© Academy of Management Journal
2020, Vol. 63, No. 3, 637–659.
https://doi.org/10.5465/amj.2018.0397

RIVALS' NEGATIVE EARNINGS SURPRISES, LANGUAGE SIGNALS, AND FIRMS' COMPETITIVE ACTIONS

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Research in competitive dynamics has primarily analyzed how characteristics of observable attacks influence firms' competitive responses. Why and how firms take action in response to critical events that affect their rivals, without being attacked themselves, is less well understood. Focusing on negative earnings surprises, we argue that a focal firm is likely to view a rival's negative earnings surprise as an opportunity to exploit its vulnerability. Therefore, such surprises are positively associated with the intensity of competitive actions initiated by a focal firm. Furthermore, the complexity and vagueness of a rival's language in an earnings conference call strengthens the positive relationship between the negative earnings surprise and the focal firm's intensity of competitive actions. We tested our arguments using data from 3,202 earnings releases and conferences calls of publicly listed firms between 2003 and 2014 in the United States. The results and robustness checks support our predictions.

The literature on competitive dynamics is anchored on the concept of competition as a dynamic process in which firms pursue competitive advantage to achieve higher performance that is subsequently eroded by their rivals' competitive actions. Thus, competition can be seen as a contest in which "firms constantly undertake offensive and defensive actions in their struggle for competitive advantage" (Chen & MacMillan, 1992: 539). Building on this conceptualization, a large body of work has focused on the basic building block of competition—the competitive action–response dyad (for a review, see Smith, Ferrier, & Ndofor, 2001). A central finding of these studies is that the most salient trigger of a firm's competitive actions is an attack by its rivals. This is because, in competitive contexts characterized by significant strategic interdependence among firms (as in oligopolistic settings), a firm's ability to create and capture value is directly affected by the competitive actions of its rivals. In such contexts, firms are motivated to react to attacks because not doing so might lead to erosion of their market position and profitability (Chen & MacMillan, 1992).

Accordingly, competitive dynamics research has mostly focused on attributes of observable attacks as predictors of competitive responses (Chen & Miller, 1994; Smith, Grimm, Gannon, & Chen, 1991; Yu & Cannella, 2007). Far less understood is when and how firms take action in response to critical events that affect their rivals, even without being attacked themselves (for a notable exception, see Uhlenbruck, Hughes-Morgan, Hitt, Ferrier, & Brymer, 2017). Yet, there is ample anecdotal evidence of such actions. For example, in August 2003, the day after Hewlett-Packard revealed disappointing earnings, Dell, its biggest rival in the PC market, immediately announced an across-the-board price cut (Huddleston, 2014). Similarly, when Kmart, a long-time rival of Walmart in the U.S. retail industry, filed for bankruptcy in January 2002, Walmart quickly imitated Kmart's Martha Stewart product line to add additional pressure to its rival (Constance, 2003).

To address this gap, in this paper we investigate the role of a critical event as a trigger of competitive actions: negative earnings surprises. Specifically, we focus on how negative earnings surprises that befall a rival affect a publicly traded firm's competitive action intensity in oligopolistic markets, even when the focal firm is not under attack by the rival. *Earnings surprises* refer to deviations in a firm's realized earnings from security analysts'

We are grateful to Bert Cannella, Jason Shaw, Yu Zhang, Associate Editor Marc Gruber, three anonymous reviewers, and various seminar participants for helpful comments and suggestions. This work was supported by the Research Grants Council of Hong Kong's General Research Fund (PolyU 255060/15B). The authors contributed equally to this paper.

consensus estimates (Degeorge, Patel, & Zeckhauser, 1999). Positive earnings surprises occur when the earnings surpass estimates and negative earnings surprises occur when they fall short. Security analysts' earnings forecasts represent an important performance target that publicly traded firms are expected to meet, as these predictions help investors evaluate a firm's stock value (Pfarrer, Pollock, & Rindova, 2010).

We hypothesize that a rival's negative earnings surprise will be positively associated with the intensity of competitive actions initiated by a focal firm. By competitive action intensity, we refer to the total volume of competitive actions a focal firm initiates against its rival in a given time period (Ferrier, Smith, & Grimm, 1999). Building upon the awareness–motivation–capability (AMC) perspective, we argue that as a highly public event (*awareness*), a rival's negative earnings surprise will open an invaluable window of opportunity for the focal firm to improve its market position. A rival firm stricken by a negative earnings surprise is less likely to challenge a focal firm's competitive moves because the urgency of meeting financial market expectations in the short run outweighs the importance of maintaining its competitive position in the long run (Zhang & Gimeno, 2010), hence increasing the focal firm's incentive (*motivation*) to act. Additionally, a rival firm's negative earnings surprise may trigger significant changes and instability in its strategy and top management, create complications and challenges to its internal coordination and organizational realignment, decrease its market value, and sharply increase its cost of capital (Gentry & Shen, 2013; Zhang & Gimeno, 2010). As a result, such an event will tilt the pre-surprise resource balance between the rival firm and the focal firm, making the focal firm a more potent competitor (*capability*) relative to the rival firm (Uhlenbruck et al., 2017). This may further incentivize the focal firm to take advantage of the troubled rival.

Moreover, drawing upon the communication literature (e.g., Li, 2008, 2010; Miller, 2010), we argue that *how* the rival firm communicates its negative earnings surprise will also affect the focal firm's intensity of competitive actions. The basic premise of our argument is that the way in which managers of a rival firm discuss their negative earnings surprises shapes the degree of vulnerability perceived by the focal firm, and thereby its propensity to take competitive actions. The more vulnerability the focal firm can detect through the language used by the rival in corporate communications following a negative earnings surprise, the more likely the focal firm is to act.

Specifically, we argue that when rivals do not use plain language in their public communications following the announcement of a negative earnings surprise, this managerial choice sends an important signal to the focal firm about the rivals' intention to obfuscate their weaknesses. The use of plain language, or "clear, straightforward expression," is the hallmark of communication effectiveness (Eagleson, Jones, & Hassall, 1990: 2); it is typically characterized by two attributes: simplicity and clarity (Eagleson et al., 1990; Kimble, 2002, 2012). Accordingly, we focus on the use of complex language (the lack of simplicity) and vague language (the lack of clarity) to investigate rivals' efforts to avoid using plain language. Research has found that managers have a tendency to use complex and vague language to hide adverse information about their firms when their performance is poor (Li, 2008; Matsumoto, Pronk, & Roelofsen, 2011). A rival firm's use of more complex and vague language can thus be viewed as an indicator of greater underlying vulnerability, motivating the focal firm to take more competitive actions. Thus, we hypothesize that the complexity and vagueness of a rival's language in an earnings conference call will strengthen the positive relationship between the rival's negative earnings surprise and the intensity of competitive actions by the focal firm. We test the proposed theory by using quarterly competitor-dyad data on publicly traded firms in the United States between 2003 and 2014. The results and their robustness checks support our predictions.

Our study makes three main contributions. First, it broadens extant competitive dynamics research to consider the important role of language in facilitating firms' competitive decision making, joining a small group of researchers who have recently started to pay attention to the influence of language on competition (e.g., Guo, Yu, & Gimeno, 2017; Porter, 1980; Rindova, Becerra, & Contardo, 2004). Most of these studies have examined how the use of certain language (e.g., vague language) can create uncertainty and difficulty for rivals to understand the competitive arena and thus reduce the intensity of competitive actions and responses. In contrast, our study shows that in specific situations (i.e., after a negative earnings surprise) the use of the same type of language (e.g., vague language) might also lead to higher competitive intensity because such linguistic cues may enable rivals to detect more vulnerability from the communicating firm. Second, our study highlights how critical events may affect cross-rival competitive behavior, extending the literature on critical events (e.g., Yu, Sengul, & Lester, 2008). To our knowledge, Uhlenbruck et al.'s (2017) study on the cross-rival effects of mergers and acquisitions is the only other competitive dynamics study in this domain. Departing from their work, we explore the cross-rival effects of negative earnings surprises and incorporate language use as an important contingency in our theoretical model. Lastly, this study contributes to the existing literature on how investment analysts and capital markets influence firm behavior and performance (e.g., Benner, 2007; Brauer & Wiersema, 2018; Zhang & Gimeno, 2010). Our study shifts attention from how missing its earnings targets may influence a firm's *own* strategy (e.g., Gentry & Shen, 2013) and future prospects (e.g., Pfarrer et al., 2010) to how such earnings surprises may influence its *rivals'* strategies. It is important to note that one recent study has examined such cross-rival effects focusing on earnings *pressure* (Zhang & Gimeno, 2010). Our research goes beyond this study by examining earnings *surprises* instead, delving deeper into the underlying processes that may govern the influence of capital markets on firms' competitive behavior.

