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Multipoint Contact Without Forbearance? How Coverage Synergies Shape Equity Analysts' Forecasting Performance

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Abstract

Research Summary: Scholars regularly use multipoint contact (MPC) to explain how encountering rivals in different domains shapes performance. While most explanations rely on mutual forbearance theory, I propose that competitive deterrence does not adequately explain how MPC shapes performance in knowledge intensive work and argue instead that cross-domain synergies may play a central role. I examine how security analysts' MPC with publicly traded firms captures synergies in their coverage portfolio, which improves forecasting accuracy and information leadership. The advantages of greater MPC for a focal analyst are counterbalanced by rivals' observational learning, which reduces the focal analyst's forecasting differentiation. A natural experiment helps corroborate my argument: rival analysts' forecasting accuracy dropped for firms in which high MPC analysts perished in the terrorist attack on September 11, 2001.

Managerial Summary: Competition in the knowledge economy often unfolds across multiple domains including product markets, geographic locations, and customer segments. In these settings, an actor's level of multipoint contact (MPC) in a domain captures the knowledge and other synergies available to the focal actor, which can improve performance in the domain. In the equity research setting, an analyst's MPC on a focal firm captures the likelihood that the analyst also covers that firm's suppliers, customers and important competitors. Using data on analysts' forecasting performance between 2001 and 2013, I find that greater levels of MPC on a focal firm predicts greater forecasting accuracy and information leadership but also lowers forecasting differentiation by attracting rivals who observe and benefit from the focal analyst's knowledge.

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Competition across multiple domains, including product markets, geographic locations, and customer segments is commonplace in the knowledge economy. A notable factor shaping an actor's performance in a focal domain of competition is multipoint contact (MPC), a structural feature that results from the overlap of multiple actors in multiple domains. Most extant explanations of the effect of MPC on an actor's performance invoke mutual forbearance theory, which posits that MPC leads to competitive deterrence by enabling rivals to retaliate in other domains against an actor who refuses to forbear in a focal domain (Bernheim *et al.*, 1990; Edwards, 1955; Karnani *et al.*, 1985; Yu *et al.*, 2013).

However, MPC and competitive forbearance are very different concepts that need not co-occur. A focal actor's MPC in a domain can be driven by any process that attracts rivals to other domains in which the actor competes. Mutual forbearance is one specific dynamic that hinges on a feedback loop between an actor's competitive intensity and rivals' strategic outcomes. For example, work on mutual forbearance between airlines assumes, quite reasonably, that changes in rival airlines' ticket prices on a route exert predictable effects on the profits of a focal airlines on that route (Gimeno *et al.*, 1999; Korn *et al.*, 1999; Singal, 1996). The feedback loop is reflected in the common knowledge that competitors' price changes can directly influence the focal airline's profits. Without a feedback loop, multipoint competitors would have no incentive to strategically reduce competitive intensity and would lack the capability to either signal or enforce mutual forbearance. In settings where a strong feedback loop cannot be firmly established, forbearance does not provide a satisfactory explanation for the effect of MPC on performance.

An actor's MPC in a focal domain describes the incidence of joint participation with competitors in other domains. Extant work shows that competitors' joint participation across domains can embed important information about how resources and knowledge relate across these domains. For example, the joint participation patterns of diversified companies across industries reflects relatedness in resources between these industries (Bryce *et al.*, 2009; Lien *et al.*, 2009; Wan *et al.*, 2011). Other research shows that workers' patterns of inter-industry labor mobility reflect the underlying skill relatedness between these industries (Neffke *et al.*, 2013; Neffke *et al.*, 2017). From this perspective, greater MPC indicates greater relatedness between the focal domain and other domains where a focal actor competes, which may provide advantageous synergies. Existing work on MPC has not adequately acknowledged the presence of this synergy channel, which may lead to incorrect inferences regarding why an actor's MPC affects performance in a focal domain.

The core argument of the present paper is that the synergy channel of MPC is likely to play a central role in explaining a focal actor's performance in knowledge-intensive tasks. First, the deterrence channel is suppressed because the uncertain and unpredictable nature of knowledge-based competition reduces actors' ability to influence their rivals' outcomes. Second, the relatedness that MPC captures can shape the extent to which actors can leverage their existing knowledge. Consider an academic field in which the knowledge structure is defined by scholars' publications in several overlapping topics. A specific scholar's MPC on a focal topic reflects the extent to which she publishes on research topics that relate closely to the focal topic. Achieving scientific impact is highly uncertain, and the scholar's lack of publication effort in a given topic is unlikely to enhance competing scholars' scientific impact on that topic. Although the required feedback loop for competitive deterrence is absent, the synergy channel of MPC is likely to shape performance. Greater MPC in the foregoing example indicates knowledge of topics that are closely related to the focal topic. Ensuring performance-enhancing synergies include accelerated learning rates (Schilling *et al.*, 2003) and incentives to further invest in the focal topic to capitalize on those synergies (Levitt *et al.*, 1988; March, 1991).

The synergy channel also has implications for the emergence and directionality of spillover effects in performance. The tendency of less knowledgeable competitors to observe and learn from the knowledge-based outputs of more knowledgeable competitors is well-documented in research on industrial agglomeration (Shaver *et al.*, 2000). In addition, concealing valuable knowledge from rivals is particularly difficult when competition extends across multiple domains (Greve, 2009). Thus the valuable knowledge of actors with greater MPC, who enjoy the benefits of relatedness, may be exposed and used by rivals. Greater MPC may therefore constrain a focal actor's ability to differentiate their output from the output of rivals who can observe and learn from the focal actor's knowledge.

The competition between sell-side security analysts (actors) in the production of publicly traded firms' (domains) earnings forecasts provides an ideal testing ground for the synergy view of MPC for two reasons. First, accurately estimating firms' future earnings requires interpreting and integrating information on the firm's accounting practices, economic fundamentals, business strategy, operations, and corporate governance (Asquith *et al.*, 2005; Beunza *et al.*, 2007). The uncertainty inherent in this task weakens the feedback loop between an analyst's competitive intensity and rivals' outcomes. Thus, analysts are unlikely to voluntarily reduce the quality of their forecasts because doing so does not necessarily help rivals improve their own forecasting accuracy. Second, the setting provides the necessary conditions for competitors to benefit from synergies in the firms they cover. Analysts can deliver valuable advice to their investment clients on a focal firm when they also cover the focal firm's industry competitors, critical suppliers and important customers (Bhojraj *et al.*, 2003; Brochet *et al.*, 2013; Guan *et al.*, 2015; Sonney, 2007).

I propose that an analyst's MPC on a focal firm indicates coverage of related firms, and that the synergies associated with this type of coverage increase the quality of the analyst's earnings forecasts for the focal firm. Greater MPC also leads to greater knowledge exposure and increases the likelihood that rivals will observe and learn from the analyst's forecasts on the focal firm, which can limit her ability to differentiate from the consensus estimate. Detailed data on analysts' annual forecasts from 2001 to 2013 allows me to capture three aspects of firm-specific forecasting performance: (1) accuracy, (2) information leadership, and (3) differentiation (Cooper *et al.*, 2001; Hong *et al.*, 2003; Irvine, 2004; Ljungqvist *et al.*, 2007; Stickel, 1992). Evidence from these three performance metrics and from a natural experiment are consistent with coverage synergies from MPC. First, greater MPC on a focal firm is systematically associated with higher forecasting accuracy on that firm, which reflects an understanding of the firm's operations and business environment. Second, greater MPC on a focal firm is also systematically associated with an analyst's information leadership, which measures the influence of the analyst's forecasts on the timing of rivals' forecasts (Cooper *et al.*, 2001). Third, rivals tend to use the forecasts of analysts with greater MPC to guide their own performance, yielding a negative effect from an analyst's MPC on forecast differentiation from the consensus estimate. Finally, rivals' forecasting accuracy dropped when high MPC analysts perished on September 11, 2001 in the terrorist attack on New York's World Trade Center. This result suggests that survivors were relying on the departed analysts' firm-specific knowledge to improve their own performance.

While most work on MPC focuses on its role in fostering mutual forbearance, this paper proposes that MPC may reflect synergies available in a focal domain to actors who compete in other related domains. Unlike mutual forbearance, the synergy channel of MPC does not require a feedback loop between an actor's competitive intensity and rivals' strategic outcomes. Even when the feedback loop is present, cross domain-synergies may operate in parallel to mutual forbearance provided actors stand to benefit from greater relatedness across their domains of competition.[1] The present paper also describes why MPC is not necessarily a "free lunch" for the actors who possess it, especially in knowledge-intensive settings (e.g., Giustiziero *et al.*, 2019). When an actor encounters rivals in multiple domains, those rivals have many opportunities to observe the actor's behavior and learn from the actor. Because of this observational learning, the actor may suffer knowledge spillovers that help her rivals and limit her ability to differentiate from them. Observational learning can therefore create a delicate interdependence between multidomain competitors in knowledge-based settings, even if mutual forbearance is not especially strong.

THEORY

Multipoint Contact with and without Competitive Deterrence

Strategy scholars have long examined MPC in association with competitive deterrence, where MPC provides opportunities to monitor and punish rivals who refuse to forbear (Baum *et al.*, 1996; Boeker *et al.*, 1997; Gimeno *et al.*, 1999; Jayachandran *et al.*, 1999). Briefly, competitors are thought to reduce their competitive intensity in one domain with the expectation that their rivals will reciprocally forbear in other domains (Baum *et al.*, 2016; Bernheim *et al.*, 1990; see Yu *et al.*, 2013 for a review). This deterrence

[1] While it is beyond the scope of this work, the synergy channel of MPC is likely to be weakened in settings in which the contribution of knowledge relatedness is low relative to other drivers of performance, such as operational efficiencies or profitable opportunities for unrelated diversification across domains.

channel is premised on a feedback loop, where an actor's increased competitive intensity in a given domain can threaten rivals' outcomes.

