{ij}^t = \frac{y_{ij}^t}{\sum_{j' \in V_i}\left\{y_{ij'}^t\right\}}, \forall j' \neq i$.

Industry Profile and Data

The industry setting for our empirical analysis is the business software and services industry, specifically during 2011 to 2016. In particular we focus our analysis in the markets related to customer experience management (CEM), which Gartner defines[5] as "the practice of designing and reacting to customer interactions to meet or exceed customer expectations and, thus, increase customer satisfaction, loyalty and advocacy." This includes several related markets that have been converging in their scope and objective to service more of the same customers, and names the markets for enterprise social listening (ESL), enterprise social networks (ESN), enterprise feedback management (EFM), digital experience platforms, and customer analytics solutions.

For this analysis we assume the perspective of managers at a focal firm, and encourage the reader to do the same. For this focal firm we select Clarabridge, which Forrester Research profiled

[5] See the definition at <http://www.gartner.com/it-glossary/customer-experience-management-cem/>.

as one of the “strong performers” in the market for enterprise social listening (ESL) platforms (Ngo & Pilecki, 2016). It is important to note that this designation puts Clarabridge above the firms that Forrester terms “contenders” or “challengers” on the low end of their evaluation spectrum but below the firms deemed “leaders” at the top. Thus we (as Clarabridge) are concerned with being aware of the leaders to whom we want to catch up but also need to be aware of the current and potential challengers as they try to cut into our market share. The ESL/ESN firms are the red colored network group in Figure 3, including ourselves (Clarabridge), Networked Insights, Brandwatch, NetBase, etc. (Ngo & Pilecki, 2016; Thompson, 2015). In 2015, IDC estimated the ESN/ESL market would grow to reach US$ 3.5 billion by 2019, at a CAGR of 19.1% (Thompson, 2015).

While multi-product firms (referred to as “generalists” hereafter), such as IBM, SAP, Oracle, Adobe, and Cisco are also involved in ESL/ESN, and thus have spanning ties to that group, their CNG is primarily customer analytics and digital experience platforms in 2016, the dark yellow group in Figure 3. Additionally, there is substantial competitive overlap for our focal firm’s network group with firms of the EFM market, including Satmetrix, Medallia, MarketTools, etc. (McInnes, 2011), shown in green in Figure 3. Finally, we highlight four potential rivals of which we (Clarabridge) might need to be aware. Among indirect competitors, IBM was at a competitive distance of 3 in 2013; this closed to 2 by 2016. During the same period, the competitive distance of Networked Insights, another of the ESL/ESN firms, decreased from 4 to 2, while one of the EFM firms, Satmetrix, decreased from 3 to 2. And we include for reference as a direct competitor, Mopinion, a firm with which we observed a competitive tie in 2015, that decreased the competitive distance of from 2 in 2013 to 1 by 2016.

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Jin-Su Kang, Gideon D Markman

Place Figure 3 here.

The data on competitive ties, as well as several of the firm-level control variables, come from CrunchBase, which is a business graph database operated by TechCrunch.[6] While this includes data on over 30,000 companies with at least one competitive tie in the global competition network (as of latest academic API access on October 26, 2016), we focus our scope of awareness to a maximum competitive distance of 3 from the focal firm as of 2016, which included 475 firms. This is intended to maintain a balance between awareness of current and potential rivals, since it is far enough to capture unexpected competition formation, but still within our managerial cognitive limitations (Cyert & March, 1963; March, 1991; Nelson & Winter, 1982) and computational limitations on commodity hardware. The idea of analyzing a network from the focal firm's perspective in this way is similar to the concept of an ego network ERGM (Salter-Townshend & Murphy, 2015).

Our process of constructing the competition network is slightly different from the three kinds of network datasets described by Burt (2009: Chapter 2), so it merits a brief clarification. Our competitive ties data reflect direct interactions in product markets similar to joint involvement data. However, instead of being recorded as counts of event co-occurrence, the data set in this study is binary. In this way is it more like the sociometric data for which respondents are asked to report on connections that exist (1 if yes or 0 otherwise) with alters. However, unlike socioemtric data, our competitive ties data are not self-reported by a representative of the firm but are instead entered in the database by the employees of the database owner, or algorithms or other users, which are later checked by employees. Thus our data reflect the market's perception (e.g., customers, analysts and other firm outsiders) of interfirm competition.

[6] Refer to the CrunchBase terms of service https://about.crunchbase.com/docs-archive/terms-of-service-20141002/.