THE AMC PERSPECTIVE AND FIRMS' COMPETITIVE ACTIONS

Since the inception of competitive dynamics as a field of research, understanding factors that trigger competitive actions and responses has been of paramount importance to researchers. The AMC framework suggests awareness, motivation, and capability as three drivers of competitive actions and responses (Chen, 1996; Smith et al., 2001). According to this framework, the level of awareness affects the extent to which a firm notices and understands the outcomes of its own actions and those of its rivals (Chen, 1996). Awareness of rivals without motivation to act, however, is unlikely to yield competitive actions. As expectancy theory (Vroom, 1964) highlights, there are two basic conditions that underlie the propensity to act: the value of the perceived reward from taking the action and the expected probability of obtaining that reward. Thus, "the motivation to retaliate will be greatest . . . when the firm feels that something important is at stake" (Chen & Miller, 1994: 86). Lastly, heterogeneous resources and capabilities are important for firms that strive for competitive advantage (Dierickx & Cool, 1989; Peteraf, 1993). Therefore, if the resources and capabilities for taking action are not available, the firm may not take action, or may delay doing so.

Previous studies, drawing insights from the AMC framework, have demonstrated that a firm's propensity to take competitive action is a function of a variety of factors. These include (1) characteristics and conditions of the focal firm, such as its age, size, past performance, and slack (e.g., Ferrier, 2001; Ferrier, Fhionnlaoich, Smith, & Grimm, 2002); (2) attributes of the competitive environment, such as the degree of industry growth and concentration (e.g., Ferrier, 2001; Young, Smith, & Grimm, 1996); and (3) attributes of the attacks and their initiators, such as the number of markets affected by an attack and the capital investment required to respond to it (Chen & MacMillan, 1992; Yu & Cannella, 2007). Yet, the current literature has stopped short of examining whether and how firms react competitively to changes in rivals' situations resulting from critical events.

Applying the AMC framework, we expect that firms will take competitive actions to capitalize on the opportunity resulting from critical events that debilitate their rivals. To derive empirically testable predictions based on our theory, we focus in the remainder of the paper on a highly salient and observable event: the announcement of a negative earnings surprise by the focal firm's rival.

NEGATIVE EARNINGS SURPRISES AND COMPETITIVE DYNAMICS

A negative earnings surprise occurs when a publicly traded firm announces earnings less than the consensus forecast of security analysts (Degeorge et al., 1999). Because the financial community highly values the expertise of security analysts, investors and fund managers commonly rely on their opinions to evaluate firms' performance (Burgstahler & Dichev, 1997; Kinney, Burgstahler, & Martin, 2002). Consequently, when a firm fails to meet the benchmark set by analysts, investors tend to react strongly and negatively: the firm's stock price declines (Skinner & Sloan, 2002), its cost of capital increases (Mikhail, Walther, & Willis, 2004), and its analyst coverage and stock ownership shrink (Barron, Byard, & Yu, 2008; Skinner, 1994; Williams, 1996). Putting the magnitude of these changes in perspective, missing earnings forecasts by 1% has been shown to be associated with a negative abnormal stock market return of 5% for value stocks and 15% for growth stocks (Skinner & Sloan, 2002).

In a context that embodies uncertainty, asymmetric information, and imperfect observability of managerial actions, negative earnings surprises result from the complex and dynamic interactions between analysts and managers (Zhang & Gimeno, 2010). There are many reasons why negative earnings surprises occur. Examples include lower-than-expected performance (Kilgore, 2017), expensive new project development (Shwiff, 2008), unsuccessful overseas expansions (The Wall Street Journal, 2008), economic downturns

(Pfarrer et al., 2010), and egregious errors in analysts' earnings forecasts (Barron et al., 2008).

Regardless of the reasons behind negative earnings surprises, there are two main explanations for investors' adverse reactions to them (Degeorge et al., 1999; Graham, Harvey, & Rajgopal, 2005; Zhang & Gimeno, 2010). First, investors use information from current earnings to evaluate firms' long-term value. Second, they take into account the fact that management has an incentive to meet earnings forecasts. There is ample empirical evidence that managers seek to avoid reporting losses and earnings decreases (e.g., Burgstahler & Dichev, 1997). Therefore, investors may perceive the firm's inability to meet earnings forecasts as an indicator of some severe underlying problems (Stein, 1989). While positive earnings surprises are perceived as "a little bit of good news," negative earnings surprises are perceived as an "extreme amount of bad news" (Brown, 2001).

Beyond the reactions of investors and the stock market, a firm's negative earnings surprise has important internal consequences. First, it may trigger significant instability in the firm's top management team. Although factors not entirely under management's control are often the cause of negative earnings surprises, CEOs nevertheless are frequently blamed for performance that fails to meet expectations. As a result, the likelihood that a CEO will be replaced increases significantly when her or his firm reports earnings disappointments (Farrell & Whidbee, 2003; Puffer & Weintrop, 1991). Given that the CEO usually assembles the top management team, a new CEO often means a new team. Second, the pressures that result from negative earnings surprises may shift the attention of managers from strategic commitments vital to a firm's long-term competitiveness to choices and actions calculated to boost its short-term earnings. In fact, in a survey of CFOs and financial executives, the majority of respondents reported that, in order to meet an earnings target, they would decrease expenditure on advertising and research and development, or delay initiating projects with positive net present value (Graham et al., 2005). Third, negative earnings surprises may trigger shifts in a firm's competitive strategy. For example, Zhang and Gimeno (2010) found that firms facing earnings pressure reduced output. In an industry that embodies oligopolistic output competition (like the U.S. electricity generation industry in their study), this effectively implies an emphasis on margins over volume—a competitively less aggressive posture.

Given these external and internal consequences, and building upon the AMC framework, we expect a negative earnings surprise hitting a focal firm's rival to be positively related to the intensity of the firm's competitive actions. Competitors act only when "they are confident in their ability to mount an effective action. They must believe that they are capable of earning the commensurate rewards" (Chen & Miller, 1994: 87). This cost–benefit calculation when taking competitive actions (see, e.g., Andrevski & Ferrier, 2019) is influenced by a negative earnings surprise.

As discussed above, a negative earnings surprise is likely to result in changes to the rival firm's management, investments, and competitive behavior, all of which contribute significant complications and challenges to its internal coordination and organizational realignment. It may also result in reduced incentives on the part of the rival firm to respond to the focal firm's competitive actions, because the urgency of meeting financial market expectations in the short run outweighs the importance of maintaining its competitive position in the long run (Zhang & Gimeno, 2010). As a result, the negative earnings surprise motivates the focal firm to take advantage of this window of opportunity. Furthermore, a rival's negative earnings surprise disrupts the resource balance between the focal firm and the rival firm, making the focal firm a more potent and capable competitor relative to the rival firm (Uhlenbruck et al., 2017).

Consider the actions of Sprint and T-Mobile as an example. In January 2017, Verizon reported adjusted earnings of 86 cents per share when analysts had expected 89 cents per share. Immediately after the announcement, competitors T-Mobile and Sprint took swift action to create "a competitive challenge" for Verizon, according to Dave Heger, a senior equity analyst with the Edward Jones investment firm; Heger further noted that "both T-Mobile and Sprint are getting more aggressive" because Verizon's negative earnings surprise offers them "a great window of opportunity to pick up customers" (Snider, 2017). Hence, we hypothesize that:

Hypothesis 1. A rival's negative earnings surprise will be positively associated with the intensity of competitive actions initiated by a focal firm.

The Moderating Role of Communication of Earnings Surprises

The true vulnerability of a firm is difficult to assess because competitors usually avoid revealing their weaknesses directly to each other. Often, firms have to infer from a rival's observable behaviors or verbal a rival's weaknesses from its observable behaviors or verbal statements (Moore, 1992). Although a rival's actions typically carry more weight than its verbal statements, waiting to see what the rival does and then responding to this can put a firm at a disadvantage. Thus, managers will be attentive to rivals' communications when evaluating their competitive positions and capabilities (Gao, Yu, & Cannella, 2017; Guo et al., 2017; Moore, 1992; Rindova et al., 2004). Although scholars have started to examine how language can be used strategically by firms to increase the level of uncertainty faced by their rivals (e.g., Guo et al., 2017; Nadkarni, Pan, & Chen, 2019), this literature has yet to consider how a firm can decipher the vulnerability of rivals through the linguistic characteristics of their public communication.

In the case of earnings releases, corporate communication becomes particularly salient. Most public firms hold large-scale telephone conference calls shortly after their earnings releases to help market participants make sense of their recently announced earnings and to provide their outlook for the future. From the firm's perspective, the conference call is a cost-efficient way of mitigating selective disclosure problems by talking to hundreds of market participants simultaneously. From the competitor's perspective, conference calls can be a vital source of information to infer the strengths and weaknesses of the communicating firm because they are not only highly public, but also highly credible. The pertinent question for our theoretical model is: Which characteristics of communication used during conference calls are most likely to signal rivals' vulnerability after these rivals miss analysts' forecasts?