The presence of a feedback loop between one actor's competitive intensity and rivals' outcomes is a reasonable assumption in a number of settings. For example, incumbent airlines can reduce the profitability of a particular route by expanding flight frequencies or using larger aircraft to discourage rivals' entry into that route (Ethiraj *et al.*, 2019). By the same token, a focal airline can also signal forbearance by increasing the price of its airfare on a certain route, which directly helps rivals' profits on that route (Gimeno *et al.*, 1999; Korn *et al.*, 1999; Singal, 1996). Similarly, a lender can signal forbearance in a given market or geographic region by raising interest rates, adding fees or scaling down advertising because such actions are likely to help rivals' profits (Haveman *et al.*, 2000; Mas-Ruiz *et al.*, 2005). The feedback loop enables the emergence of mutual forbearance in these settings because the focal actor (i.e., the airline or lender) can directly help rivals' outcomes by reducing competitive actions in a domain, while simultaneously signaling an expectation of reciprocal treatment from rivals in other domains. By contrast, in settings where the feedback loop is weak or absent, multipoint competitors would lack the incentive to strategically reduce competitive intensity and would lack the capability to effectively signal their intention to forbear or to punish rivals.

At least two factors weaken the feedback loop required for the emergence of competitive deterrence. The first factor is the presence of systematic outcome uncertainty, which reduces actors' control over their own outcomes. Uncertainty introduces noise that can interrupt the ability to effectively signal or correctly interpret rivals' signals of deterrence (Thomas *et al.*, 2006). The second factor that weakens the feedback loop and presence of mutual forbearance is the availability of substitutes (Ethiraj *et al.*, 2019). Competitors' market power over customers declines with customers' increased ability to substitute away from a product or service. Substitutability in a domain makes multipoint competitors less likely to reduce their competitive intensity because the potential threat from customers' exit exceeds the potential benefits from deterrence. As such, MPC scholars who study mutual forbearance among airlines typically eliminate very short routes from their analyses (e.g., Gimeno *et al.*, 1999), where the threat of customer exit to other forms of transportation reduces the likelihood of mutual forbearance between airlines.

A case in point where outcome uncertainty and substitutability are likely to interrupt competitive deterrence is the competition between sell-side analysts in forecasting firms' future earnings. Investors seek analysts who can produce accurate and timely earnings forecasts, one of the most anxiously anticipated news items on Wall Street (Cohen *et al.*, 2010a).[2] Individual analysts who cover the same firms compete with each other on the quality of their forecasts. Generating quality forecasts requires understanding the nuances of a firm's economic fundamentals, accounting practices, business strategy, operations, and corporate governance (Asquith *et al.*, 2005; Beunza *et al.*, 2007). The complexity of factors affecting firms' future earnings adds substantial uncertainty to analysts' forecasts. This uncertainty is reflected in the weak relationship between an analyst's decision to increase competitive intensity on a focal firm, say by devoting more time and resources to its coverage in a given quarter, and the quality of her forecasts at the end of the period.[3] Uncertainty also suggests that an analyst would be unable to tell whether a rival's inaccurate forecast is the result of a decrease in effort or an error in the rival's assessment of the factors influencing a firm's future earnings.

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[2] Since 2001 the equity research business model has primarily relied on brokerage commissions from investors, particularly institutional investors, who settle trades associated with specific analysts' research through the analyst's employer (Ljungqvist *et al.*, 2007).

[3] In comparison, consider the relative control over competitive outcomes experienced by airlines. One airline's change in ticket prices in one period has a well understood and rapid effect on both its own and its rivals' profits.

In addition to outcome uncertainty, sell-side analysts face the latent threat of substitution from in-house, buy-side analysts employed by institutional investors, who in turn represent sell-side analysts' most important clients. Buy-side analysts conduct similar research as their sell-side counterparts and tend to rely on the latter's narrower coverage and deeper knowledge of specific firms to complement their own analysis of current and prospective investment targets (Barker, 1998). The potential substitutability by internal buy-side analysts means that investors' demand is quite elastic to changes in the price or quality of sell-side research.[4] A voluntary reduction in forecasting quality (i.e., competitive deterrence) is therefore unlikely because doing so risks pushing dissatisfied investors toward using their own in-house research.

Together, outcome uncertainty and substitutability weaken the presence of the feedback loop required for competitive deterrence. The absence of mutual forbearance as a dominant dynamic between analysts provides an auspicious opportunity to examine whether the synergy channel can provide a more satisfying explanation for the role of MPC in shaping performance.

Multipoint Contact and the Synergy Channel

Covering a group of firms related in important ways helps analysts develop deeper firm-specific knowledge that benefits their investment clients. According to a sell-side analyst interviewed for this research, "*expanding coverage to related companies is common practice, as this approach aligns naturally with an analyst's expertise and makes the learning curve manageable. Portfolio managers [i.e., analysts' clients] also appreciate research that carefully considers all sector activity including*

[4] The substitutability of sell-side analyst research with in-house research recently came to a head with the enforcement, starting in January 2018, of the revised Markets in Financial Instruments Directive (MiFID II). This regulation prevents brokers from bundling sell-side research as an "added service" to execution services such as settling trades. The simple act of making the price of research explicit is expected to reduce investors' demand for sell-side research dramatically. A large survey shows an overwhelming majority of investors (78%) have plans to source less research from sell-side analysts as a result of MiFID II (see https://www.cfainstitute.org/-/media/documents/support/advocacy/mifid_ii_new-paradigm-for-research-report.ashx, last accessed on 11/3/19).

competitors, suppliers and customers." Despite the overarching importance of coverage relatedness, several factors introduce heterogeneity into analysts' coverage choices. First, differences in coverage may reflect differences in analyst's individual schemas regarding what constitutes a firm's most critical competitors, customers, or suppliers (Bhojraj *et al.*, 2003). Second, analysts sometimes venture into unrelated coverage to satisfy client interest on a particular company that is outside their current expertise. Finally, differences in employer resources such as access to sales and trading forces and to junior analysts can lead to differences in the number of firms covered (which typically ranges from eight to 18 for most analysts). Figure 1 illustrates typical overlap in the portfolios of three analysts (*A*, *B*, and *C*), all of whom cover a focal firm *1** as well as two additional firms each (*2*, *3*, *4*, and *5*).

<<INSERT FIGURE 1 AROUND HERE>>

Figure 1 illustrates a global analyst-firm network structure characterized by substantial-but-imperfect overlap in coverage. Differences in coverage reflect analyst heterogeneity, whereas similarity in coverage reflects the benefits of redeploying existing knowledge and other resources across multiple domains of competition. These benefits are substantial, such that the coverage universe of the group of analysts covering a focal firm will typically include that firm's close industry competitors, as well as the focal firm's critical suppliers and important customers (Brochet *et al.*, 2013; Guan *et al.*, 2015; Sonney, 2007).

Prior work on relatedness shows that the joint participation of competitors across domains can embed important information about how resources and knowledge relate across these domains. Pairs of industries that attract more of the same diversified companies exhibit greater resource relatedness (e.g., Bryce *et al.*, 2009; Lien *et al.*, 2009), and industries that attract a similar set of mobile workers display greater skill relatedness (Neffke *et al.*, 2013; Neffke *et al.*, 2017). Similarly, the underlying businesses of firms attracting coverage from the same analysts tend to be more closely related (Beatty *et al.*, 2013). For example, the ten firms attracting the highest number of analysts covering Apple Inc. in 2013 included five of Apple's close competitors (Hewlett Packard, Dell, IBM, RIM, and Nokia), as well as five critical suppliers of Apple's electronic and data storage components (NetApp, Fusion-io, Western Digital, Seagate Technology, and Qualcomm). The network in Figure 1 can be transformed into a firm-firm network (Figure 2) to illustrate this principle.[5]

<<INSERT FIGURE 2 AROUND HERE>>

Ties in Figure 2 represent the number of analysts each pair of firms has in common, with thicker lines representing greater relatedness to the focal firm *1**. MPC is specific to each analyst-firm pair and refers to the relatedness of the focal firm to other firms the analyst covered. Thus, analyst *A* has greater MPC on focal firm *1** than her rivals, because the rest of analyst *A*'s portfolio (i.e., firms *2* and *3*) is related more closely to the focal firm *1** than the portfolios of rivals *B* and *C*. I next explore how the relatedness in coverage captured by MPC shapes analysts' forecasting performance.

The Synergy Channel and Forecasting Performance

Research on cross-domain learning suggests that the speed of knowledge accumulation about a focal domain increases when actors have been exposed to related domains (Schilling *et al.*, 2003). Research on social networks shows that participating in related domains has a positive effect on actors' knowledge-related outcomes, including venture capitalists' interpretation of new information (Ter Wal *et al.*, 2016), as well as R&D workers' ability to integrate information from various sources (Tortoriello *et al.*, 2014) and transfer knowledge (Reagans *et al.*, 2003). For analysts, MPC on a focal firm indicates the extent to

[5] The analyst-firm graph in Figure 1 is an example of a two-mode network (Borgatti *et al.*, 1997; Breiger, 1974; Newman *et al.*, 2002; Prato *et al.*, 2013), which can be easily transformed into a firm-firm network as in Figure 2 (see Appendix A).

which other firms an analyst covered are related in important ways to the focal firm. Analysts with greater MPC on a focal firm will therefore have more opportunities to develop a deeper, more nuanced understanding of the focal firm than rivals who cover unrelated firms.