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RESULTS

Competition Network TERGM and Tests of Hypotheses

The summary statistics of dyadic observations for the sample of 475 firms in the 3rd order network of the focal firm (Clarabridge) are presented in Table 1.[7] The presentation of regression models in Table 2 is as follows. We first present the baseline model with control variables as a base of comparison, followed by models I-III addressing hypothesis 1-3 and the full model (IV), respectively. The TERGM coefficients MPLE estimates are presented in Table 2 with the confidence intervals from 1,000 bootstrap resamples (B. A. Desmarais & Cranmer, 2012). Since the distributions of the resampled coefficients for several predictors are not normally distributed, we do not report Z-scores or their corresponding p-values. Instead we cautiously regard as "significant" any effect whose 95% resampling confidence interval does not contain 0.

Place Table 1 here.

In Table 2, Model I shows that firms with higher network risk are more likely to encounter competition with the positive, significant coefficient. This means that firms which are more centrally located within the competition network (i.e., shorter distance to all indirect competitors on average) or are members of a densely competitive competition network group are more likely to experience direction competition. Interpreting the effect size is difficult since it represents the effect of change from no competitive tie to having a competitive tie given all the other competitive ties in the network. We save micro-interpretations of the TERGM for the later discussion at the end of this section.

[7] Correlations for the dyadic observations of the network model are not reported as they violated assumptions (non-linearity, dependence) make the p-values (which were all but one significant at < 0.001) deleteriously misleading.

Both parts of hypothesis 2 -- the relation between indirect and direct competition, and the interaction of competitive distance with that relationship -- are tested in model II with separate terms for each cycle length (3 through 5). First, the significance (interpreted cautiously) of the cycle terms provides supporting for a significant relationship between indirect and direct competition). The positive effect of 3-cycles and 4-cycles implies that firms with more cycles of short lengths have higher likelihood to confront direct competition turned from indirect competition. The size of the effect decreases with length of the cycle, from 3-cycles to a smaller positive effect of 4-cycles, and finally a negative effect of 5-cycles. Additional analysis in other product markets (results not reported here) corroborated this trend of decreasing cyclic effect size which consistently becomes negative at length 5 and stays negative (mostly insignificant) at 6 and above. This provides support for rejecting the null hypothesis of H2b (no competitive distance interaction) because more local competition of short path lengths is positively related to direct competitive ties, whereas more competition of greater distances (at 5 and above) decreases the likelihood of forming direct competitive ties. This means that firms should focus their resources and attention among 4^{th} order (and lower order) indirect competitors, since the low probability of direct competition from competitors farther away than that would certainly make the search and awareness costs outweigh their benefit.

Place Table 2 here.

Finally, hypothesis 3, structural similarity, is tested in model III. The TERGM results' significant negative coefficient presents a counterintuitive finding that does not support hypothesis 3, that less absolute difference of constraint, or more structural similarity, is positively related to direct competition; on the contrary, instead of no relationship, it is strongly significantly negative. Stated another way, more structural similarity actually suppresses competition formation. While the effect of one firm's constraint (the firm-level direct effect, not the dyadic interaction) is not significant in model III, it becomes significant in model IV when all effects are included. The counteracting effects of firm-level and dyadic constraint are both substantial in model IV. This result is curious in light of past competitive dynamics research. While it is possible that this is an artifact of the data source, in which competitive instances between flagship companies and their numerous, dissimilar rivals may be overrepresented, it is also entirely possible that this presents evidence of a forbearance mechanism in the competition formation process. Such a competition suppression tendency would imply that while competition is much less likely for firms with more constraint (less structural holes) on average, the likelihood of a competitive tie with a specific potential competitor strongly depends on the difference of their local network structures. In the presence of such a mutual forbearance tendency, competition between a product market-spanning firm and a firm constrained internally within their product market would actually become more likely than competition forming between two equally positioned spanning firms or, likewise, two internal firms. This is indeed an intriguing discovery that merits further investigation.

The full model, model IV in Table 2 shows consistent results with models I-III, providing further support for the first two hypotheses. The full model accounts collectively for the separately tested effects of position, distance, and structure and does so with highest predictive accuracy (precision-recall and area under the ROC curve results not reported here), so we utilize model IV in the following micro-level analysis of the TERGM results for specific firm competition.

Controls and Goodness of Fit

We included several firm-specific and network level controls which are generally likely to affect competition formation or were found to be in need of controlling by past network literature. The edges term, in particular, is conventionally the ERGM baseline effect. The geometrically weighted edgewise shared partners (GWESP) term represents the shared competitor distribution and is useful for preventing model degeneracy (i.e., when all ties are predicted to equal 1 or all are predicted to be 0) (eg, Hunter and Handcock, 2006; Hunter 2007). Including a lagged dependent variable captures the stability of the competition network over time, also referred to as the tie memory or persistence (Cranmer et al., 2014). Additionally, we include a measure of shared competitor similarity (Adamic & Adar, 2003)to capture the competitor proximity of structural equivalence not included in our equivalence abstraction, structural similarity (i.e., absolute difference of constraint).