Drawing from the communication research in psychology, political science, accounting, and finance, we focus on one important type of language that has been widely recognized as the hallmark of communication effectiveness: plain language, which refers to "clear, straightforward expression" (Eagleson et al., 1990: 2). Plain language makes communication more effective because it has clear one-to-one mapping in its meanings (Russell, 1923; Zhang, 2011) and it requires less time and cognitive effort to process and understand (Flesch, 1979; Shockley & Fairdosi, 2015). Due to its effectiveness, an initiative by President Nixon and the U.S. government to promote the use of plain language in 1972 has become a widely accepted practice of governments (Kimble, 2012; McKinley, 1998; SEC, 1998), legal professionals (Burton, 2018; Garner, 2013), and educators (Eagleson et al., 1990) across the globe.

Despite the ever-increasing support for using plain language, business obfuscation has risen exponentially over the last several decades (e.g., Dyer, Lang, & Stice-Lawrence, 2017; Jones & Shoemaker, 1994; Kellaway, 2017). Written and verbal communications by corporations are full of jargon and confusing terms, such as *mission critical*, *turnkey*, and *interoperable*. Prior research has provided ample evidence that the language used in communication is often a strategic choice by managers. For instance, managers may manipulate their language to attribute success to their own brilliance and problems to external environments in order to sound more competent and in control (Salancik & Meindl, 1984; Staw, McKechnie, & Puffer, 1983), to dodge difficult conversations when scrutinized by analysts (Mayew & Venkatachalam, 2012), and to add uncertainty to their competitors' decision making (Guo et al., 2017; Nadkarni et al., 2019). More importantly, prior studies have found that while managers have no problem using simple and concise language to report good news when their firms perform well (e.g., Schrand & Walther, 2000), they strategically use more complex and vague language to hide adverse information when their firms perform poorly (e.g., Li, 2008; Miller, 2010).

Building on the prior literature that has emphasized simplicity and clarity as two characteristics of plain language and communication effectiveness (e.g., Burton, 2018; Eagleson et al., 1990; Kimble, 2012), we focus on rivals' use of complex (the lack of simplicity) and vague (the lack of clarity) language to capture their efforts to avoid using plain language. We expect that the likelihood that a focal firm will take competitive actions in response to a rival's negative earnings surprise will increase when the rival firm's managers use more complex and vague language in their earnings conference call after a negative earnings surprise. This is because, applying the AMC logic, the use of vague and complex language will enhance the rival firm's perceived vulnerability to the focal firm and, as a result, the focal firm will be more motivated and confident in its ability to launch successful attacks.

It is important to note that although both complex and vague language enhances the rival firm's perceived vulnerability to the focal firm, these two language forms do so via different mechanisms: complex language reduces communication effectiveness by increasing the amount of time required to receive, process, and understand information, whereas vague language has the same effect by diminishing the clarity of information presented and increasing the chances of misunderstandings and multiple interpretations.

Complex language. Complex language refers to the use of many different and connected words and sentences to make the content of the communication difficult to understand. It often includes the use of inflated vocabulary, excessive wordiness, and long-winded sentences with multiple subordinate clauses and prepositional phrases (Garner, 2013; Kimble, 2002). The longer the sentence and words in a message, the more ideas audience members have to hold in their minds in suspense until they can make a final decision on what all the words and sentences mean together (Flesch, 1979). As a result, a message with a higher level of linguistic complexity is harder to understand because it requires additional time and cognitive efforts to process and comprehend.

Research in law, political science, accounting, and finance has shown that the complexity of language used in communication is often a strategic choice by the communicator to be more or less forthcoming. For example, members of the U.S. Supreme Court strategically alter the complexity of the language they use to describe their opinions according to the level of political resistance they anticipate (Owens, Wedeking, & Wohlfarth, 2013; Staton & Vanberg, 2008). Similarly, firms tend to use more complex language in corporate communications when their performance is poor (Lang & Lundholm, 1993; Li, 2008; Loughran & McDonald, 2011; Miller, 2010; Schrand & Walther, 2000). Thus, we argue that when managers of a rival firm use complex language after announcing a negative earnings surprise, this managerial choice will serve as an indicator of the rival's greater underlying vulnerability to the focal firm, motivating the focal firm to take more competitive actions. Accordingly, we hypothesize that:

Hypothesis 2. The complexity of a rival's language in an earnings conference call will strengthen the positive relationship between the rival's negative earnings surprise and the intensity of competitive actions by the focal firm.

Vague language. Vague language refers to the use of linguistic devices to make the meaning of communication nonspecific and imprecise (Channell, 1994). It includes, for example, the use of qualifiers before numbers (e.g., *about*, *around*, *nearly*) and the use of approximation terms (e.g., *may*, *could be*, *perhaps*). Also known as "words with blurred edges" (Peirce, 1902: 748), vague language often has one-to-many mappings in its meaning (Channell, 1994; Zhang, 2011). As a result, it puts more demands on the audience to make sense of the information presented (Hiller, 2011). It is important to note that even a noncomplex message can be vague and difficult to understand. For instance, John Chambers, the former CEO of Cisco, once wrote in an email to his employees that "We'll wake the world up and move the planet a little closer to the future" (Kellaway, 2017). While the message is short and not complex, its precise meaning is extremely hard to understand due to the vagueness of the language.

Vague language has been found to decrease precision and hamper interpretation in various settings, such as health care, academic writing, and courtrooms (e.g., Cutting, 2007; Sabet & Zhang, 2015). Prior research has demonstrated that organizations use vague language to conceal their strategic intentions (e.g., Denis, Dompierre, Langley, & Rouleau, 2011; Sillince & Mueller, 2007) and to hide their strengths and weaknesses from their competitors (e.g., Guo et al., 2017; Nadkarni et al., 2019). Thus, just as for complex language, we argue that the choice of vague language in a rival's corporate communications after a negative earnings surprise will serve as an indicator of its greater underlying vulnerability, motivating the focal firm to take more competitive actions. Thus, we hypothesize that:

Hypothesis 3. The vagueness of a rival's language in an earnings conference call will strengthen the positive relationship between the rival's negative earnings surprise and the intensity of competitive actions by the focal firm.

METHOD

Sample

We tested our proposed theory by using quarterly data on publicly listed firms in the United States from 2003 to 2014, inclusive. We gathered this data from four sources: RavenPack News Analytics database (for firms' competitive actions), Thomson Reuters StreetEvent (for transcripts of conference calls), Thomson Reuters I/B/E/S estimates (for firms' quarterly earnings and analysts' consensus forecasts), and Compustat Fundamentals Quarterly (for all remaining firm- and industry-level variables). Reliable data on corporate communication (i.e., transcripts of conference calls) were available starting in 2003, and 2014 was the most recent full year of data at the time of our data collection.

We used four criteria to construct our working sample. First, we focused on dominant-business firms (i.e., firms with 70% or more sales revenue coming from a single four-digit SIC industry). The focus on dominant-business firms is a common practice in the competitive dynamics literature (see, e.g., Chen, 1996; Ferrier et al., 1999), because it is difficult to identify action–response dynamics between diversified firms. Second, we restricted our sample to oligopolistic industries (i.e., industries with a Herfindahl–Hirschman

Index [HHI] between .20 and .60 [Besanko, Dranove, Shanley, & Schaefer, 2002]), in which a few firms account for a relatively large market share and are strategically interdependent. The reason behind this choice is that predicting rivals' actions is particularly important in settings in which one firm's outcomes depend essentially on the decisions of other firms, and vice versa. Third, we excluded firms that were either too small (i.e., not having 5% market share in any year of our observation window) or lacked continuous data. Finally, we dropped instances of simultaneous earnings announcements because it is impossible to distinguish empirically the cross-rival effects of one announcement from another. As a result of this process, we obtained 130 competitor-dyads in 38 industries, corresponding to 3,202 firm–rival-quarter observations with complete information.

Dependent Variable: Competitive Action Intensity

We measured the intensity of competitive action as the total number of tactical competitive actions initiated by a firm in the 90 days after a rival's earnings release.[1] Competitive action refers to externally directed, specific, and observable moves by a firm to enhance its competitive position (Ferrier et al., 1999; Smith et al., 1991). Competitive dynamics research has differentiated between two main types of competitive actions: (1) strategic actions that involve significant resource commitments, such as new market entry; and (2) tactical actions that do not involve significant resource commitments, such as pricing changes (Chen, Smith, & Grimm, 1992; Connelly, Tihanyi, Certo, & Hitt, 2010; Smith et al., 1991). We focused on tactical competitive actions because it is implausible that strategic actions requiring significant resource commitments, and hence relatively long lead times (for operational planning, regulatory permits, financial planning, etc.), would be made in response to a rival's earnings surprise within 90 days.[2]

As in prior competitive dynamics research (Connelly et al., 2010; Ferrier, 2001), we measured tactical competitive actions as the total number of *pricing actions*, *marketing actions*, *product or service improvements*, *minor production adjustments*, and *legal actions* using the RavenPack News Analytics database. RavenPack collects action-level data from 22 different newswires and sources, such as *The Wall Street Journal* and *MarketWatch*. It identifies and classifies news articles into categories of action for more than 36,000 firms, including all of our sample firms (Twedt, 2016). Because the steadily increasing volume of news sources calls for a more automated approach than the manual coding used in prior research (Chen et al., 1992; Smith et al., 1991), RavenPack has been increasingly used in recent research in management (e.g., Connelly et al., 2017; Hayward & Fitza, 2017) and finance (e.g., Hafez, 2011; Kolasinski, Reed, & Ringgenberg, 2013; Twedt, 2016). The average number of tactical actions taken by our sample firms was 2.10. Some firms took no tactical action after a rival's earnings release (the bottom quartile), but others took three or more actions (the top quartile). The number of tactical actions was six or more for the top 10% of firms in our sample.