In addition to the learning synergies available from covering related firms, MPC also captures the analyst's likely exposure to timely information about critical competitors, customers, and suppliers in the focal firm's ecosystem. Exposure to the focal firm's related firms can impart material information about the future performance of the focal firm, such as supplier capacity constraints, competitors' product developments, and early information about clients' plans to expand or contract orders. In line with this argument, analysts seem to gain forecasting accuracy when covering a focal firm's closest industry competitors, as well as suppliers and customers operating in different industries (Guan *et al.*, 2015; Sonney, 2007).

A substantial aspect of analysts' job entails exploring new technologies adopted by the firms they cover (Benner, 2010) and searching for unique and diverse knowledge that can provide an edge in predicting future earnings. This exploratory component of analysts' work poses a challenge to the supposition that coverage of closely related firms is uniformly advantageous. One alternative perspective is that covering narrowly related firms could constrain analysts' ability to obtain diverse and unique information (Burt, 1992; Ter Wal *et al.*, 2016). This argument suggests that extensive MPC could lead not to a knowledge advantage, but instead to information redundancy, which would hurt performance.

Informational constraints could be overcome if analysts primarily selected disparate, unrelated firms to cover. Such a strategy, however, would impose a tremendous learning cost in terms of time and effort. Instead of covering wildly divergent firms, sell-side analysts can expand the diversity and uniqueness of their knowledge by going beyond the material produced for investors by the firms' management (e.g., 10-Ks, management's earnings guidance, and proxy statements). An important source of additional information for developing a knowledge advantage are relationships with industry experts and firm insiders (Cohen *et al.*, 2010b; Washburn *et al.*, 2014). For example, clients praised a software analyst ranked in the prestigious *Institutional Investor* magazine for having "the deepest knowledge of software's inner workings and great relationships in the Valley" (October 2013). Perhaps surprisingly, greater MPC is likely to incentivize the cultivation of these valuable relationships.

Cultivating and maintaining relationships with industry experts and company insiders requires costly investments of time and effort, and analysts face intense pressure to efficiently allocate these scarce resources. Thus, analysts may forego pursuing relationships with low expected payoffs. The return on expending time, effort, and social capital on cultivating a contact is more justifiable when the information gained about a firm applies to several other firms in the analyst's coverage portfolio. In line with this logic, companies have been shown to forego investing in exploratory technologies unless those technologies can be applied across a wide range of processes (Levitt *et al.*, 1988; March, 1991). Similarly, analysts prioritize relationships with contacts that can benefit multiple firms in their coverage portfolio. For example, an analyst would be more motivated to pursue and cultivate a relationship with an expert on a specific technology if this technology is a critical component for several firms in the analyst's portfolio. Greater MPC is therefore likely to incentivize investing in sources of private information that are relevant to the focal firm because the benefits of a successful search would apply to multiple firms the analyst covers.

The synergy channel's various benefits suggest that greater MPC on a focal firm should positively predict the quality of an analyst's forecasts on that firm. A well-established metric reflecting analysts' firm-specific knowledge is the accuracy of earnings per share (EPS) forecasts. Accurately forecasting a firm's future EPS demonstrates the analyst understands major aspects of the firm's operations, as well as the market ecosystem affecting demand for the firm's products and services (Loh *et al.*, 2006). Forecasting accuracy is conducive to establishing greater credibility with investors (Ljungqvist *et al.*, 2007), receiving recognition in the industry's most prestigious rankings (Stickel, 1992), and increasing upward mobility into higher-status employers (Hong *et al.*, 2003).

In addition to issuing accurate forecasts, analysts with a knowledge advantage may issue forecasts that contain previously unknown information about a firm. When a focal analyst introduces new information, rivals may quickly evaluate the credibility of the source to determine if they should initiate a search for new information or stick to their current view. In this regard, analysts with a knowledge advantage introduce information that is likely to influence rivals' search behavior (Jegadeesh *et al.*, 2010). Accounting scholars developed the concept of information leadership, which captures the extent to which a focal analyst's forecasts prompt rivals to update their own forecasts more than rivals' forecasts influence the focal analyst (Cooper *et al.*, 2001). Information leadership captures aspects of forecast quality complementary to accuracy (Baum *et al.*, 2016). Like accuracy, information leadership is associated with substantial benefits for analysts, including higher compensation (Groysberg *et al.*, 2011; Irvine, 2004).

In summary, greater MPC on a focal firm reflects coverage of closely related firms, which accelerates learning rates; increases exposure to relevant information about a firm's critical competitors, customers, and suppliers; and incentivizes the cultivation of private information sources relevant to the focal firm. This leads to my first set of hypotheses:

***H1A**:* An analyst's MPC on a focal firm is positively associated with the accuracy of forecasts on that firm.

H1B*:* An analyst's MPC on a focal firm is positively associated with the information leadership of forecasts on that firm.

Observational Learning and Forecasting Differentiation

According to the synergy channel, MPC on a focal firm improves the quality of forecasts on that firm. High quality forecasts are most beneficial for the analyst's reputation when the analyst can differentiate their forecasts from the consensus estimate (Ljungqvist *et al.*, 2007).[6] Maintaining highly differentiated forecasts, however, can be difficult. Analysts who cover the same firms routinely listen to each other's questions and exchanges with firm management during earnings calls. They can also access the extensive reports that other analysts write for investors in which they explain in detail how they arrived at a particular forecast or recommendation (Merkley *et al.*, 2017). Thus, analysts' knowledge on a firm is exposed to rivals, which has important implications for analysts' ability to differentiate their forecasts.

At least two factors suggest that analysts with greater MPC on a focal firm may be particularly constrained in their ability to differentiate their forecasts on that firm. First, an actor's ability to conceal valuable knowledge decreases when rivals are met in multiple domains (Greve, 2009). While the knowledge of two analysts covering the same firm is mutually exposed to each other, analysts' overall knowledge exposure in a focal firm can differ widely when more than two analysts cover the firm. These differences in exposure are illustrated by the three analysts in Figure 1 who cover the focal firm *1**. Recall that analyst *A* has greater MPC on firm *1** than *B* and *C*. Note, too, that analyst *A* can be observed by rival *B* on firm *2* and by rival *C* on firm *3*. By contrast, analyst *B* (*C*) is not observed by rivals on firm *5* (*4*). Thus, the greater exposure of high MPC analysts makes their knowledge appear more salient to

[6] For example, in 2007 a once obscure analyst named Meredith Whitney rose to fame for accurately predicting Citigroup's precarious financial position while her rivals' held on to bullish and retrospectively misguided predictions for months (Lewis, April 9 2008).

rivals than the knowledge of lower MPC analysts. Greater exposure also increases the extent to which rivals will evaluate this knowledge as being relevant to their own performance (Goldstone *et al.*, 2005; Rendell *et al.*, 2010; Wisdom *et al.*, 2013).

Second, the differences in forecasting quality suggested by the synergy channel of MPC also play a role in observational learning because lower MPC analysts typically have more to learn from higher MPC analysts than vice versa. To the extent that MPC is positively associated with forecasting quality (as predicted in Hypotheses 1a and 1b), greater MPC on a focal firm increases the likelihood that an analyst is a source of learning for rivals, while lower MPC on a focal firm increases the likelihood than an analyst uses rivals' knowledge to boost their own performance. A similar process is observed in industrial agglomerations, where firms with superior capabilities often have more to lose and less to gain than less capable rivals, who can learn about their products at little to no cost (Shaver *et al.*, 2000).

In summary, greater MPC increases knowledge exposure to rivals and may also indirectly increase the attractiveness of these analysts as a source of learning for rivals. These dynamics introduce a possible downside of MPC. When the focal firm reveals its actual annual earnings, the forecasts of a high MPC analyst may appear undifferentiated from the consensus because the consensus has trailed toward that analyst's position. This leads to the second hypothesis:

> ***H2****:* An analyst's MPC on a focal firm is negatively associated with forecast differentiation on that firm.

Implications for Rivals' Performance

The synergy channel posits that rivals' observational learning may hinder forecasting differentiation for high MPC analysts. This mechanism diverges from extant accounts that attribute a negative association between analysts' MPC and forecast differentiation to mutual forbearance. Prior work has proposed a deterrence channel in which high MPC analysts reduce their investment in a focal firm, resulting in undifferentiated forecasts on that firm (Bowers *et al.*, 2014). By contrast, the synergy channel suggests that lack of differentiation is a byproduct of a directional process of observational learning; that is, lower MPC rivals observe and learn from higher MPC analysts. The competitive deterrence channel and the synergy channel can be contrasted empirically by examining how the sudden exit of high MPC analysts from firms' coverage network affected the forecasting accuracy of remaining rivals.[7]

The competitive deterrence channel accommodates two possible effects on rivals' forecasting quality, which depend on whether a firm was located within the departing analyst's sphere of influence or within rivals' sphere of influence (Baum *et al.*, 2016). A central assumption of mutual forbearance is that actors reduce competitive intensity only when a credible threat of retaliation exists (Yu *et al.*, 2013). If the focal firm was within the departing analyst's sphere of influence, the analyst's exit removes the threat of retaliation for remaining rivals, who can then increase their forecasting quality in the focal firm. If instead the focal firm was within rivals' sphere of influence, the departing analyst's exit is of little consequence to the performance of remaining rivals. The deterrence channel, therefore, predicts either a positive effect or a null effect on rivals' forecasting quality from the departure of a high MPC analyst. By contrast, the synergy channel of MPC suggests that remaining rivals would lose an important source of knowledge. Thus, the exit of a high MPC analyst should negatively affect remaining rivals' forecasting quality on a focal firm. This leads to the third and final hypothesis:

> ***H3****:* An analyst's MPC on a focal firm is negatively associated with changes in rivals' forecasting accuracy on that firm after the focal analyst's departure.