For firm specific controls, we include age and operating status homophily (public vs private), since the length of operation (among surviving firms) and status of the firm are correlated with opportunities for resource accumulation and expansion, which entail gaining more competitors on average, and past research on firm networks has uncovered changes in structural patterns as the networks evolve during firm lifespans (Hite & Hesterly, 2001). The competitive dynamics literature is replete with evidence of the mutual forbearance effect of multimarket contact (e.g., Gimeno, 1999; Gimeno & Woo, 1999; Korn & Baum, 1999; Prince & Simon, 2009). Thus location matters, and we include one term for headquarters geographic homophily (same state in the USA or region in other countries), and another term for firm branch multi-market contact. Finally, we include one term for CNG homophily to ensure that the network risk measure (H1) is significant while also accounting for the direct effect of network group membership.

The assessment of goodness of fit for any model from the family of exponential random graph models is somewhat involved but incredibly important. In particular our TERGM model IV, is essentially only valid if the network statistics capture the corresponding endogenous dependencies (Hunter, Goodreau, & Handcock, 2008; Leifeld et al., 2016b). To assess this, we simulated 100 distinct networks from the parameters and covariates of model IV and use this simulated sample as a baseline for comparison with the observed network finding that model IV is particularly representative of the middle period (2013) but generally well fit overall.[8]

Competition Network TERGM Micro-Interpretation

The results of the competition network TERGM (model IV) can provide valuable insight for managers. Specifically, the likelihood of competition formation with specific potential rivals or groups of rivals can be computed while conditioning on the information from all the other firms in the network (Bruce A Desmarais & Cranmer, 2012; see Leifeld et al., 2016b for explanation of computations). Figure 4 shows the conditional probability of a competitive tie between our focal firm and each of the four potential rivals introduced above, $\mathbb{P}(Y_{ij}^{t} = 1 | \mathbf{Y}_{-ij}^{t}, \{\mathbf{Y}\}_{t-5}^{t-1}, \{\mathbf{X}\}_{t-5}^{t}, \boldsymbol{\theta})$, given the other competitive ties, the past competition during the last 5 years, and the covariates included in the model. The most prominent potential rival, IBM, consistently has had much higher probability of direct competition formation, than the other potential rivals. The TERGM results (model IV) provide insight as to why this is. IBM is an older public firm, which in general have greater resources with which to operate, contributing to greater likelihood of competition formation. The other three potential competitors by contrast are younger private firms. Most importantly, though, IBM as multi-product generalist whose local competition network is less constrained within one product market and instead spans between multiple product markets, called structural holes (Burt, 1992). Since network constraint has a large negative effect on the likelihood of direct competition formation (i.e. higher constraint values means less likelihood of structural

[8] We ran at three different time periods (2011,2013,2016) during the beginning middle and end of our data set's time window. On average the network characteristics of dyad-wise shared partners, edge-wise shared partners, degree distribution and geodesic (shorted path) distance all suitably reflect our observed network, and they are especially accurate during the middle period due to changes in network composition after 2012; this is because the TERGM estimates reflect an average over the included time periods. Results are available upon request.

holes), IBM, in general, has a higher probability of forming direct competition with any other firm (notwithstanding the absolute difference of constraints for the specific dyad). The other potential competitors are single-product (or limited products) firms (called "specialist" hereafter). This group has on average higher constraint as they are more contained within their focal network group limited to one or a couple product markets, thus, they are less likely to form competition on average.

Place Figure 4 here.

Among the three specialists (Satmetrix, Mopinion, and Networked Insights), there was a trend of increased probability of competition formation from 2013 to 2016, which is consistent with the decreased competitive distances shown in Figure 3 (left versus right network panels, respectively). In 2013, the specialist with the highest probability of market entry (i.e., direct competitive tie formation) was Mopinion. The observation of that tie in 2015 provides support for the model's predictive capability, which is greatly improved by the lagged dependent variable (DV) capturing the competitive stability or network memory over time (Cranmer et al., 2014). Interestingly, Networked Insights developed a higher probability of competition formation during 2015-2016 than Mopinion had in 2014, the year before it became a rival, so from our perspective if we were managers of the focal firm (Clarabridge), we should be very aware of Networked Insights!

Of course we, as managers of the focal firm, must also be aware of IBM since they have consistently had the highest probability of market entry. Indeed, they are likely already involved in the product market, though our competitive ties data originating from firm outsiders have not yet reflected an instance of direct competition (or such overlap represents a missing observation in the database). However, IBM must be regarded differently, as a separate type of competitor than the other three, since market entry behavior and competitive motivations of generalists differ from specialists and other niche players (Markman & Waldron, 2014). In this respect, evaluating IBM relative to itself over time, the slight decrease in probability of competition formation with IBM from 2014 to 2015 and leveling in 2016 is perhaps the more useful measure, which indicates a relative stability of their competitive situation.