Independent Variable: Rival's Negative Earnings Surprise

To capture earnings surprises, we calculated the difference between a firm's reported quarterly earnings and security analysts' consensus estimates (i.e., the median forecasted earnings for that fiscal quarter among all analysts who covered the firm). We then scaled this value by the firm's stock price at the end of the previous quarter (Barron et al., 2008; Kasznik & Lev, 1995; Westphal, Park, McDonald, & Hayward, 2012). Consider, for instance, a firm with earnings of $1.50, against a consensus estimate of $1.35, and stock price of $5.00. In this case, the firm would have generated a (positive) earnings surprise of 3% (= (1.5 – 1.35) / 5). Like Kasznik and McNichols (2002) and others, we assumed that an earnings release does not meet expectations and is a "surprise" when the deviation is at least half a percent.

In our analysis, we accounted for the separate and independent effects of negative and positive earnings surprises of a rival on the focal firm. Accordingly, *rival negative earnings surprise* equaled the absolute value of the difference between the rival firm's actual earnings and analysts' consensus estimates—scaled by the rival's stock price at the end of the previous quarter—for all observations in which earnings were lower than consensus estimates and 0

[1] Note that this variable is calculated relative to the time of a rival's earnings release. For instance, if the focal firm had taken two actions that fell within the 90-day window after a rival's earnings release, regardless of whether these actions took place in the same quarter or in different quarters both actions would be counted. There are only 184 instances in our final sample that had fewer than 90 days between rivals' earnings releases. The results were insensitive to their inclusion or exclusion.

[2] We found in a supplementary analysis that the impact of rivals' negative surprises on a focal firm's strategic actions was positive but statistically insignificant. This is in line with our expectation.

otherwise. Defined symmetrically, *rival positive earnings surprise* equaled the absolute value of the difference between the rival firm's actual earnings and analysts' consensus estimates—scaled by the rival's stock price at the end of the previous quarter—for all observations in which earnings were higher than consensus estimates and 0 otherwise. We used the absolute value of the rival firm's deviation from consensus estimates because a focal firm's competitive actions are likely to increase with the magnitude of this deviation.[3]

Moderators

We used rivals' conference calls as the source of communication. These calls are the timeliest and most readily available form of corporate communication after earnings announcements that give the focal firm an opportunity to evaluate its rivals' vulnerability. Over the last two decades, the rapid increase in the use of corporate conference calls by publicly traded companies has made such calls almost a standard method for firms to communicate with financial analysts and investors. Because the aim of these calls is for managers to disclose their current and future plans and offer their explanation of the firm's performance, conference calls are normally held along with earnings releases, typically on the same day, a few hours after the release (e.g., Bushee, Matsumoto, & Miller, 2003; Matsumoto et al., 2011). Moreover, conference calls are accessible to virtually everyone. According to the Regulation Fair Disclosure, publicly traded companies are required to disclose material information to all investors simultaneously. To comply, most public companies release their conference calls through their websites or webcasts for all interested parties to access.

Complex language. We measured the language complexity of conference calls using the Fog Index, one of the most widely used measures of language complexity in prior studies (e.g., Biddle, Hilary, & Verdi, 2009; Dougal, Engelberg, Garcia, & Parsons, 2012; Li, 2008; Miller, 2010; Reilly & Richey, 2011). This measure is based on two aspects of language complexity: average sentence length and number of complex words used (i.e., words containing three or more syllables):

$$\text{Fog Index} = 0.4 \times \left[\left(\frac{total\ \ words}{total\ \ sentences}\right) + 100 \times \left(\frac{Complex\ words}{total\ \ words}\right)\right]$$

The score indicates how many years of formal education a person needs to have in order to understand a message on the first reading. For example, the reading level of a U.S. high school senior will be required for a message with a Fog score of 12. Thus, a wide audience can understand a message that receives a Fog score of 8, but one that scores 18 and above would be incomprehensible to the general public. The following statement with a Fog index of 35.2 by Williams Companies (2003) falls into this category:

> Obviously, we are a different company today than we were a year ago. We have embraced a more conservative and disciplined financial paradigm, and so we are proactively managing cash and we are reducing our costs while employing a more disciplined capital allocation plan, and we are utilizing more balanced financial performance metrics, and we'll be looking at cash and returns on investments and earnings.

As reported in Table 1, the mean of language complexity in our sample was 15.58, meaning that a typical conference call would be appropriate for a junior in college in the United States to understand. About 1% of the conference calls in our sample received a Fog score of over 20, which means that those conference calls were close to incomprehensible.

Vague language. We measured the vagueness of rivals' conference calls using a word-count approach, which has been increasingly recognized and used in management research (e.g., Barr, Stimpert, & Huff, 1992; Guo et al., 2017; Kaplan, 2008; Petkova, Rindova, & Gupta, 2013). This approach captures how prominent a language characteristic is (in our case, vagueness) in a document, conversation, or presentation (in our case, conference calls following earnings releases). Specifically, we follow Guo, Yu, and Gimeno (2017) and calculate language vagueness as a count of vague words and expressions normalized by the total number of words in each conference call to control for call length. We identify vague words and phrases using Hiller's *Communication Vagueness Dictionary*, which contains 362 vague words and expressions on 10 dimensions of vagueness (for a detailed description, see

[3] In (unreported) supplementary analyses, we used (1) dichotomous variables coded 1 for negative earnings surprises if earnings were below the consensus forecast and 0 otherwise (vice versa for positive earnings surprises), and (2) the raw values of the difference between earnings and consensus estimates, unadjusted for stock price. The hypothesized results were qualitatively unchanged in each of these models. As we report in the robustness checks section, the results were also qualitatively unchanged when we used standardized unexpected earnings (SUE) instead.

TABLE 1
Means, Standard Deviations, and Bivariate Zero-Order Correlations

	Variable	Mean	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1.	Firm action intensity	2.10	2.91															
2.	Rival negative earnings surprise	0.01	0.09	0.01														
3.	Rival positive earnings surprise	0.04	0.07	−0.00	−0.09													
4.	Rival complex language	15.58	1.51	−0.05	0.01	−0.02												
5.	Rival vague language	2.72	0.81	−0.03	0.03	−0.02	−0.07											
6.	Firm prior performance	0.06	0.57	−0.01	0.02	0.03	0.03	−0.01										
7.	Firm slack	2.12	1.08	−0.09	−0.02	−0.06	−0.10	0.01	0.01									
8.	Firm action volume	1.62	4.29	0.11	−0.00	−0.02	−0.00	−0.01	0.00	−0.01								
9.	Rival prior performance	0.05	0.54	−0.01	0.02	0.02	−0.02	0.01	0.38	0.01	0.00							
10.	Rival slack	2.07	0.90	−0.12	0.01	−0.03	−0.07	0.07	−0.00	0.17	−0.01	0.02						
11.	Rival action volume	1.92	4.38	0.00	−0.00	−0.00	−0.01	−0.01	−0.00	−0.04	−0.00	0.00	−0.01					
12.	Firm–rival market power similarity	0.67	0.27	−0.03	−0.02	−0.10	0.14	0.00	−0.00	0.09	−0.03	−0.02	0.06	0.03				
13.	Firm–rival size similarity	0.96	0.08	−0.17	0.01	−0.01	0.15	−0.03	−0.00	0.22	0.01	−0.00	0.21	0.01	0.34			
14.	Firm–rival market overlap	0.97	0.07	0.07	−0.01	−0.06	0.04	0.03	−0.01	0.04	0.00	−0.00	0.06	0.00	0.14	−0.02		
15.	Industry concentration	0.32	0.09	−0.02	−0.01	0.07	−0.09	−0.10	0.00	0.10	0.02	−0.00	0.15	−0.01	−0.25	−0.09	−0.15	
16.	Industry growth	0.02	0.28	0.00	0.02	−0.01	−0.02	−0.02	0.00	−0.02	−0.01	0.01	0.01	−0.01	−0.05	0.01	−0.00	−0.01

Notes: $N = 3{,}202$. Correlations with an absolute value greater than 0.03 are significant at $p < .05$.