METHODS

[7] Hypothesis 3 focuses on forecasting accuracy, which does not depend on rivals' estimates but solely on a focal analyst's estimates relative to the firm's actual earnings.

Data and sample

I extracted unadjusted, detailed files from the Institutional Brokers' Estimate System (IBES) for all available analyst forecasts of annual earnings between 2001 and 2013. The start of the period was chosen because of the *post hoc* changes found in the pre-Reg FD IBES data (Mola *et al.*, 2009). Ljungqvist and colleagues (2009a) documented the improved quality of the IBES dataset after 2000. Following previous research on analysts' forecasts, I excluded stale forecasts issued before the previous year's actual earnings were announced (Loh *et al.*, 2006) and forecasts from anonymous analysts (Fang *et al.*, 2009). I merged the IBES data with accounting and financial data obtained from Compustat and the Center for Research in Security Prices (CRSP). The institutional holdings data source was Form 13F that investment companies and professional money managers are required to file with the U.S. Securities and Exchange Commission (SEC) each quarter (Boldin *et al.*, 2008). I removed stocks with missing returns in CRSP for the corresponding year or that were priced under one dollar at the time of the analyst's estimate (Cohen *et al.*, 2012; Fang *et al.*, 2009). I matched the identity of the analysts ranked by *Institutional Investor* magazine with each analyst's individual code in the IBES dataset using a translation file from Thomson Reuters.

To test Hypothesis 3, I examined the effects of the tragic deaths of 16 analysts who worked in the World Trade Center at Keefe, Bruyette, & Woods, Inc. and Sandler O'Neill + Partners during the September 11, 2001 terrorist attacks. By studying the exogenous changes stemming from this catastrophic event, scholars can shed light on otherwise unobservable causal mechanisms, such as the impact of information asymmetry in asset pricing models (Kelly *et al.*, 2012). I test the effect of these departed analysts' MPC on the firms they were covering at the time of their death on changes to survivors' forecasting accuracy. To be included in the sample, a surviving analyst had to have published pre-9/11 and post-9/11 forecasts on at least one firm in each of two groups: (1) the 173 firms that a victim had covered (i.e., the treatment group) and (2) the 280 firms that had not been covered by any of the victims in the pre-9/11 period (i.e., the control group).

Dependent variables

Forecasting accuracy, information leadership, and differentiation

To test Hypotheses 1a and 1b on analysts' forecasting quality, I followed past work to operationalize (1) forecasting accuracy and (2) information leadership in EPS forecasts. The *Accuracy* variable is simply negative forecasting error for analyst *i* covering stock *k* in year *t*, as proposed by Hong and Kubik (2003):

$$Accuracy = -\left(\frac{|F_{ikt} - A_{kt}|}{P_{kt-1}} \times 10,000\right),$$

where F_{ikt} is the last forecast issued by analyst *i* for firm *k* in year *t* before the firm published its actual earnings, A_{kt}. The absolute difference is scaled by the firm's lagged stock price P_{kt-1} and is multiplied by 10,000 to express the forecast error in terms of basis points.

Information Leadership is calculated as the ratio of the sum of the number of days between each forecast estimate and the dates of the preceding two estimates (X1 and X2) and the sum of the number of days between each estimate and the following two estimates (Y1 and Y2) (Jegadeesh *et al.*, 2010):

$$Information\ Leadership = \frac{\sum_{n=1}^{N}(X1_{ikn} + X2_{ikn})}{\sum_{n=1}^{N}(Y1_{ikn} + Y2_{ikn})},$$

where *n* refers to each forecast issued by analyst *i* on firm *k* in each year *t*. [8]

[8] Analysts tend to adjust their annual forecasts mechanically to reflect the surprise contained in quarterly earnings announcements; these forecast revisions are unlikely to contain new information. I controlled for the tendency of analysts to revise year-end forecasts following the release of quarterly earnings by eliminating forecast revisions that occurred within five days of the quarterly earnings report (Cooper *et al.*, 2001).

The dependent variable for testing Hypothesis 2 is the difference between a focal analyst's annual forecast on a focal firm and the consensus estimate for all analysts covering that firm. I calculate *Differentiation* as follows:

$$Differentiation = \frac{|F_{ikt} - C_{kt}|}{|A_{kt}|}$$

where C_{kt} is the outstanding consensus estimate of all analysts covering firm k at the time firm k reports its EPS numbers for year t. To reduce skewness, I report results using the log of *Accuracy, Information Leadership*, and *Differentiation*, but the main results hold when using the untransformed variables.

The dependent variable for testing Hypothesis 3 is the accuracy of EPS forecasts, as previously calculated, made by 188 surviving analysts on the earnings of 453 firms (173 affected firms and 280 control firms) with a fiscal year ending on 31 December 2001. The pre-9/11 period started in January 2001, when the first annual forecasts were made and ended September 10, 2001. The post-9/11 period started on 9/17/2001 when the markets re-opened and ended when the last firms released their actual earnings in February 2002.

Independent Variables

Multipoint contact

To define analyst i's MPC on firm k, I first define relatedness w_{km} as the number of overlapping analysts between the focal firm k and another firm m ($k \neq m$). Analyst i's MPC on firm k, is a function of k's relatedness with other firms, m:

$$MPC_{ik} = \sum_{k \neq m} (w_{km} - \sigma_{ik})\sigma_{im}, \qquad (1)$$

where σ_{ik} and σ_{im} are binary indicators equal to one (zero otherwise) if the focal analyst covers firm k (m).

In terms of the two-mode analyst–firm network, Equation (1) refers to the number of unique 3-step paths separating each analyst from each firm.[9]

I update analyst–firm MPC annually to reflect coverage changes affecting the focal analyst, the focal firm, rival analysts, or other firms in the analyst's portfolio. Because the range of coverage for firms and the size of an analyst's coverage portfolios vary substantially, adding a 3-step path could be trivial in one instance but could constitute a significant change in another instance. I address this issue by using a percentile ranking approach (Hong *et al.*, 2003). *MPC (percentile)* is the analyst's percentile ranking in the distribution of MPC for all analysts covering a focal firm. *MPC (percentile)* ranges from zero, when the other firms in analyst *i*'s portfolio had the least relatedness to the focal firm *k,* to 1 when the other firms in *i*'s portfolio had the greatest relatedness among all analysts to focal firm *k*.

To test the Hypothesis 3, I constructed the variable *Victim's MPC,* which refers to the departed analyst's pre-9/11 MPC, as previously calculated, on each of the firms they covered. *Victim's MPC* captures the departed analyst's knowledge advantages in the months preceding 9/11, as well as surviving rivals' reliance on this knowledge to guide their forecasts. For treatment firms, *Victim's MPC* has a mean of 0.13 and a standard deviation 0.17 (*Victim's MPC* is zero for firms in the control group, which by definition did not receive coverage from victims).

Control variables

The accuracy, information leadership, and differentiation of earnings forecasts are influenced by analysts' career concerns, as well as by the characteristics of their employers, their clients, and the covered firms (Mehran *et al.*, 2007). To ensure the robustness of my results, I used a comprehensive set of control variables that are known to affect forecasting accuracy, information leadership in forecasts, and forecast

[9] In Appendix B, I show that this relatedness-based definition of MPC is mathematically equivalent to the traditional competitive-overlap-based definition advanced by mutual forbearance scholars.

differentiation. These controls include characteristics of the forecasting environment and heterogeneity in firms and analysts. I also control for the possibility that effects are driven by firms' categorical similarity in the minds of investors using the variable *Categorical coherence*, as calculated in previous work (Zuckerman *et al.*, 2004), as well as the possibility of relational influences between analysts using a measure of contact to *Former colleagues* in a focal firm. Table 1 describes each of these variables and the logic for inclusion.

<INSERT TABLE 1 ABOUT HERE>

To test Hypothesis 3, I created *Post-9/11,* a binary indicator equal to one for the period from 9/11 until the last sampled firm revealed actual annual earnings (17-September-2001 to 22-February-2002) and zero otherwise (10-January-2001 to 10-September-2001). Controls for market volatility (using the VIX index), cumulative stock returns, and average market value were updated weekly. I used average values for the periods before and after 9/11 to control for forecast dispersion and changes in the size of each analyst's portfolio.

Analyses

Hypotheses 1a and 1b predict a positive effect from MPC on forecasting accuracy and information leadership respectively, whereas Hypothesis 2 predicts a negative effect from MPC on forecasting differentiation. I use OLS regressions to test Hypotheses 1a, 1b, and 2. All regressions include highly restrictive Analyst × Firm fixed effects to control for time-invariant, unobserved heterogeneity in the forecasts of specific analysts on specific firms. Various controls, including year fixed effects, further account for the potential impact of market conditions. I report robust standard errors clustered by analyst.

For Hypothesis 3, observed changes in analysts' accuracy for affected firms relative to unaffected firms can be causally attributed to *Victim's MPC* using a difference-in-differences (D-in-D) identification strategy (Angrist *et al.*, 2009; Hong *et al.*, 2010). One of the advantages of the D-in-D strategy is the ability to address endogenous processes that can challenge the causal relationship between MPC and accuracy suggested by Hypothesis 1A. For example, if rivals were to systematically imitate the coverage choices of accurate analysts, this process would result in greater accuracy, causing MPC to increase. Because imitation in coverage choices is typically slow, the sudden, exogenous shock to the coverage network used to test Hypothesis 3 mitigates concerns of reverse causality.

To test H3, I also estimated regressions with restrictive Analyst × Firm fixed effects to control for time-invariant, unobserved heterogeneity and to capture changes net of average forecasting accuracy for each firm–analyst pair. Coefficients reflect changes in accuracy for forecasts a surviving rival issued for firms in the treatment group relative to changes in accuracy for forecasts the *same* surviving rival issued for firms in the control group.