DISCUSSION AND CONCLUSION

The construct of Awareness in the AMC framework has guided firms and scholars to appreciate and study rivals, but as noted, there is very little clarity on how to develop such awareness or of whom firms should be aware. Addressing this gap in practice and theory requires a rigorous empirical assessment to show which distant, seemingly unrelated, players might become direct competitors. This study combined logic and methods from the network and competitive dynamics literatures, and longitudinal data, to further enhance the concept of awareness in the AMC framework by assessing the evolution of *competition* networks and the formation of competitive engagement. Studying several network groups entailing direct and indirect competitors—475 firms in the business software and services industry—over six years (2011-2016), we uncover a *competitive distance threshold* below which the likelihood of indirect rivals becoming direct rivals requires increased awareness and attention. Contrary to traditional competitive dynamics research which increases awareness by profiling rivals based on their similarities—e.g., in product, resources, capabilities, etc.—we show that greater awareness must be directed to rivals not only when they are dissimilar, but especially if they are embedded in different network groups, not similar ones. We also contribute to the competitive dynamics literature by enhancing the scope of awareness from focusing primarily on current competitive intensity in a single space to also addressing the process of *competition formation* across markets.

As documented elsewhere, the greatest competitive threats often come from the least expected players (Markman, Waldron, & Panagopoulos, 2016), so research and practice suggest that firm should be aware of precisely those they do not think they should be aware of. An additional challenge that afflicts the awareness construct in the AMC framework is the tendency to focus on and be aware of known rivals, which often bounds out non-rivals. Put differently, non-rivals have no competitive track record, so they do not matter until after they become competitors. Our study distinguishes between direct and indirect competitors—the rivals of one's rivals, and their competitors, etc. who may operate in different markets and industries—and it clarifies how and which indirect competitors become direct rivals. We show, for instance, that the relationship between distant, often unexpected competition and direct competition is impacted by the firm's structural embeddedness as well as the relational distance and structural similarity of the firm dyad.

Evidence from the business software industry shows that a firm's closeness to indirect competitors and competition network group (or inter-group) density among indirect competitors increases the likelihood of direct competition. Our study also identifies a competitive distance threshold above which the costs of awareness would surely outweigh their benefits. This line of research is important conceptually and practically because it outlines the range of indirect competitors to be aware of. Contrary to competitive dynamics research, which emphasizes similarity as a strong antecedent of hostile engagements—that firms with a similar profile are likely to become competitors—we found that indirect competitors with *dissimilar* local network structure require the most caution as they are most likely to turn into direct rivals. Clarifying this finding requires further analysis but it also underscores the importance non-rival competition for which more research on how indirect competitors become direct rivals is urgently needed. This in turn offers the potential to greatly enhance our understanding of awareness and its role in competitive dynamics.

Our results provide clear managerial implications. Leaders need to take a three-dimensional view of numerous product market spaces with encroaching competition over time to identify potential foes, since unexpected rivals and unanticipated actions can have the direst consequences. This was a lesson learned the hard way by digital camera manufacturers and makers of GPS and numerous other products that never expected to be supplanted by a smart phone.[9] Indeed it is a lesson that is being retaught again and again, just as rising popularity of mobile payments led by IT companies are shaking the stronghold business model of credit card companies and how Bitcoin is disrupting the entire banking industry.[10] While there has been extensive discussion in support of the AMC paradigm, the competitive dynamics field has yet to dissect the issue of awareness to see if its prevailing understanding and extent metrics are sufficiently suited to address the question of who *really* merits one's awareness. We argue that a conceptualization of awareness which concerns itself strictly with current rivals is essentially playing only two of the three dimensions needed to survive in today's game.

Future Research:

No study is perfect and neither is ours, but imperfections often guide future research directions. For example, despite intermittent checks by the database operator, the CrunchBase business graph data might contain unobserved competitive ties, so the level of missed observations cannot be assessed fully. Moreover, there is noticeable difference in the sparsity of data available

[9] See, for example, news articles by the Guardian <https://www.theguardian.com/technology/2014/aug/04/cameras-keycards-everyday-devices-killed-off-by-the-smartphone-gadgets>, The Wall Street Journal< http://www.wsj.com/articles/hilton-books-upgraded-technology-1406503197>, and Cnet < https://www.cnet.com/news/how-smartphones-are-slowly-killing-the-camera-industry/ >.
[10] Refer to the following article by Forbes <http://www.forbes.com/sites/forbesleadershipforum/2014/08/08/mobile-payments-will-make-credit-and-atm-cards-almost/#99765a239e5>.

before 2012 in our focal markets and before 2008 in general. Additional analysis should be completed to compare the findings of this study computed via MPLE with the alternative method, Markov Chain Monte Carlo MLE (MCMLE) in order to check consistency and robustness (Desmarais & Cranmer, 2012). This type of future research is already ongoing and will be completed soon by the authors.