Hiller, 2011). These include the use of qualifiers before a number to make it less specific (e.g., *about*, *around*, *nearly*), the use of nonnumerical terms to refer to indefinite amounts (e.g., *a couple*, *a little*, *a high rate of*), the use of approximation terms (e.g., *may*, *could be*, *perhaps*), and the use of bluffing terms to shift the responsibility of making sense of the information onto receivers (e.g., *as a matter of fact, in any event, as far as*). Hiller's dictionary was originally developed to analyze university lectures (Hiller, Marcotte, & Martin, 1969) but has since been widely used to detect lack of clarity in communications in many other settings, such as program evaluations (e.g., Wilson & Wineburg, 1993), questionnaire designs (e.g., Ford, Stetz, Bott, & O'Leary, 2000), political speeches (e.g., Hogenraad & Garagozov, 2014), and firms' annual reports (e.g., Guo et al., 2017).

Control Variables

We include a range of control variables in the regressions to account for alternative explanations of competitive action intensity by the focal firm. These variables are chosen largely because they affect one or more dimensions of the AMC framework, as suggested by prior research. Below, we organize our discussion of these variables based on their level of analysis.

At the firm level, we control for *firm prior performance* (measured by lagged return on equity normalized by industry average). Previous studies using the AMC framework have shown that poor past performance motivates firms to take more competitive actions, but good past performance may lead to competitive inertia (Hambrick, Cho, & Chen, 1996; Miller & Chen, 1994). Hence, a firm's past performance is an indicator of its motivation to take competitive action (Ferrier, 2001; Ferrier et al., 2002). In addition, we control for *firm slack* (measured by focal firm's current ratio) to account for organizational slack. Uncommitted financial resources is the buffer of resources that permit organizations to take greater risks and more competitive actions (Cyert & March, 1963). Hence, firm slack, in particular unabsorbed financial slack, is an important indicator of a firm's capabilities to take competitive action, according to prior research using the AMC framework (e.g., Ferrier, 2001; Marcel, Barr, & Duhaime, 2011). We also control for *firm action volume* (measured by the average number of tactical competitive actions that a focal firm took in the previous four quarters). Prior research has shown that firms with a history of intense competitive activity tend to take more competitive actions, and an expectation that rivals with such histories may increase their competitive activity after performance shortfalls motivates a focal firm to act first (Miller & Chen, 1994). Because the firm-level characteristics mentioned above can have cross-rival effects, we control for these firm characteristics in the rival firm as well, as *rival prior performance*, *rival slack*, and *rival action volume*.

At the firm–rival dyad level, we control for three variables: *firm–rival market power similarity*, *firm–rival size similarity*, and *firm–rival market overlap*. According to prior research, market power and size similarity between a focal firm and a given rival affects the level of competitive tension between them. Specifically, according to the AMC framework, the more similar the focal firm is to a rival, the more attention the former will devote to the latter; the more similar the resource endowments of the two firms are, the more motivated they will be in responding to each other's attacks (Chen & Hambrick, 1995; Chen, Su, & Tsai, 2007). We calculate firm–rival market power similarity by 1 minus the absolute difference in market share between the focal and rival firm normalized to a 0–1 range across the sample:

$$\text{Firm-rival market power similarity}_{\text{ij}} = 1 - \frac{|Market\ share_i - Market\ share_j|}{\max\limits_{k,l}|Market\ share_k - Market\ share_l|}$$

The subscripts *i* and *j* refer, respectively, to the focal and rival firms, and *k* and *l* refer to the maximum and minimum values in our sample. Likewise, firm–rival size similarity is calculated by 1 minus the absolute difference in total assets between the focal and rival firm normalized to a 0–1 range across the sample:

$$\text{Firm-rival size similarity}_{\text{ij}} = 1 - \frac{|Total\ assets_i - Total\ assets_j|}{\max\limits_{k,l}|Total\ assets_k - Total\ assets_l|}$$

The firm–rival market power similarity measure takes the value of 0 (minimum similarity) when the difference in market share between two firms equals the maximum difference in our sample, and takes the value of 1 (maximum similarity) when both firms have the same market share. Similarly, the firm–rival size similarity measure takes the value of 0 when the difference in total assets between two firms equals the maximum difference in our sample, and takes the value of 1 when both firms have the same total assets. Finally, as strategic interdependence between two competitors increases with the number of markets in which they are both present (Bernheim & Whinston, 1990), we control for *firm–rival market overlap*, measured by the percentage revenue of the focal firm that comes from markets in which both the focal firm and its rival operate.

At the (four-digit SIC) industry level, we control for two industry characteristics that have been shown to influence a firm's propensity to take competitive action. First, we control for *industry concentration*, which is calculated using a HHI. As well-established by prior research, industry concentration is an important predictor of a firm's competitive behavior (Ferrier, 2001; Scherer & Ross, 1990). Second, we control for *industry growth*, which is calculated as the percentage change in an industry's gross sales between the current and previous quarters. In industries with high growth, rivalry is generally less intense because firms can grow without stealing business from each other (Porter, 1980). In contrast, in low (or negative) growth industries, rivalry is generally more intense because firms are likely to take more competitive actions in order to survive and maintain their competitive positions (Ferrier, 2001).

Table 1 reports the summary statistics and correlations between the variables. In our sample, an average firm had \$2.11 of liquid assets available to cover each dollar of its short-term debt (slack). These firms operated in oligopolistic industries with moderate to high concentrations (average HHI = 0.32), growing on average at 2.3%. Multicollinearity does not appear to be a concern when assessed by variance inflation factors (mean VIF = 3.18). Further, the results remained unchanged when we excluded moderately correlated control variables (e.g., firm–rival prior performance, firm–rival market power and size similarity, and industry concentration).

Estimation

Our dependent variable, firm competitive action intensity, is a count variable. When the dependent variable is discrete and limited to nonnegative values (with many observations having a value of 0), Poisson and negative binomial models are the recommended empirical approaches. We used a random-effects negative binomial model to test our hypotheses. We chose this model for three reasons. First, a Hausman test indicated that it is appropriate to use random-effects in our analyses ($\chi^2 = 46.42$, $p = 0.69$). Second, the superior flexibility of the negative binomial distribution allows the mean and variance to differ. In contrast, a Poisson distribution assumes that the mean and variance are the same. Third, negative binomial models are more appropriate in situations of overdispersion (Cameron & Trivedi, 1986; Hausman, Hall, & Griliches, 1984). The likelihood-ratio test of overdispersion was statistically significant, indicating that our dependent variable was most closely aligned with the negative binomial distribution. Random-effects specification allowed the dispersion parameter (variance divided by the mean) to be the same for each firm–rival dyad, but to vary across dyads according to a β distribution. We included year-quarter and industry fixed effects to account for unobserved heterogeneity across time periods and industries, respectively, and clustered standard errors by firm–rival dyad. We also lagged the control variables by one quarter to alleviate the potential issue of simultaneity.

RESULTS

We hypothesized that rivals' negative earnings surprises are positively associated with the intensity of tactical actions by the focal firm (Hypothesis 1). The regression results reported in Table 2 support this hypothesis: the coefficient of the rival's negative surprise (Model 2) is positive and statistically significant ($p < .05$), as predicted. In terms of economic significance of the results, holding all other variables at their mean values, a one standard deviation increase in negative earnings surprise is associated with an 11.85% increase in the focal firm's tactical competitive actions.

Hypotheses 2 and 3 concern the moderating effects of complex language and vague language, respectively, on the relationship between a rival's negative earnings surprise and the intensity of a focal firm's tactical actions. The regression results support these hypotheses: the coefficients of interaction terms with complex language (Models 3 and 5) and vague language (Models 4 and 5) are both positive and statistically significant, as predicted. As graphed in Figure 1, increases in the use of complex language in rivals' conference calls amplify the impact of rivals' negative earnings surprises on the intensity of focal firms' tactical actions, which is consistent with Hypothesis 2. Similarly, as graphed in Figure 2, increases in the use of vague language in rivals' conference calls amplify the impact of rivals' negative earnings surprises on the intensity of focal firms' tactical actions, which is consistent with Hypothesis 3.