RESULTS

Table 2 displays the descriptive statistics and zero-order correlations for all variables.

<INSERT TABLE 2 ABOUT HERE>

Table 3A displays four models that test Hypotheses 1a and 1b. The sign and direction of control variables align with what has already been documented extensively (Clement, 1999; Clement *et al.*, 2011; Hong *et al.*, 2003; Hong *et al.*, 2000; Irvine, 2004; Loh *et al.*, 2006). The results in Model 2 show a positive effect of *MPC (percentile)* on forecasting accuracy ($p < 0.000$). Forecasting accuracy increases by approximately 8% when an analyst moves from a value of zero to one in the *MPC (percentile)* distribution. Similarly, results in Model 4 (Table 3A) testing Hypothesis 1b, show a positive effect of *MPC (percentile)* on analysts' information leadership on a focal firm ($p < 0.000$). Information leadership increases by about 2.6% when an analyst moves from a value of zero to one in *MPC (percentile)*.

Notably, the effects of *MPC (percentile)* are in the opposite direction of the two control variables that capture an analyst's social embeddedness with rivals (*Former colleagues*) and the employer's social embeddedness via banking deals with firms in the industry (*Banking deals-industry*). The coefficients for these controls suggest that MPC in the analyst–firm network reflects knowledge synergies and information advantages from covering related firms rather than biases that may arise from social influence between former colleagues or from conflicts of interest between an employer's equity research and investment banking functions.

<INSERT TABLE 3A ABOUT HERE>

Channel check

It is important to note that under some conditions, the deterrence channel could also explain a positive relationship between MPC and accuracy. For example, an analyst who believes a focal firm is outside her rivals' sphere of influence may choose to invest greater resources in covering that firm, which can lead to greater accuracy from MPC. This alternative explanation can be evaluated by considering the moderating effect of uncertainty on the relationship between MPC and forecasting accuracy. Uncertainty makes it more difficult to predict how a stock will move. If competitive deterrence were the dominant channel, high uncertainty about a focal firm would weaken the relationship between MPC and accuracy by reducing analysts' and rivals' control over how they perform on a focal firm (i.e., high uncertainty would weaken the feedback loop). If the synergy channel is more important than deterrence, firm uncertainty should strengthen the relationship between MPC and accuracy on a focal firm. This is because the marginal value of having a more related portfolio would be greater when forecasting the earnings of a difficult-to-predict firm.

A measure for firm-level outcome uncertainty used in prior research is analysts' forecast dispersion (e.g., Haunschild, 1994). Dispersion reflects the inherent difficulty of deciphering a focal firm's prospects (Diether *et al.*, 2002; Jackson, 2005; Johnson, 2004). Thus, according to the synergy (deterrence) channel, the accuracy from analyst *i*'s greater MPC should increase (decrease) as a function of the forecast dispersion of focal firm *k*. Table 3B contains results from models that extend Model 2 in Table 3A by adding the interactive effect of forecast dispersion and MPC. The models in Table 3B provide further support for the synergy channel of MPC. The positive effect of *MPC* × *Dispersion* reveals that the benefits of MPC on accuracy increase when forecast dispersion is high ($p = 0.022$). Analysis of marginal effects holding *Dispersion* at its minimum (maximum) level in the sample show a 6% (22%) increase in accuracy when increasing *MPC (percentile)* from zero to one.

<INSERT TABLE 3B ABOUT HERE>

To test Hypothesis 2, which predicts a negative effect of MPC on forecast differentiation, I regressed the independent variables used in Table 3A on *Forecast Differentiation*. Model 2 (Table 4) shows that *MPC (percentile)* has a negative effect on the distance between an analyst's forecast and the consensus estimate ($p = 0.003$). Forecast differentiation decreases by about 3.3% when an analyst moves from a value of zero to one in *MPC (percentile)*. Although MPC is strongly associated with knowledge advantages that enable making accurate forecasts and issuing forecast updates that influence rivals (Models 2 and 4 in Table 3A), this knowledge also attracts rivals' forecasts, making it difficult to differentiate from the consensus estimate (Model 2 in Table 4).

<INSERT TABLE 4 ABOUT HERE>

Hypothesis 3 predicts reductions in surviving rivals' accuracy as a function of the MPC of departed analysts. Table 5 displays models that test the impact on rivals' accuracy of the sudden loss of forecasters with various levels of MPC on each stock. Model 1 in Table 5 displays coefficients for the control variables. Model 2 includes the main effect of the *Post-9/11* period and the interaction with *Victim's MPC*. Model 2 shows that the forecasting accuracy of surviving analysts decreased post-9/11 as a function of victims' MPC on a focal firm (p = 0.045). Differences in marginal effects show that forecasting accuracy for survivors decreased by 84% more when a stock lost a victim who had a value of one for *MPC (percentile)* compared to a stock that lost a victim who had a value of zero for *MPC (percentile)*. The effects of losing analysts in the 9/11 tragedy had a substantial impact on survivors' accuracy for nearly three months.[10] This result points to survivors having established a degree of reliance on the knowledge of high MPC analysts who lost their lives on 9/11.

<INSERT TABLE 5 ABOUT HERE>

Alternative Explanations and Robustness Tests

A possible explanation for the results in Table 5 is that the reduced competition from the exit of analysts from a firm's coverage may have decreased the effort and motivation that surviving analysts exerted on covering the firm after the shock, which can reduce their forecasting accuracy (Hong *et al.*, 2010). To address this alternative explanation, I control for *Competitive intensity*, the average number of unique analysts covering a focal firm, measured at the pre- and post-shock periods (Table 5). *Competitive intensity* accounts for changes from the pre-shock period in the amount of competition that each survivor on each firm in the post-shock period faced. The effect of *Post-9/11* × *Victim's MPC* is robust to including this control variable.

[10] In additional tests, the effects of *Victim's MPC* on survivors' accuracy dampen and disappear if the post-9/11 period is extended to include the subsequent fiscal year, possibly as equity research departments reorganized the coverage of affected firms.

Another possible explanation is that the reduction in forecasting accuracy reflects an increase in aggregate uncertainty in the business environment, which had a sizable hampering effect on corporate investment rates (Kim *et al.*, 2016). In this explanation, the uncertainty in the overall business outlook, rather than the loss of knowledgeable rivals, is the main impediment to survivors' forecasting accuracy. I address this possible explanation empirically by adding a control for the weekly VIX index, a measure of overall market uncertainty. Recent research also suggests that 9/11 may have shifted the preferences and job choices of professional workers (Carnahan *et al.*, 2017). In the present case, it is easy to imagine that the dramatic impact of the tragedy on survivors could have reduced the amount of effort survivors were willing to invest into their forecasts in the months following 9/11. A general decrease in analyst's ability or desire to invest in accuracy would not explain the current findings because my models compare relative changes in accuracy within a specific analyst–firm combination with relative changes for firms in the control group.

The coefficient of interest in Model 2 of Table 5 (*Post-9/11* × *Victim's MPC*) could be driven by yet another alternative process; namely, the accuracy of surviving analysts decreased for firms in the treatment group because less information was available about firms that lost a covering analyst. Because this alternative does not rely on the victim's MPC on the focal firm, I tested this explanation by replacing *Victim's MPC* with an indicator of whether a firm belonged to the treatment group (*Treated firm* = 1) or not (*Treated firm* = 0). If the results are driven by changes in the information available about treatment firms rather than by the victim's level of MPC, the coefficient for the *Treated firm* variable should capture variation in forecasting accuracy better than *Victim's MPC*. This alternative explanation lacks statistical support. The coefficient on the *Post-9/11* × *Treated firm* variable (Table 5, Model 3) is smaller in magnitude and has larger standard errors than the coefficient on *Post-9/11* × *Victim's MPC* (Table 5, Model 2). This result provides additional evidence that the survivors' forecasting accuracy decreased specifically due to the loss of a high MPC analyst.

An assumption of D-in-D models is that the treatment and control groups have parallel trends before the treatment event. If analysts were equally accurate on both groups of firms before 9/11, then resetting the treatment date to an earlier time should not produce significant results. Model 4 (Table 5) tests the parallel trends assumption by replacing 9/11 with 6/01, a date that halves the number of pre-9/11 forecast estimates. The coefficients in Model 4 (Table 5) are reassuring in that the placebo regression does not capture a loss of accuracy in the post-6/01 period from the MPC of future victims, who continued actively forecasting until 9/11.

DISCUSSION

Prevalent accounts of multipoint contact focus almost exclusively on how MPC shapes performance by triggering competitive deterrence. I argue that the feedback loop required for deterrence may be absent in several competitive environments, where MPC nonetheless captures synergies available from participating in related domains. I propose that under these conditions, the association between greater MPC and performance is influenced by the synergies available to an actor competing in domains related to the focal domain. These dynamics generalize to several settings in which related knowledge domains can confer an advantage, including competition for patents in different knowledge domains (Jaffe *et al.*, 2002; Theeke *et al.*, 2017). Although MPC can reflect greater knowledge synergies, under conditions of observability, high MPC actors risk attracting rivals' emulation.

The empirical results support the impact of MPC on three important dimensions of competitive advantage in the equity research setting: (1) the quality of actors' knowledge (H1), (2) the uniqueness of their knowledge (H2), and (3) rivals' reliance on observed knowledge (H3). Greater MPC reflects financial analysts' coverage of firms related more closely to the focal firm, which affords relevant information, facilitates interpretation, and provides incentives to invest in cultivating private sources of firm-specific knowledge. Thus, greater MPC in a firm's coverage network is associated with more accurate and influential earnings forecasts (Table 3A, Models 2 and 4). Similarly, MPC captures a focal analyst's exposure to rivals who can observe and are motivated to learn from the analyst's knowledge about the focal firm. The implied directionality in observational learning hampers high MPC analysts' ability to differentiate forecasts from the consensus estimate (Table 4, Model 2). Rivals tend to rely on the knowledge of high MPC analysts to improve their own forecasts, thereby losing accuracy in the absence of this knowledge (Table 5, Model 2).