This study takes a first step toward understanding interdependent competition formation as an early-awareness paradigm that may prove useful for extending the Awareness aspect of the AMC framework. The formation of competition is a process which both precedes and interacts with the trend of competitive intensity among rivals, eventually affecting the timing and amount of competitive (re)actions. This study, however, as a first step, limits itself to fully understanding only the formation of competition, not its intensity. The most conceptually interesting and valuable link yet to be drawn, for both competitive dynamics theoreticians and practitioners, is arguably the association between competition formation and competitive intensity. This might address such questions as, how long before an indirect competitor becomes a direct competitor (e.g., initiating competitive actions at or above a given rate)? Future research that can incorporate distant indirect competitive ties with competitive (re)actions, mingling relations with events through time, may be able to further our understating of the links between competition formation and the intensity of competition. This could prove valuable for future extensions of the Motivation and Capability aspects of the AMC framework—just as this study extends the Awareness aspect—thereby broadening and generalizing the tradition of competitive dynamics to account for both current and potential rivals and their coevolution over time.

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LIST OF TABLES

Table 1. Competition Network Dyads Summary Statistics

	Mean	SD	Med	Min	Max
1. HQ geographic homophily	0.2	0.4	0.0	0.0	1.0
2. Firm Age	24.8	19.9	19.0	0.0	106.0
3. Firm Branch MMC	0.0	0.1	0.0	0.0	0.8
4. Competition Persistence (DV lag)	0.0	0.1	0.0	0.0	1.0
5. CNG Homophily	0.2	0.4	0.0	0.0	1.0
6. Shared Competitor Similarity	0.1	0.3	0.0	0.0	32.8
7. Network Risk	16.0	3.2	16.4	0.0	40.5
8. Constraint	1.0	0.4	1.0	0.0	2.0
9. Absolute Difference of Constraint	0.4	0.3	0.3	0.0	1.0
10. 3-Cycles	0.2	0.6	0.0	0.0	35.0
11. 4-Cycles	1.2	4.3	0.0	0.0	126.0
12. 5-Cycles	12.5	34.9	1.0	0.0	1320.0

n = 324,586

Table 2. Temporal ERGM Regression Results (6 Periods, Years 2011-2016, 475 Firms)

		Control	I	II	III	IV
Network Risk	H1		0.239*			0.456*
			[0.145; 0.289]			[0.343; 0.488]
3-Cycles				1.220*		0.756*
				[0.490; 1.743]		[0.542; 1.072]
4-Cycles	H2a			0.134*		0.066*
				[0.112; 0.190]		[0.052; 0.095]
5-Cycles	H2b			-0.017*		-0.017*
				[-0.021; -0.014]		[-0.022; -0.014]
Constraint					-0.482	-6.921*
					[-2.731; 0.831]	[-7.885; -3.554]
Absolute Difference of Constraint	H3				3.350*	5.158*
					[2.707; 5.109]	[3.999; 6.442]
Constant (network edges)		-8.173*	-11.585*	-8.365*	-9.479*	-11.798*
		[-11.235; -7.431]	[-13.569; -9.994]	[-10.995; -7.918]	[-12.691; -7.622]	[-14.471; -10.236]
GWESP		0.268	-0.205*	0.135	-0.002	-0.124
		[-0.270; 0.649]	[-0.333; -0.107]	[-0.423; 0.552]	[-0.272; 0.119]	[-0.530; 0.101]
Competition Persistence (DV lag)		10.438*	10.815*	10.395*	10.948*	10.372*
		[8.832; 16.054]	[9.120; 13.804]	[8.788; 16.701]	[8.988; 18.057]	[8.754; 14.001]
Firm Age		0.016*	0.016*	0.011*	0.015*	0.012*
		[0.012; 0.020]	[0.010; 0.020]	[0.005; 0.017]	[0.010; 0.019]	[0.005; 0.019]
Firm Branch Multi-Market Contact		0.55	-0.607	-0.819	-0.193	-1.316
		[-0.927; 1.734]	[-1.234; 0.517]	[-2.660; 0.614]	[-1.068; 1.131]	[-2.847; 0.430]
Geographic Homophily		-0.234	-0.211	-0.247	-0.23	-0.144
		[-0.346; 0.067]	[-0.297; 0.021]	[-0.364; 0.038]	[-0.347; 0.048]	[-0.262; 0.069]
Network Group Homophily		2.449*	3.602*	2.070*	3.380*	4.074*
		[1.441; 3.845]	[3.350; 4.452]	[1.273; 4.038]	[2.896; 4.607]	[3.598; 5.370]
Operating Status Differential Homophily: Private		-0.831*	-1.106*	-0.333*	-0.676*	-0.825*
		[-0.967; -0.736]	[-1.275; -0.914]	[-0.514; -0.192]	[-0.884; -0.523]	[-1.046; -0.495]
Operating Status Differential Homophily: Public		-0.271	-0.195	0.027	-0.213	0.019
		[-2.128; 0.233]	[-1.854; 0.277]	[-1.008; 0.397]	[-2.369; 0.333]	[-0.645; 0.339]
Shared Partner Similarity		1.339	1.213*	-0.755	1.622*	-0.215
		[-0.115; 2.219]	[0.352; 1.530]	[-1.651; 0.466]	[0.353; 2.674]	[-0.507; 0.182]
Num. obs.		34,669	323,045	97,918	225,298	324,586