We also found, in a supplementary analysis including a three-way interaction term ($p = 0.006$), that a focal firm's intensity of competitive actions following a rival's negative earnings surprise is likely to be even higher when the language used in the rival's conference calls is *both* complex *and* vague. As we mentioned earlier, although complex

TABLE 2
Random-Effects Negative Binomial Regressions Explaining Firm Competitive Action Intensity

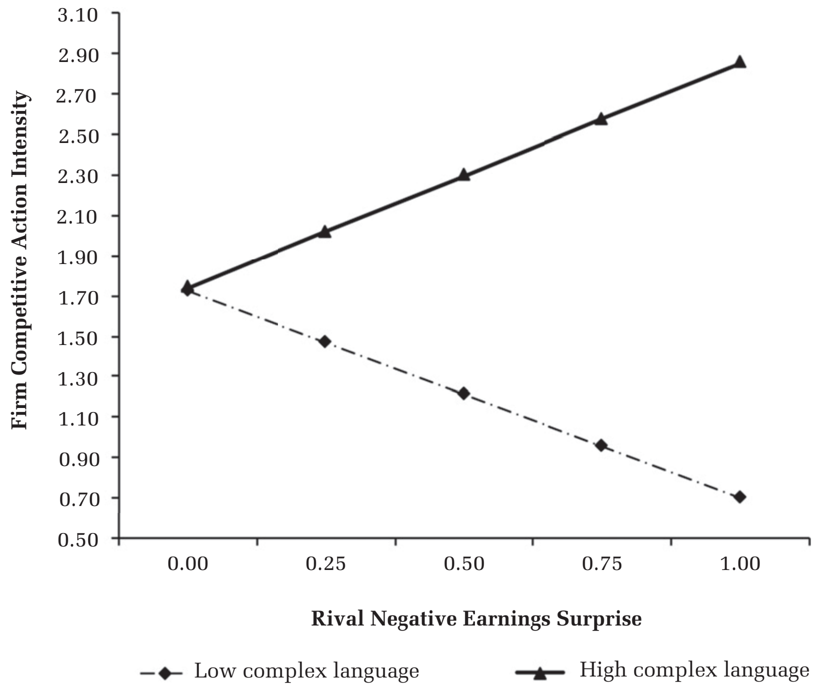
	(1)	(2)	(3)	(4)	(5)
Rival negative earnings surprise		0.29*	−8.89*	0.22*	−10.22*
		(0.14)	(3.76)	(0.11)	(3.53)
Rival positive earnings surprise		0.33	0.26	0.35	0.29
		(0.22)	(0.22)	(0.23)	(0.23)
Rival negative earnings surprise			0.71*		0.81*
× Rival complex language			(0.29)		(0.27)
Rival negative earnings surprise				0.75*	1.36*
× Rival vague language				(0.33)	(0.60)
Rival complex language	0.01	0.01	0.01	0.01	0.00
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Rival vague language	−0.04	−0.04	−0.04	−0.06	−0.07
	(0.08)	(0.08)	(0.08)	(0.08)	(0.07)
Firm prior performance	−0.01†	−0.02†	−0.01†	−0.02†	−0.01†
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Firm slack	0.06	0.06	0.06	0.06	0.06
	(0.12)	(0.12)	(0.12)	(0.12)	(0.11)
Firm action volume	0.03†	0.03†	0.03†	0.03†	0.03†
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Rival prior performance	−0.01*	−0.01*	−0.01*	−0.01*	−0.01*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Rival slack	0.08	0.08	0.09	0.08	0.09
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Rival action volume	0.38**	0.38**	0.38**	0.38**	0.38**
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Firm–rival market power similarity	−0.85	−0.89	−0.94	−0.88	−0.93
	(1.98)	(2.01)	(2.03)	(2.01)	(2.03)
Firm–rival market size similarity	1.38†	1.39†	1.35†	1.39†	1.35†
	(0.76)	(0.77)	(0.78)	(0.77)	(0.78)
Firm–rival market overlap	−0.20	−0.23	−0.23	−0.23	−0.23
	(1.18)	(1.19)	(1.18)	(1.18)	(1.17)
Industry concentration	4.33**	4.39**	4.35**	4.39**	4.34**
	(1.64)	(1.66)	(1.66)	(1.66)	(1.66)
Industry growth	−0.03	−0.03	−0.03	−0.03	−0.04
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Fixed-effects					
Industry	Included	Included	Included	Included	Included
Year quarter	Included	Included	Included	Included	Included
Log-likelihood	−5539.23	−5536.19	−5530.01	−5534.02	−5525.34

Notes: $N = 3{,}202$; robust standard errors, clustered by dyad, in parentheses; constant included in all models; two-tailed tests.
† $p < .10$
* $p < .05$
** $p < .01$

and vague language each enhance the rival firm's perceived vulnerability to the focal firm, they do so via different mechanisms. Thus, it stands to reason that a rival's corporate communications after a negative earnings surprise will serve as an indicator of even greater underlying vulnerability when its choice of language is both complex and vague. As graphed in Figure 3, being both complex and vague invites even more competitive action. Taken together, the results provide evidence for the salience of rivals' communication as a contingency in the relationship between rivals' negative earnings surprises and the intensity of focal firms' tactical actions.

With respect to our control variables, we first found that the prior performance of a focal firm and its rival are both negatively related to the focal firm's propensity to take competitive actions. Second, we found that the action volume of a focal firm and its rival are both positively related to the focal firm's

FIGURE 1
Interaction Effect between Rival Negative Earnings Surprise and Complex Language on Firm Competitive Action Intensity



propensity to take competitive actions. Third, we found that the focal firm's intensity of competitive actions increases with the firm–rival size similarity. Lastly, we found that a focal firm's competitive intensity is likely to increase as its industry becomes more concentrated. All of these findings are aligned with the predictions of existing literature. Most year-quarter and industry fixed effects were statistically significant, reflecting the influence of temporal and industry-specific factors on firms' competitive intensity.

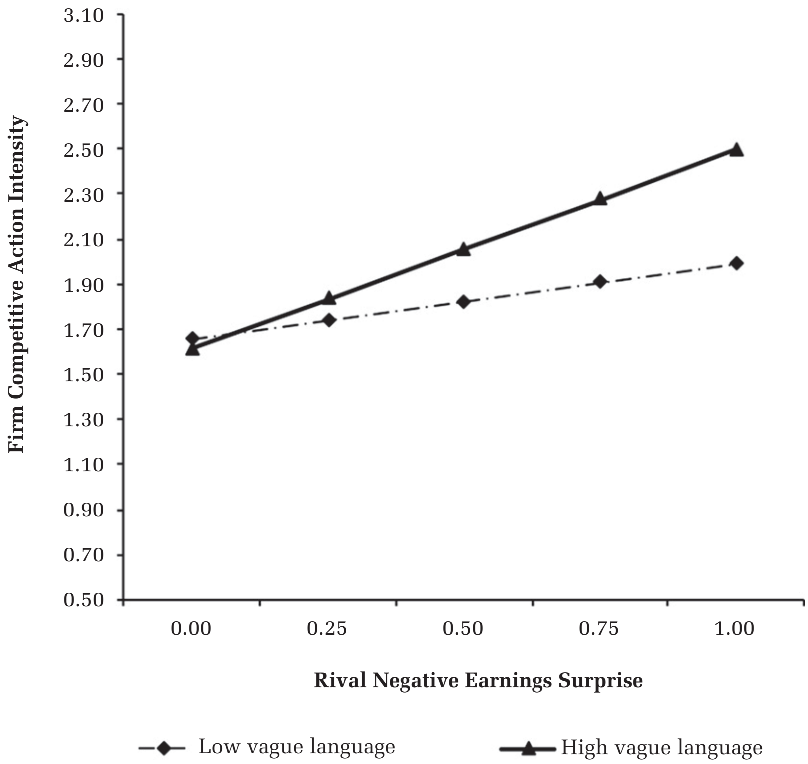
Robustness Checks

We ran a number of tests to check the robustness of the results. We first checked whether the results are sensitive to different measures of earnings surprises. The measure that we used (the difference between reported earnings and analysts' consensus estimates divided by the firm's stock price) not only has the advantage of accounting for vast differences in stock prices that range between pennies and hundreds of thousands of dollars, but is also the current standard in empirical studies of earnings surprises, enhancing the comparability of our study with others on earnings surprises.[4] Nonetheless, we replicated the results using two versions of standardized unexpected earnings: (1) the difference between actual and expected earnings divided by the standard error of estimate of the trend-fitting equation (e.g., Ball & Brown, 1968; Latane & Jones, 1977), and (2) the difference between actual earnings per share (EPS) and mean surprise divided by the standard deviation of the analysts' estimates (e.g., Anson, Chambers, Black, Kazemi, & Association, 2012; I/B/E/S, 2000). These results are consistent with our main regressions.

Second, rivals that announced negative earnings surprises may have differed systematically from those that did not. To check for a potential sample-selection bias, we performed a Heckman estimation using a maximum likelihood estimator

[4] We searched studies of earnings surprise in six leading accounting and finance journals over the past 15 years and were able to find only two papers making use of SUE (Shanthikumar (2012), using the old time-series approach, and Bebchuk, Cohen, and Wang (2013), using the later version of SUE described above) out of 20 papers that we identified. All other studies used stock price to scale unexpected earnings, just as we do.