The present paper bridges work on MPC with the literature that uses the distribution of competitors across domains to capture relatedness (Bryce *et al.*, 2009; Lien *et al.*, 2009; Neffke *et al.*, 2018; Wan *et al.*, 2011). Although most work in the MPC tradition focuses on the role of MPC in creating mutual forbearance, scholars should be aware that MPC also captures the relatedness of the domains in which an actor competes. In the application to equity research, the synergy channel of MPC provides an overarching theory that can explain the impact of MPC on forecasting quality and forecast differentiation.

More broadly, the present work has implications for theories of evaluation in financial markets. Foundational scholarship in this area has proposed that a focal firm's average MPC (called categorical coherence in that work) captures how well the firm corresponds with investors' categorical schemas (Zuckerman, 2000, 2004; Zuckerman *et al.*, 2004). Rather than ease of categorization, the present work suggests that synergies can explain lower stock volatility (Zuckerman, 2004) and generous valuations (Zuckerman, 1999) afforded to firms when their covering analysts hold highly related portfolios. High average MPC (i.e., high coverage coherence) means that a focal firm is covered by analysts with extensive knowledge about the firm's ecosystem of interdependencies with other firms, including close competitors, critical suppliers, and customers. The ensuing knowledge advantages could enable these analysts to produce earnings forecasts and stock recommendations that investors view as more reliable and less speculative, exerting downward pressure on stock volatility and upward pressure on valuations.

Limitations

The present work sought to establish a synergy channel of analysts' MPC based on evidence from several dimensions of forecasting performance. The panel data methods employed are well suited to this purpose; indeed, they permit modeling exogenous changes to firms' coverage, which would be difficult with approaches that accommodate endogenous network processes, including Stochastic Actor Oriented Models (SAOMs) (Hollway *et al.*, 2017; Snijders *et al.*, 2013; Wang *et al.*, 2013). At the same time, analysts' are known to influence each other's coverage choices (Rao *et al.*, 2001), and the present study's research design does not address questions regarding the endogenous evolution of MPC. Rivals may not be confined to learning from the domain-specific knowledge of high MPC actors, but may also imitate their entry decisions into a domain (Anand *et al.*, 2009; Ethiraj *et al.*, 2008). These endogenous factors may undermine or reinforce the synergy channel, and future work can shed light on the evolution of MPC over time, including factors that lead to convergence and divergence in domain overlap (Stadtfeld *et al.*, 2016).

A second limitation is that the synergy channel of MPC depends on a strategy of related diversification as an important factor guiding competitors' domain selection. For example, the synergy channel would be weakened if most actors followed a strategy of unrelated diversification, because MPC would not capture the underlying relatedness of domains of competition. Relatedness seems to play an important role in the competitive decisions actors make across various knowledge intensive settings (e.g., Giustiziero *et al.*, 2019), but different concerns such as operational efficiencies may matter more than relatedness in other settings. In fact, when the feedback loop is strong, actors may create MPC by seeking out rivals to establish and enforce mutual forbearance (Gimeno, 2002). Further work is required to understand the full influence of MPC, particularly when competitive conditions are likely to activate both competitive deterrence and the synergy channel. A critical challenge will be identifying separate contingencies that can contrast the feedback loop required for competitive deterrence with the requirements of cross-domain synergies.

Much research has examined how MPC shapes performance through competitive deterrence. I extend the meaning of MPC to encompass a synergy channel, which can shape performance even when mutual forbearance is not particularly strong. Although the relatedness of domains captured by an actor's MPC may increase output quality in a focal domain, it can also reduce the ability to differentiate from rivals. The present study provides an initial effort toward understanding these interdependent effects of the synergy channel of MPC.

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Appendix A: From Actor–Domain to Domain–Domain Networks

The distribution of actors across domains of competition, illustrated in Figure 1 for analysts covering firms, is contained in a binary adjacency matrix **X** of *K* domains and *I* actors (dimensions $K \times I$). Each (k, i)th entry in **X** is equal to one if actor *i* competes in domain *k* and zero otherwise. Two different one-mode networks, **W** and **Y,** can be derived from **X** such that all of the information in both **W** and **Y** is contained in **X** (Newman *et al.*, 2002). Let **W** be the domain × domain square symmetric matrix (**W = XX′)** capturing domains' relatedness (this network is illustrated in Figure 2), and **Y** be the actor × actor square symmetric matrix **(Y = X′X)** capturing actors' competitive overlap. Diagonal entries in **W** are the number of actors who compete in domain *k*, and diagonal entries in **Y** denote the total number of domains in which actor *i* competes. Off-diagonal entries in **W** (w_{km}) are the number of common actors competing in a *k*, *m* pair of domains ($k \neq m$); off-diagonal entries in **Y** (y_{ij}) are the number of common domains in which a pair of actors *i* and *j* compete ($i \neq j$).

The transformation of the two-mode network **X** into two one-mode networks **Y** and **W** suggest two alternative definitions of MPC. The traditional definition of MPC used in previous work is based on matrix **Y**, the patterns of competitive overlap between an actor *i* and all rivals competing in *k*. I use a mathematically equivalent definition based on network **W**, which captures the relatedness of *k* to other domains *m* in which actor *i* competes. These two expressions and a proof of their equality are provided in Appendix B.

Appendix B: MPC as Measure of Domain Relatedness

I define MPC as a function of w_{km} which captures the relatedness of *k* to other domains *m* in which actor *i* competes:

$$MPC_{ik} = \sum_{k \neq m} (w_{km} - \sigma_{ik})\sigma_{im} \qquad (1)$$

where σ_{ik}, σ_{im} are binary indicators equal to one if actor *i* competes in domain *k(m)*, and zero otherwise.

In previous work MPC is defined as a function of y_{ij} the competitive overlap between *i* and rivals *j* competing in *k*:

$$MPC_{ik} = \sum_{i \neq j} (y_{ij} - \sigma_{ik})\sigma_{jk} \qquad (2)$$

where σ_{jk} is a binary indicator equal to one if rival *j* competes in domain *k*, and zero otherwise.[11]

[11] In other work this variable is typically normalized by the product of the number of domains in which *i* competes and the number of competitors in domain *k* (Baum *et al.*, 2016; Bowers *et al.*, 2014).

Below I prove that Equation (1) = Equation (2) for any i, k actor–domain pair. First, expand both expressions:

$$(2) = \sum_{i \neq j} (y_{ij} - \sigma_{ik})\sigma_{jk} = \sum_{j=1}^{J} y_{ij}\sigma_{jk} - \sum_{j=1}^{J} \sigma_{ik}\sigma_{jk} - y_{ii}\sigma_{ik} + \sigma_{ik}^2$$

$$(1) = \sum_{k \neq m} (w_{km} - \sigma_{ik})\sigma_{im} = \sum_{m=1}^{M} w_{km}\sigma_{im} - \sum_{m=1}^{M} \sigma_{ik}\sigma_{im} - w_{kk}\sigma_{ik} + \sigma_{ik}^2$$

Note that w_{kk}, the number of actors in $k = \sum_{j=1}^{J} \sigma_{jk}$, and y_{ii}, the number of domains for $i = \sum_{m=1}^{M} \sigma_{im}$

given that $\sum_{j=1}^{J} \sigma_{ik}\sigma_{jk} = w_{kk}\sigma_{ik}$, and $\sum_{m=1}^{M} \sigma_{ik}\sigma_{im} = y_{ii}\sigma_{ik}$, it suffices to show that

$$\sum_{j=1}^{J} y_{ij}\sigma_{jk} = \sum_{m=1}^{M} w_{km}\sigma_{im}$$

$$\sum_{j=1}^{J} y_{ij}\sigma_{jk} = \ldots \begin{bmatrix} 0 \cdots & \overset{i^{th}\text{ element}}{1} & \cdots 0 \end{bmatrix}_{(1\times I)} * X'XX' \begin{bmatrix} 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \end{bmatrix}_{(\mathrm{K}\times 1)} \leftarrow k^{th} \text{ element} \qquad (3)$$

$$\sum_{m=1}^{M} w_{km}\sigma_{im} = \ldots \begin{bmatrix} 0 \cdots & \overset{k^{th}\text{ element}}{1} & \cdots 0 \end{bmatrix}_{(1\times K)} * XX'X \begin{bmatrix} 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \end{bmatrix}_{(I\times 1)} \leftarrow i^{th} \text{ element} \qquad (4)$$

Equation (3) and Equation (4) are transposes of one another that evaluate to a scalar.

Therefore, $\sum_{j=1}^{J} y_{ij}\sigma_{jk} = \sum_{m=1}^{M} w_{km}\sigma_{im} \Rightarrow (1) = (2)$

Q.E.D.