[*] 0 outside the 95% bootstrapped confidence interval
1,000 bootstrap resampled 95% confidence intervals shown in brackets

LIST OF FIGURES

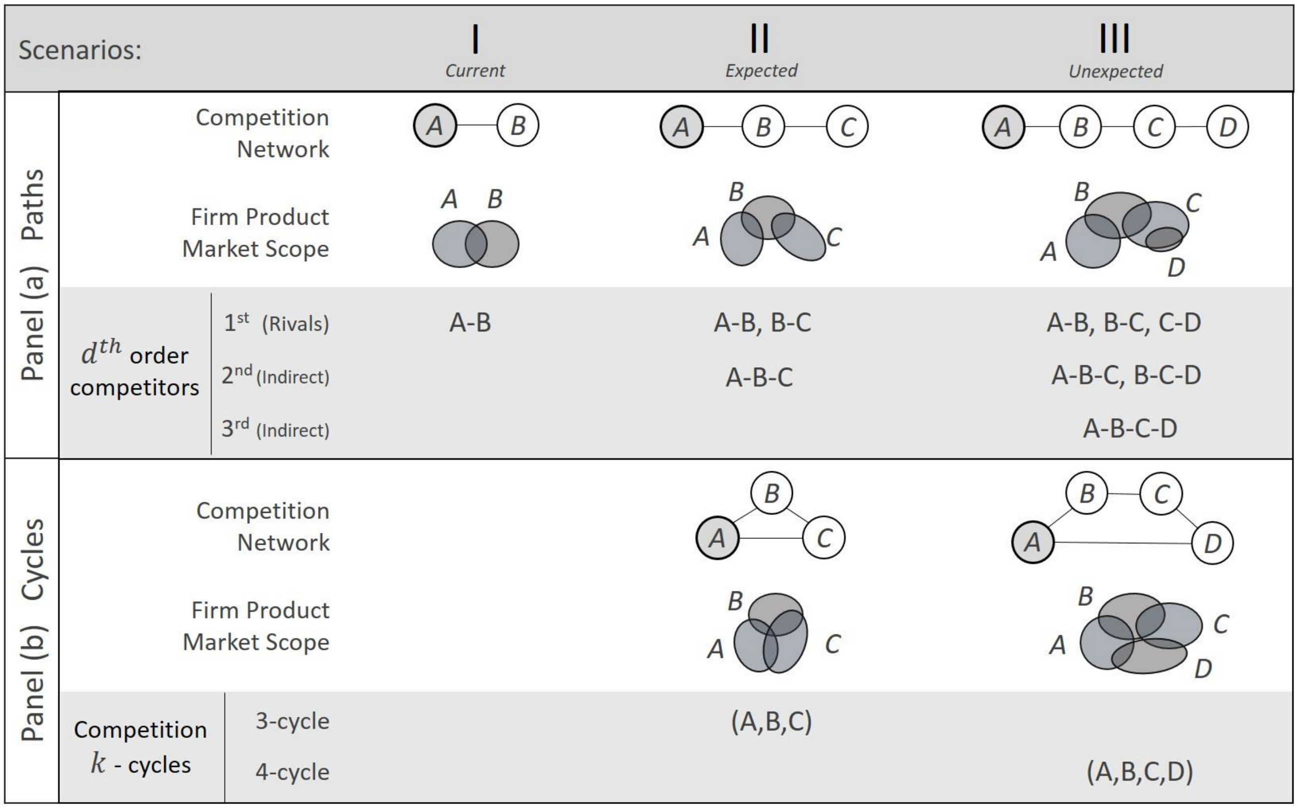

Fig. 1. Perceptions of competition formation. For focal firm (A), expected (II) and unexpected (III) competition formation are shown as paths (a) and cycles (b). Current competition (I) is included for reference. (Note: The competition networks are undirected.)