FIGURE 2
Interaction Effect between Rival Negative Earnings Surprise and Vague Language on Firm Competitive Action Intensity



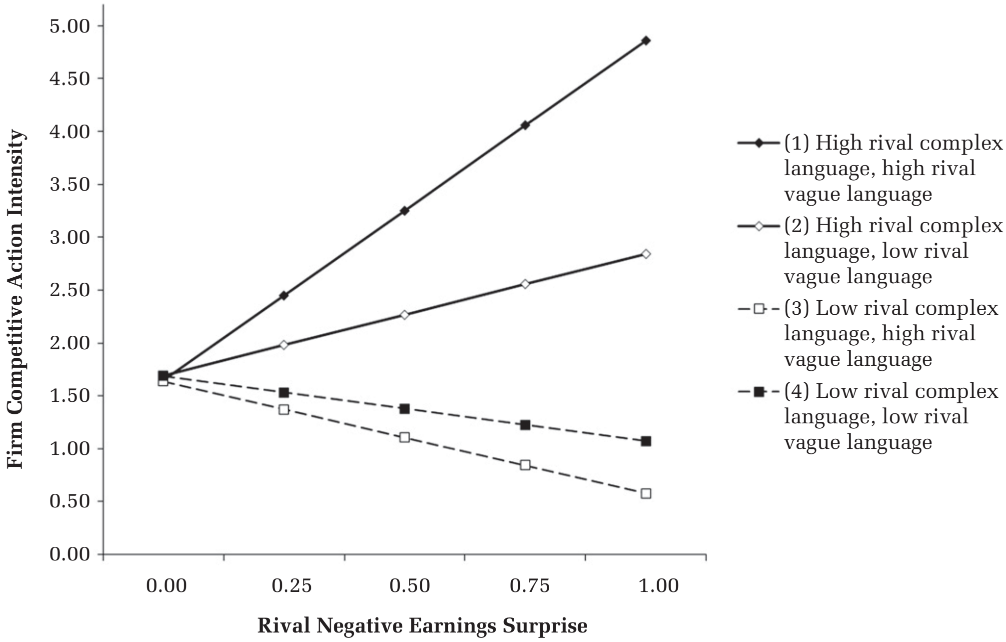
developed by Terza (1998) for count-data models with endogenous sample selection. We included the number of analysts following a rival and the standard deviation in analysts' earnings forecast as additional predictors of the likelihood of a negative earnings surprise in the first-stage regression. Both variables are statistically significant, suggesting that the exclusion restrictions are satisfied (Bascle, 2008; Certo, Busenbark, Woo, & Semadeni, 2016). In the second-stage regression, λ is not statistically significant ($p = 0.28$), indicating that selection is not a major issue in our analyses.

Next, we turn to potential endogeneity in our models. Following Semadeni, Withers, and Certo (2014), we identified *Friday release* (a dummy variable that equals 1 if a rival's earnings are released on a Friday, 0 otherwise) as an instrument for rival negative earnings surprises and conducted a relevance test. Prior accounting and finance research has shown that firms tend to release bad news (e.g., negative earnings) on Fridays because investors tend to underreact to information released on that day (e.g., Bagnoli, Clement, & Watts, 2005; DellaVigna & Pollet, 2009). Friday release ($p = 0.001$) is a positive and significant predictor of rival negative earnings surprise in the first-stage regression, as expected.[5] We then conducted a Durbin–Wu–Hausman test to check for the presence of endogeneity in the second stage. The test statistic is insignificant ($p = 0.23$), suggesting that we cannot reject the null hypothesis that the rival earnings surprise variables are exogenous. This result gives us confidence that the impact of potential endogeneity on the reported results is limited.

Finally, we conducted additional analyses to check the robustness of the results by (1) using Poisson regressions, instead of negative binomial regressions; (2) including additional control variables (namely, a dummy for *meeting analysts' expectations*; *firm absorbed slack*, measured by the ratio of selling, general, and administrative expenses to sales; *firm age*,

[5] The Cragg–Donald χ^2 test rejected the null of underidentification ($p = 0.001$). In addition, the F-statistic for the first-stage regression was 10.34, which exceeded the 8.96 threshold that Stock, Wright, and Yogo (2002) provided for one instrument. These results suggest that our instrument satisfies the relevance condition.

FIGURE 3
Three-way Interaction Effect of Rival Negative Earnings Surprise, Complex Language, and Vague Language on Firm Competitive Action Intensity



measured by years since founding, and *firm–rival capital expenditure similarity*, measured by 1 minus the absolute difference in capital expenditure between the focal firm and rival firm normalized to a 0–1 range); (3) using *financial distress* (measured by a reverse-coded Altman *Z*-score [see Chakravarthy, 1986; Ferrier et al., 2002]) as an alternative measure for *firm prior performance* and *rival prior performance*; and (4) excluding 184 instances in which there were multiple announcements within the 90-day period that we used to observe focal firm action. The results remained qualitatively unchanged in all these analyses.

Supplementary Analyses

We also ran a number of supplementary analyses to explore some alternative explanations and extensions of our theoretical model. First, it is possible that rivals may take more competitive actions after experiencing negative earnings surprises. This is because, as the performance feedback literature has suggested (e.g., Greve, 2003), when firms fall short of their performance benchmarks they actively search for solutions to their lower-than-expected performance, and take more actions as a result. In such a case, an increase in a focal firm's action intensity may be a response to increased competitive activity of the rival and not to the rival's negative earnings surprise, as we have argued. To explore this, we calculated the total number of competitive actions taken by rivals after their earnings release, and included this number in the regressions as a control.[6] We found a positive, but not statistically significant, relationship between rivals' post-earnings actions and focal firms' intensity of action. Moreover, the coefficient of rivals' negative earnings surprises remained unchanged.

Second, we considered the possibility that some firms may be more (or less) likely to respond to a given rival's earnings surprise compared to others (e.g., Armstrong & Collopy, 1996). To explore this, we ran supplementary analyses using a range of firm-level (prior performance, slack, action volume, age, and market importance) and firm–rival-level (firm–rival size similarity, firm–rival market power similarity, and firm–rival market overlap) characteristics as moderators of the hypothesized positive relationship between rival negative earnings surprise and focal firm competitive action intensity.[7] As an extension of this, we

[6] On average, focal firms took 0.29 actions within 60 days after their rivals' earnings surprises.

[7] Two of the listed variables are additional control variables that we do not include in our model specification but report in the robustness checks. Firm age is measured by years since founding, and market importance is measured by the percentage of total sales of a firm that comes from the focal industry.

also checked industry-level moderators (namely, industry concentration and growth) to see whether the hypothesized relationship is more pronounced in some industries than others. Consistent with previous studies (Chen, 1996; Chen & Hambrick, 1995; Guo et al., 2017), the results indicate that the positive effect of a rival firm's negative earnings surprise on the focal firm's competitive action intensity is more pronounced when the two firms are similar in size or have high market overlap; when the focal firm is young in age; when the market is more important to the focal firm; and when the industry is more concentrated.

Third, and in line with the strategic noise literature (Elsbach, Sutton, & Principe, 1998; Graffin, Carpenter, & Boivie, 2011), it is plausible that rivals may try to "muddy the water" through corporate communications before they announce an earnings surprise. To check this, we followed McWilliams and Siegel (1997) and calculated "strategic noise" using the number of press releases by the rival firm that announces an earnings surprise the day of the earnings surprise and the day prior to it. In the regressions using this variable, the coefficient of strategic noise is negative and significant at 10% ($p = 0.09$), and the coefficient of the interaction term between strategic noise and rival negative earnings surprise is positive and significant at 10% ($p = 0.07$).[8] These results (weakly) suggest that strategic noise generated by rivals around an earnings release tends to increase the focal firm's competitive activity when the release is a negative earnings surprise (note that this resonates with the logic underlying our language variables). Importantly, the main results of our study remain unchanged. However, these findings should be interpreted with caution because of the very small number of press releases in the run-up to earnings surprises in our data.

Fourth, the communication style of the person(s) who spoke to investors may explain part of the variance. Although there seems to be no reason to believe that the resulting variation will be systematic, to check this possibility we reran our regressions by dropping observations with changed speaker(s) in the last four quarters before the current earnings surprise event (or in the last two or three quarters, if there were fewer than four quarters of data before the current earnings surprise event).[9] In the regressions using the subsample excluding observations with different speakers, the results were qualitatively unchanged and all variables of interest kept their sign and significance (indeed, some results were more significant), increasing our confidence that the reported results are not driven by the communication style of the person(s) who spoke at earnings calls.

Lastly, it is possible that the earnings surprises of rivals with different strategic orientations may trigger different competitive reactions from focal firms. For example, some rivals may adopt a more patient capital mentality, such as family firms (e.g., Gomez-Mejia, Cruz, Berrone, & De Castro, 2011) and state-owned firms (e.g., Bruton, Peng, Ahlstrom, Stan, & Xu, 2015; Dewenter & Malatesta, 2001). When that is the case, a rival that appears vulnerable in the short run is actually stronger in the long run, which may affect the focal firm's propensity to take competitive actions. To check this explanation within the confines of our data, we ran subsample analyses (the corresponding data are available for most, but not all, firms in our sample) using the concentration of ownership in the hands of large blockholders as a proxy for rival firms' strategic orientation. Publicly traded firms with diffused ownership tend to value short-term growth more than long-term survival compared to firms with large blockholders (Fitza & Tihanyi, 2017). In these analyses, contrary to expectations, the coefficient of the percentage of shares of the rival owned by large blockholders is positive but not statistically significant (and positive and significant at 5% using the number of large

[8] We replicated these regressions using another measure of "strategic noise"—the number of press releases by the rival firm that announces an earnings surprise within a + or −1-day window of the earnings surprise, as in Graffin et al. (2011). In these regressions, the coefficients of strategic noise and the interaction term between strategic noise and rival negative earnings surprise were signed as they were in the regressions reported above, but neither coefficient was statistically significant.