Both Equation (1) and Equation (2) refer to the number of unique three-step paths connecting any actor *i* and any domain *k* in an actor-domain network. The equality of both definitions can be confirmed in Figure 1. For example, there are two unique three-step paths between analyst *A* and focal firm *1*:*

(1) $\mathrm{MPC}_{A1*} = (y_{AB} - \sigma_{A1*})\sigma_{B1*} + (y_{AC} - \sigma_{A1*})\sigma_{C1*} = 1 + 1 = 2$

(2) $\mathrm{MPC}_{A1*} = (w_{1*2} - \sigma_{A1*})\sigma_{A2} + (w_{1*3} - \sigma_{A1*})\sigma_{A3} + (w_{1*4} - \sigma_{A1*})\sigma_{A4} + (w_{1*5} - \sigma_{A1*})\sigma_{A5} = 1 + 1 + 0 + 0 = 2$

Table 1: Control Variables

Level	Variable	Description and Rationale for Inclusion
Year/firm/analyst	*No. revisions*	The natural log of the number of annual forecast revisions an analyst makes for each firm, used to proxy analysts' interest, effort and attention to a stock (Mola *et al.*, 2009).
	Days to actual EPS	The natural log of the number of days from an analyst's last forecast until a company releases its actual earnings. Forecasts closer to the release of actual earnings tend to be more accurate because of the availability of more up-to-date information (Clement, 1999).
	Former colleagues	The percent of rivals with whom an analyst shares any past co-employment, using historical IBES files back to 1983. Controls for possible flows of private information between competing analysts.
	Years covering firm	Number of years since an analyst began covering a specific firm, which has been associated with a lower propensity to herd (Ljungqvist *et al.*, 2009b).
	Banking deals-industry	Amount of annual business (IPOs and SEOs) in a firm's Fama French industry underwritten by an analyst's employer in billions, from SDC Platinum Global New Issues. The volume of banking business in the industry is associated with conflicts of interest that can bias analyst estimates (Jackson, 2005).
Year/firm	*Log Market value*	The natural logarithm of a firm's market value (no. of shares outstanding × share price) at the end of the previous year, which controls for the size of a firm's market presence.
	Cumulative returns	The stock's performance using holding period cumulative returns
	No. of analysts	The number of analysts covering a firm, which controls for the volume of information production (Boehmer *et al.*, 2009).
	Leverage	The ratio of the book value of debt to total capital (debt plus equity), which accounts for variation in a firm's capital structure.
	Institutional ownership (%)	The percentage of outstanding shares institutional investors owned, which influences trading activity and price movements (Loh *et al.*, 2011).
	Institutional ownership (HHI)	A Herfindahl-type index of the concentration of ownership among institutional investors, which can make their impact concentrated or diffuse (Ljungqvist *et al.*, 2007).
	Coverage coherence	The average similarity of the portfolios of all analysts covering a stock, which captures investors' ease of categorizing a firm's stock (Zuckerman, 2004).
	SD earnings	Captures volatility in firm's operations: the std. dev. of the ratio of quarterly operating income before depreciation, divided by average total assets, measured over the 20 quarters before the earnings announcement date (Berkman *et al.*, 2009).
	Forecast dispersion	Standard deviation of EPS forecasts, scaled by the absolute value of analysts' mean forecasts. Controls for uncertainty in the information environment arising from divergent interpretations about a company's future earnings.
	Consensus error	The difference between the actual EPS of firm k in year t and the outstanding consensus estimate of all analysts covering firm k at the time the firm announced its EPS numbers. This variable controls for the average accuracy of the cohort of analysts covering firm k.
Year/analyst	*Portfolio size*	The count of the number of firms an analyst covered in a year, used to proxy for the demands on an analyst's attention (Mikhail *et al.*, 1997).

	Employer size	The total number of analysts employed at the same organization as a focal analyst. Larger equity research departments can provide more resources to support an analyst's research.
	Ranked analyst	A binary variable coded as 1 if an analyst was ranked in the prior year's edition of *Institutional Investor (I.I.)* (0 otherwise). Ranked analysts tend to be more accurate forecasters (Stickel, 1992) and also elicit more attention from rivals.

Table 2. Summary Statistics and Correlations (2001-2013)

	Mean	SD	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
1. Forecasting accuracy	-3.30	1.78																					
2. Information leadership	0.72	0.48	0.03																				
3. Differentiation	0.99	0.90	-0.41	-0.01																			
4. Days to actual EPS	4.83	0.62	-0.21	-0.10	0.12																		
5. No. revisions	1.51	0.48	0.01	-0.02	0.07	-0.23																	
6. Market value	7.74	1.73	0.29	0.03	-0.07	-0.09	0.14																
7. Leverage	0.36	0.18	-0.04	0.06	0.06	-0.09	0.07	0.26															
8. Cumulative returns	0.14	0.50	-0.01	-0.00	-0.06	-0.00	-0.01	0.03	-0.00														
9. Inst. ownership (HHI)	0.06	0.06	-0.18	-0.01	0.03	0.02	-0.08	-0.42	-0.06	-0.02													
10. Inst. ownership (%)	0.70	0.21	0.10	-0.01	0.04	-0.00	0.12	0.19	0.02	0.02	-0.36												
11. No. of analysts	17.38	10.58	0.17	-0.00	0.02	-0.06	0.16	0.72	0.08	-0.02	-0.32	0.20											
12. Coverage coherence	0.18	0.10	0.06	0.03	0.02	-0.09	0.16	0.36	0.27	0.01	-0.13	0.12	0.31										
13. SD earnings	0.06	0.05	-0.08	-0.02	0.04	0.04	0.00	-0.13	-0.29	0.02	0.11	-0.03	-0.02	-0.12									
14. Consensus error	0.13	0.25	-0.49	-0.01	0.36	0.15	-0.02	-0.16	0.03	-0.10	0.09	-0.04	-0.11	-0.04	0.01								
15. Forecast dispersion	0.22	0.32	-0.31	-0.01	0.33	-0.04	0.05	-0.22	0.01	-0.03	0.13	-0.05	-0.08	-0.04	0.06	0.32							
16. Portfolio size	16.86	8.77	-0.01	0.00	0.04	-0.04	0.10	0.02	0.09	0.02	0.02	-0.05	-0.03	0.09	-0.06	0.01	-0.00						
17. Years covering firm	4.14	3.85	0.04	0.02	-0.01	-0.01	0.16	0.22	0.13	0.01	-0.11	0.08	0.12	0.18	-0.08	-0.03	-0.06	0.15					
18. Banking deals (industry)	0.28	1.26	-0.01	0.01	0.03	-0.03	0.04	0.05	0.05	-0.01	-0.01	-0.01	0.02	0.07	-0.03	0.01	0.02	0.07	0.01				
19. Former colleagues	0.04	0.08	-0.06	0.00	-0.02	0.05	-0.15	-0.13	0.01	0.00	0.14	-0.12	-0.13	-0.01	-0.01	0.04	0.04	0.01	-0.02	0.01			
20. Employer size	66.05	61.87	0.05	0.09	0.00	-0.03	0.07	0.16	0.10	-0.04	-0.06	0.04	0.07	0.19	-0.05	-0.01	-0.02	0.06	0.04	0.16	0.03		
21. Ranked analyst	0.13	0.33	0.04	0.05	-0.01	-0.05	0.13	0.16	0.10	-0.00	-0.05	0.04	0.07	0.18	-0.04	-0.02	-0.02	0.17	0.19	0.11	0.01	0.42	
22. MPC (percentile)	0.51	0.31	0.02	0.04	-0.01	-0.03	0.17	0.00	-0.00	0.00	0.00	-0.00	0.00	-0.01	0.00	-0.01	0.00	0.39	0.14	0.07	0.07	0.20	0.26

Note. 382,383 observations for 8,549 analysts covering 5,513 firms

Table 3A: The Impact of Analyst–Firm MPC on Analysts' Forecasting Quality

	Model 1	Model 2	Model 3	Model 4
	Forecasting Accuracy		Information Leadership	
Days to actual EPS	-0.450	-0.450	-0.087	-0.087
	(0.006)	(0.006)	(0.002)	(0.002)
No. revisions	-0.047	-0.050	-0.064	-0.065
	(0.007)	(0.007)	(0.003)	(0.003)
Market value	0.565	0.566	-0.009	-0.009
	(0.011)	(0.011)	(0.003)	(0.003)
Leverage	-0.480	-0.479	0.016	0.016
	(0.036)	(0.036)	(0.013)	(0.013)
Cumulative returns	-0.334	-0.335	0.000	0.000
	(0.007)	(0.007)	(0.002)	(0.002)
Inst. ownership (HHI)	-0.717	-0.715	0.005	0.006
	(0.154)	(0.154)	(0.048)	(0.048)
Inst. ownership (%)	0.242	0.243	-0.052	-0.051
	(0.048)	(0.048)	(0.015)	(0.015)
No. of analysts	-0.009	-0.009	0.001	0.001
	(0.001)	(0.001)	(0.000)	(0.000)
Coverage coherence	-0.285	-0.221	-0.144	-0.122
	(0.074)	(0.076)	(0.027)	(0.028)
SD earnings	0.418	0.415	0.030	0.029
	(0.153)	(0.153)	(0.046)	(0.046)
Consensus error	-2.067	-2.067	0.019	0.019
	(0.022)	(0.022)	(0.005)	(0.005)
Forecast dispersion	-0.208	-0.208	0.002	0.002
	(0.014)	(0.014)	(0.004)	(0.004)
Portfolio size	0.003	0.001	0.001	0.000
	(0.001)	(0.001)	(0.000)	(0.000)
Years covering firm	-0.092	-0.092	0.003	0.003
	(0.002)	(0.002)	(0.001)	(0.001)
Banking deals–industry	-0.013	-0.013	-0.002	-0.002
	(0.005)	(0.005)	(0.002)	(0.002)
Former colleagues	-0.372	-0.394	-0.020	-0.028
	(0.063)	(0.064)	(0.020)	(0.020)
Employer size	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Ranked analyst	0.040	0.037	0.009	0.008
	(0.016)	(0.016)	(0.008)	(0.008)
MPC (percentile)		0.076		0.026
		(0.018)		(0.007)
Constant	-4.210	-4.236	1.294	1.285
	(0.097)	(0.097)	(0.032)	(0.032)
F test (against base model)		17.45		13.67
		Prob > F = 0.0000		Prob > F = 0.0002

Notes.