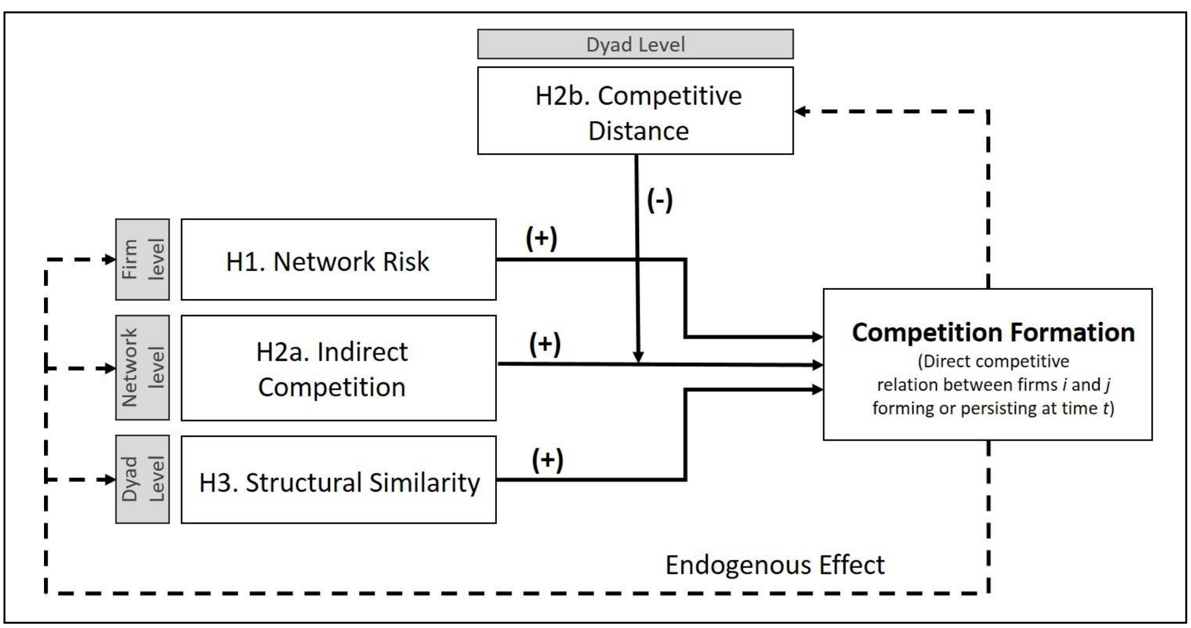

Fig. 2. Early Awareness Model of Competition Formation in Dynamic Competition Networks