[9] Given the imperfect recording of names and the large number of calls in our dataset, we used a computational approach to identify speakers attending earnings calls. We decomposed data on the first six corporate participants of conference calls into grams of two moving characters. For example, "John Smith" would split into "Jo" "oh" "hn" "n__S" "Sm" "mi" "it" "th." We then used the Jaccard index to calculate the similarity score between decomposed characters of corporate participants for different calls for the same company. Next, we created a dummy variable to identify the conference call observations that received a similarity score of at least .90 relative to other conference calls by the same company. Using this approach, we identified 365 observations that had a similarity score of less than .90 compared to other observations of the same company. We excluded these observations in the supplementary regressions.

blockholders instead). Pending further research, one possible explanation for this is that the performance of rivals with large blockholders tends to be more stable and their negative earnings surprises thus create an even more rare (and valuable) opportunity for the focal firm to take advantage of.

DISCUSSION

In this study, we argue that critical events that befall a rival may be indicative of its vulnerability, and thus motivate a focal firm to act. In line with this expectation, the results show that a rival's negative earnings surprise is positively associated with the competitive action intensity of a focal firm. We also present evidence that the language used by rivals in their communications following a negative earnings surprise moderates this relationship. We found that the use of complex and vague language by rivals in their conference calls strengthened the positive relationship between the rival's negative earnings surprise and the intensity of the focal firm's action.

This study extends competitive dynamics research in two major ways. First, it considers the importance of language as an indicator of rivals' underlying conditions and a facilitator of the focal firm's competitive decision making. A small but growing body of literature has recently started to explore the influence of language on competition (Guo et al., 2017; Nadkarni et al., 2019; Rindova et al., 2004). For example, Guo, Yu, and Gimeno (2017) found that the use of vague language in airlines' annual reports reduced the likelihood that their rivals would invade their territories. Similarly, Nadkarni et al. (2019) found that the temporal vagueness and distance of a firm's press releases on competitive action slowed down their rivals' response speed. However, studies to date have focused primarily on how the use of language (e.g., vague language) by rivals can create doubts for the focal firm and hence delay its action or response. Departing from these studies, we show that the use of complex and vague language by rivals might instead *increase* the focal firm's propensity to act in specific situations (i.e., after the rival's negative earnings surprise).

Second, the predominant focus of most studies using the AMC framework in competitive dynamics has traditionally been observed actions as predictors of rivals' competitive responses. We differ by underscoring how critical events may affect cross-rival competitive behavior through their impacts on the awareness, motivation, and capability of the focal firm. This extends prior research that has primarily used this framework as a tool to explain the action–response dynamism to using it as an underlying mechanism to explore the effects of a wider range of strategic factors. The only other study in this domain, to our knowledge, is that of Uhlenbruck et al. (2017), which focused on mergers and acquisitions. The authors explored how resource similarity and market commonality affect a firm's action volume and complexity following its rival's acquisition. Instead, we study cross-rival effects of negative earnings surprises and incorporate language use as an important contingency in our theoretical model.

In parallel, our study also contributes to the broader communications literature. Although the cheap talk theory holds that a firm's communication should have no material impact on either its performance or the market's reaction, an increasing number of studies in management, accounting, and finance have found evidence that a firm's communications matter greatly (e.g., Li, 2008, 2010; Martens, Jennings, & Jennings, 2007; Miller, 2010; Muslu, Radhakrishnan, Subramanyam, & Lim, 2015). These studies have mostly focused on how various characteristics of a firm's public communications (e.g., tenor, readability, and future-orientation) are associated with its future earnings and stakeholders' reactions. We extend this line of research by examining the impact of firm communications on competitive interactions. We not only found significant two-way interactions between two language variables (vagueness and complexity) and negative earnings surprises but also found a significant three-way interaction among vagueness, complexity, and negative earnings surprises. These results provide evidence for the salience of rivals' communication as a tool firms can use to convey invaluable information to their competitors in competitive settings.

Lastly, our study contributes to a growing body of literature on how capital markets and investment analysts influence firm behavior and performance (e.g., Benner, 2007; Brauer & Wiersema, 2018; Gentry & Shen, 2013; Zhang & Gimeno, 2010). Most studies in this field have examined how missing its earnings targets may influence a firm's *own* strategy (e.g., Gentry & Shen, 2013) and future prospects (e.g., Pfarrer et al., 2010). However, limited attention has been paid to the cross-rival effect of these earnings surprises. Although Zhang and Gimeno (2010) investigated how earnings pressure (which is different from our focus on earnings surprises) experienced by a focal firm will influence its rivals' actions, they did not consider the underlying mechanisms and contingencies that may govern this relationship, which constitutes one major contribution of our research.

Future Research Directions

This study highlights a number of avenues for future research. First, given the critical roles played by top managers in most competitive decisions, an interesting area of future research would be to explore the impact of the top management team (TMT) on the relationship between negative earnings surprises and competitive action intensity. For example, high levels of TMT heterogeneity may facilitate group learning, avoid blind spots in decision making, and thus lead to lower likelihood of earning surprises. If this is the case, and the TMT composition of the rival is observable to a focal firm, negative earnings surprises of a rival with a heterogeneous TMT will send an even stronger signal of its vulnerability.

Second, future research should explore various attributes of competitive actions that we were not able to unpack due to data restrictions. For instance, announcements of actions (which could be true expressions of future intentions or a bluff) are different from actual execution of the action (Hambrick et al., 1996). Similarly, actions that are intended as a response (in our case, to a rival's negative earnings surprises) are different from actions that are planned well in advance (Ferrier, 2001). Incorporating these distinctions into empirical analyses will bring granularity to the theoretical mechanisms that we present. In parallel, beyond the volume of competitive actions, it will be helpful for future studies to examine how firms may react with a more- or less-complex action repertoire; i.e., the degree to which a sequence of actions contains actions of different types (Ferrier, 2001). Additionally, future research should consider differences across action types. Although we look at five tactical actions taken together, a pricing action is not necessarily equivalent to a marketing action or a legal action. In supplementary analyses, we reestimated the models by dropping one action type at a time from the measurement of the dependent variable (competitive action intensity). The results were unchanged, confirming the robustness of our findings.

Third, although we constrain our sample to dominant business firms and oligopolistic industries, future research should expand the analyses to other types of firms and industries. As with most studies in competitive dynamics research, the story we try to tell is more observable in oligopolistic settings in which there is a high level of strategic interdependence among rivals. Yet, cross-rival responses to critical corporate events are not necessarily limited to standard oligopolistic industries and dominant-business firms.

Fourth, our results imply that in order to avoid inviting competitive attacks following a negative earnings surprise, firms might want to prerecord simple and clear earnings calls and avoid spontaneous communications with the public after the calls. In fact, these implications of our findings are consistent with what is happening in the real world. According to a 2016 report by the National Investor Relations Institute (see Dizik, 2017), companies are becoming increasingly wary about talking to analysts. For example, the percentage of companies prerecording formal earnings call comments before a live question-and-answer session increased from 10 to 15% between 2014 and 2016. This new communication pattern warrants future research, and we need a better understanding of how it can affect the rival's behavior differently.

Moreover, it would be interesting to delve into means of communication other than conference calls and explore whether these alternatives affect rivals' competitive behaviors differently. Although we believe conference calls represent the most timely and relevant communication channel for examining firms' earnings results, rivals might also be attentive to other communication means, such as management discussions in annual reports, presentations at investor conferences, and corporate news releases. Relatedly, in addition to what managers choose to communicate and how they do it, future research could examine how other information cues, such as managers' voices, silences, and facial characteristics, influence rivals' competitive decisions. Prior research has shown that organizations that are sophisticated in their use of information may rely on a variety of cues to arrive at their judgments. For instance, Mayew and Venkatachalam (2012) found that the affects displayed by managers' voices during conference calls are indicators of their firm's financial condition. Hollander, Pronk, and Roelofsen (2010) studied the effects of managers' decisions to not answer certain questions in the course of conference calls and found strong evidence that investors interpreted such silences negatively. Likewise, visual cues can also be important. Madera and Hebl (2012) showed that in job interviews, facial blemishes, such as scars, port-wine stains, or birthmarks, on the faces of applicants consumed more cognitive effort by interviewers, and that this effort led to reduced memory of what was said in the interview.

Lastly, building on the theoretical mechanisms that we developed in this study, future research could explore other events that may increase rivals' perceived vulnerability and thus provoke the focal firm to act. Such events can be firm-specific crises, such as a CEO's sudden death, media attacks, production interruptions, and lawsuits. It would be interesting to examine how the nature of these events and the characteristics of the rival firm affect the focal firm's propensity to act. For instance, Yu et al. (2008) proposed that the negative impact of a firm-specific crisis with ambiguous causes and consequences may spread from the focal firm to other firms of the same cognitive category in stakeholders' minds. Under such circumstances, it might not be wise for the focal firm to act because that firm might become tarred by the same brush.

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