Based on 324,266 observations (2001- 2013).
All models include (analyst × firm) fixed effects as well as year fixed effects.
Robust standard errors clustered by analyst in parentheses.

Table 3B: Firm Uncertainty Moderates the Impact of MPC on Forecasting Accuracy

	Model 1	Model 2
Days to actual EPS	-0.450	-0.450
	(0.006)	(0.006)
No. revisions	-0.050	-0.050
	(0.007)	(0.007)
Market value	0.566	0.566
	(0.011)	(0.011)
Leverage	-0.479	-0.479
	(0.036)	(0.036)
Cumulative returns	-0.335	-0.335
	(0.007)	(0.007)
Inst. ownership (HHI)	-0.715	-0.715
	(0.154)	(0.154)
Inst. ownership (%)	0.243	0.243
	(0.048)	(0.048)
No. of analysts	-0.009	-0.009
	(0.001)	(0.001)
Coverage coherence	-0.221	-0.221
	(0.076)	(0.076)
SD earnings	0.415	0.413
	(0.153)	(0.153)
Consensus error	-2.067	-2.067
	(0.022)	(0.022)
Portfolio size	0.001	0.002
	(0.001)	(0.001)
Years covering firm	-0.092	-0.092
	(0.002)	(0.002)
Banking deals (industry)	-0.013	-0.013
	(0.005)	(0.005)
Former colleagues	-0.394	-0.394
	(0.064)	(0.064)
Employer size	-0.000	-0.000
	(0.000)	(0.000)
Ranked analyst	0.037	0.037
	(0.016)	(0.016)
Forecast dispersion	-0.208	-0.258
	(0.014)	(0.025)
MPC (percentile)	0.076	0.056
	(0.018)	(0.019)
MPC x Dispersion		0.093
		(0.041)
Constant	-4.236	-4.226
	(0.097)	(0.097)

F test (against base model)	5.29 Prob > F = 0.0215

Notes.
Based on 324,266 observations (2001- 2013).
All models include (analyst × firm) fixed effects as well as year fixed effects.
Robust standard errors clustered by analyst in parentheses.

Table 4: The Impact of Analyst–Firm MPC on Forecast Differentiation

	Model 1	Model 2
Days to actual EPS	0.175 (0.004)	0.175 (0.004)
No. revisions	0.059 (0.004)	0.060 (0.004)
Market value	-0.099 (0.007)	-0.099 (0.007)
Leverage	0.197 (0.023)	0.196 (0.023)
Cumulative returns	-0.065 (0.004)	-0.065 (0.004)
Inst. ownership (HHI)	-0.040 (0.086)	-0.041 (0.086)
Inst. ownership (%)	0.311 (0.028)	0.311 (0.028)
No. of analysts	0.006 (0.001)	0.006 (0.001)
Coverage coherence	0.059 (0.044)	0.031 (0.046)
SD earnings	0.130 (0.100)	0.131 (0.100)
Consensus error	0.695 (0.013)	0.695 (0.013)
Forecast dispersion	0.393 (0.010)	0.393 (0.010)
Portfolio size	-0.000 (0.001)	0.000 (0.001)
Years covering firm	0.024 (0.001)	0.024 (0.001)
Banking deals–industry	0.009 (0.003)	0.009 (0.003)
Former colleagues	-0.020 (0.037)	-0.011 (0.037)
Employer size	0.000 (0.000)	0.000 (0.000)
Ranked analyst	-0.011 (0.010)	-0.010 (0.010)
MPC (percentile)		-0.033 (0.011)
Constant	0.073 (0.058)	0.084 (0.058)
F test (against base model)		8.98 Prob > F = 0.0003

Notes.
Based on 324,266 observations (2001- 2013)

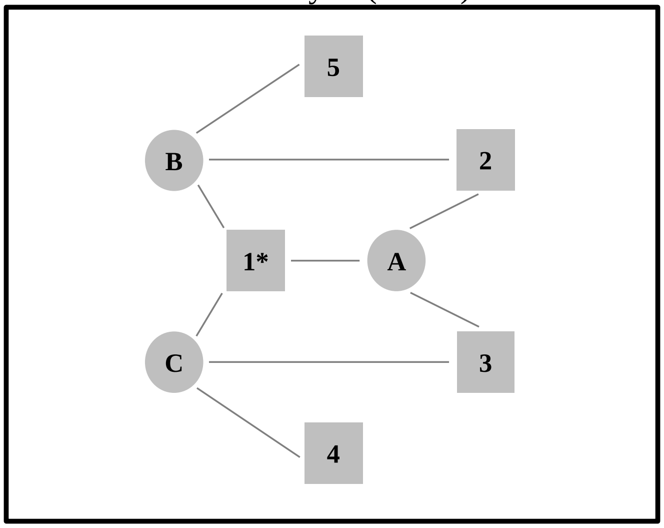
All models include (analyst × firm) fixed effects as well as year fixed effects.
Robust standard errors clustered by analyst in parentheses.

Table 5: Effect of victims' MPC on survivors' forecasting accuracy

	Model 1	Model 2	Model 3	Model 4
Portfolio size	-0.011	-0.012	-0.012	0.029
	(0.005)	(0.005)	(0.005)	(0.007)
Weekly avg. market value	0.462	0.478	0.479	0.166
	(0.145)	(0.146)	(0.150)	(0.125)
Weekly market uncertainty	-0.060	-0.060	-0.060	0.043
	(0.009)	(0.009)	(0.009)	(0.008)
Weekly cumulative returns	-0.367	-0.391	-0.378	0.930
	(0.512)	(0.507)	(0.511)	(0.654)
Monthly dispersion	0.063	0.062	0.057	0.206
	(0.279)	(0.285)	(0.282)	(0.329)
Competitive intensity	0.061	0.056	0.059	0.151
	(0.021)	(0.021)	(0.021)	(0.032)
Post 9/11 period	1.433	1.480	1.502	
	(0.092)	(0.094)	(0.113)	
Post 9/11 x Victims' MPC		-0.610		
		(0.297)		
Post 9/11 x Treated stock			-0.122	
			(0.092)	
Post 6/01 period				0.816
				(0.146)
Post 6/01 x Victims' MPC				-0.422
				(0.521)
F-statistic	58.72	52.90	53.46	17.87
Adj. *R*-squared	0.663	0.663	0.663	0.555

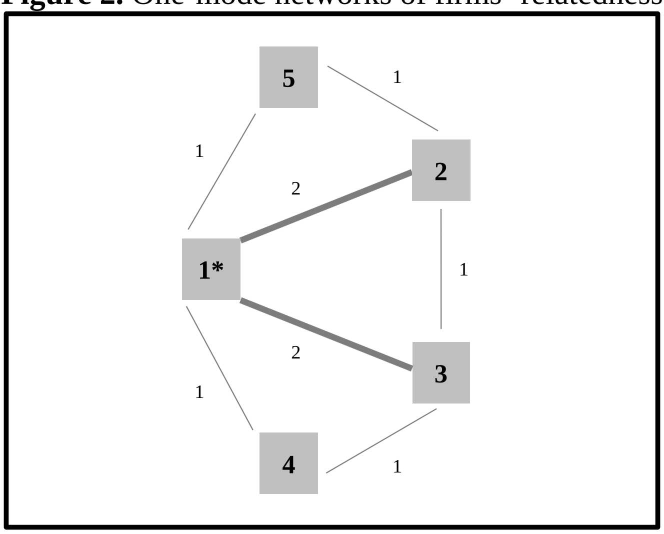
Note.
N = 3,240 observations for 188 analysts and 453 firms.
Includes forecasts issued between January 2001 and February 2002.
All models include 1,620 (analyst × firm) fixed effects.
Robust standard errors with two-way clustering in parentheses (week of forecast and analyst × firm panel).

Figure 1. Two-mode network of analysts (circles) and covered firms (squares)



Note. Ties represent that an analyst covers a firm.

Figure 2. One-mode networks of firms' relatedness



Note. Tie thickness and weights correspond to the number of analysts each pair of firms has in common.

Multipoint Contact Without Forbearance? How Coverage Synergies Shape Equity Analysts' Forecasting Performance

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Abstract

Research Summary: Scholars regularly use multipoint contact (MPC) to explain how encountering rivals in different domains shapes performance. While most explanations rely on mutual forbearance theory, I propose that competitive deterrence does not adequately explain how MPC shapes performance in knowledge intensive work and argue instead that cross-domain synergies may play a central role. I examine how security analysts' MPC with publicly traded firms captures synergies in their coverage portfolio, which improves forecasting accuracy and information leadership. The advantages of greater MPC for a focal analyst are counterbalanced by rivals' observational learning, which reduces the focal analyst's forecasting differentiation. A natural experiment helps corroborate my argument: rival analysts' forecasting accuracy dropped for firms in which high MPC analysts perished in the terrorist attack on September 11, 2001.

Managerial Summary: Competition in the knowledge economy often unfolds across multiple domains including product markets, geographic locations, and customer segments. In these settings, an actor's level of multipoint contact (MPC) in a domain captures the knowledge and other synergies available to the focal actor, which can improve performance in the domain. In the equity research setting, an analyst's MPC on a focal firm captures the likelihood that the analyst also covers that firm's suppliers, customers and important competitors. Using data on analysts' forecasting performance between 2001 and 2013, I find that greater levels of MPC on a focal firm predicts greater forecasting accuracy and information leadership but also lowers forecasting differentiation by attracting rivals who observe and benefit from the focal analyst's knowledge.

KEYWORDS
analysts, multipoint contact, mutual forbearance, relatedness, networks