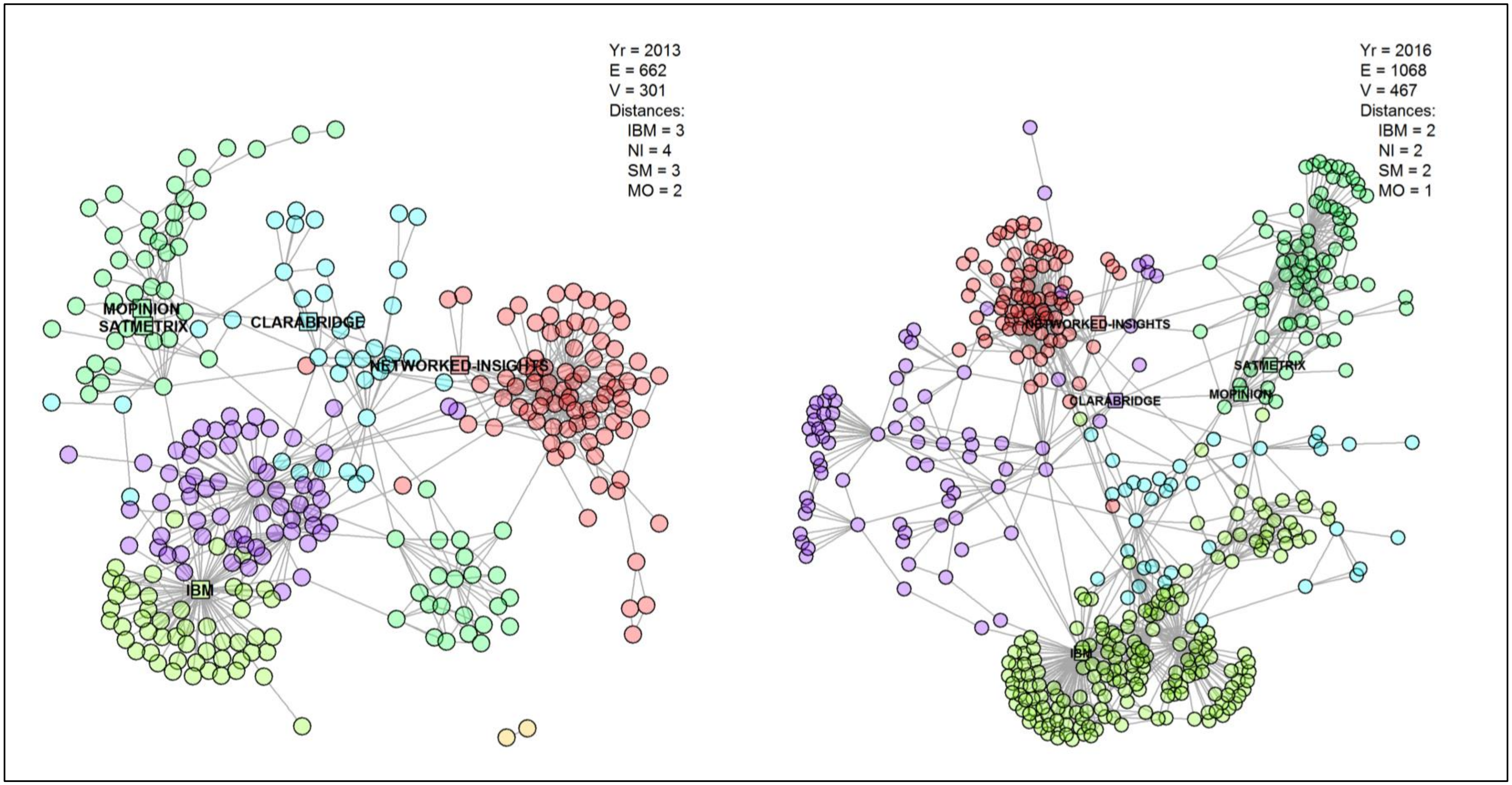

Fig. 3. Competition networks of up to 3rd order indirect competitors from the focal firm (Clarabridge) at years 2013 (left) and 2016 (right). The focal firm and four of its potential rivals (IBM, Satmetrix (SM), Networked Insights (NI), Mopinion (MO)) are labeled and depicted with square nodes. The number of competitive ties (E) and firms (V) are listed in the legend with the competitive distances between focal firm and potential rival. Isolates are omitted for clarity. Note: Node colors signify competition network group membership related to the following product/service markets as interpreted by the authors for the 2016 network: green (Enterprise Feedback Mgmt., Online Surveys), red (Enterprise Social Listening/Networks), purple (Machine Learning/Artificial Intelligence), yellow (Customer Analytics, Digital Experience), blue (Statistics and Business Analytics)

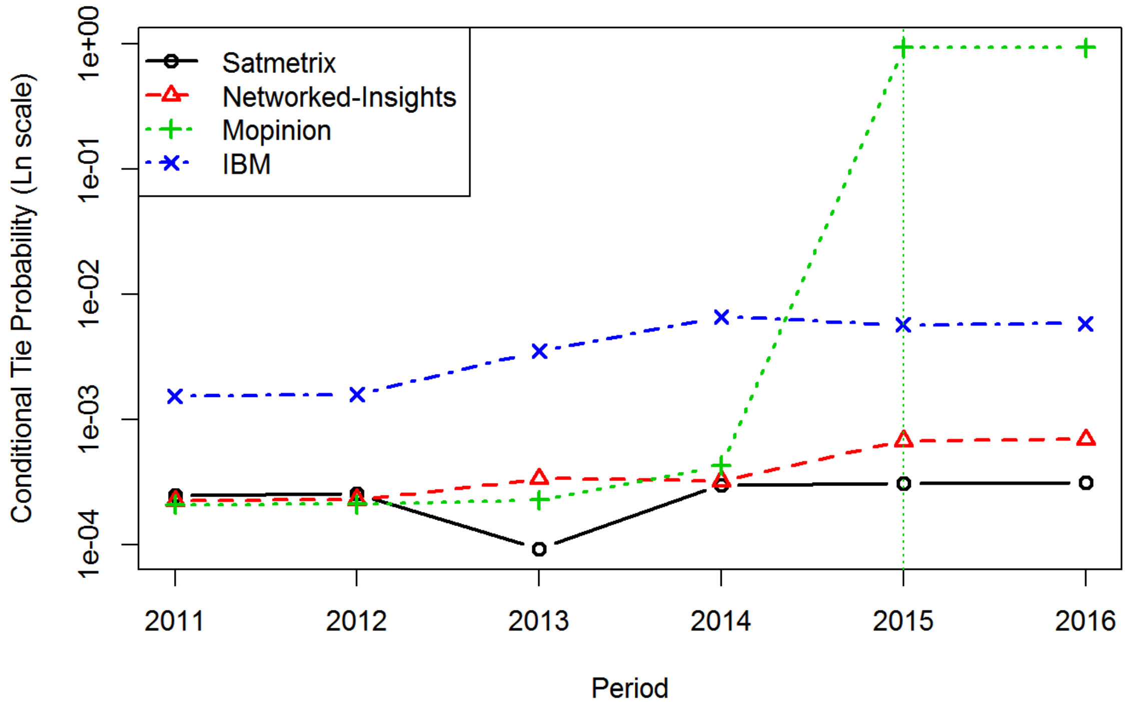

Fig. 4. Conditional probability of a competitive tie for focal firm (Clarabridge) with four potential rivals, computed from TERGM model IV. The vertical dotted line indicates when a direct competitive tie was observed.