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COMPETITIVE PARITY, STATUS DISPARITY, AND MUTUAL FORBEARANCE: SECURITIES ANALYSTS' COMPETITION FOR INVESTOR ATTENTION

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Most studies of responses to change in competitive environments focus on competitor-specific adaptations. However, rivals are often acutely aware of one another, and this awareness should influence their competitive behavior. In this study, we focus on three market structures that affect competitive behavior: competitive parity, status disparity, and multipoint contact. In particular, we examine how securities analysts responded to a regulatory discontinuity, Regulation Fair Disclosure ("Reg-FD"), which promotes competitive parity by eliminating privileged access to proprietary firm information as a critical source of competitive advantage. We predict and find that Reg-FD activated mutual forbearance among analysts linked through multipoint contact. We also predict and find that high-status analysts forbear more strongly. Analysts' responses to heterogeneity in competitive advantage thus depend importantly on their competitive overlap and status, which has implications for both their behavior and the information they provide to investors.

Management scholars have shown increasing interest in the causes of competition and rivals' responses to it (e.g., Barnett & Hansen, 1996; Barnett, 1997). Of particular note are a growing number of studies that examine how actors respond to regulatory or other unexpected industry-wide events that transform their competitive environment (e.g., Smith & Grimm, 2006; Audia, Locke, & Smith, 2000). While it seems natural to expect actors to be acutely aware of their competitors under such conditions, these studies tend to focus on how actors adapt to their new circumstances without considering the actors' awareness of their relationships with one another. Absent attention to this awareness, scholars' understanding of actors' competitive responses in these situations is necessarily incomplete. To bring attention to this issue, we examine how actors' awareness of their competitive relationships influences their responses to a regulatory change that abruptly eliminates a critical source of competitive advantage. Actors' competitive relationships depend not only on their market encounters, but also on their relative ranks, and thus prominence, in social hierarchies. Therefore, we examine how two dimensions of competitive relationships—multipoint contact and status—influence actors' responses to a change in the basis of competition.

Mutual forbearance theory provides an account of behavior among actors who compete simultaneously in several domains, such as products or markets (e.g., Barnett, 1993; Baum & Korn, 1996). The theory predicts that when actors meet in multiple domains, each can forbear from competition by permitting the other to dominate some domains, while maintaining a threat of competitive responses in the others and escalating competition (striking where it is most costly) if the rival makes an aggressive move (Karnani & Wernerfelt, 2006; Wernerfelt, 1985). Additionally, in many markets, particularly where quality is consequential and uncertain, a hierarchical ordering of actors develops. Prior research indicates that actors' willingness to make strategic choices is a function of their hierarchical positions, or status (Benjamin & Podolny, 1999; Magee & Galinsky, 2008; Podolny, 1993). Although a great deal of empirical evidence has accumulated in support of the basic mutual forbearance and status predictions, their boundary conditions can be better understood by examining them in the context of environmental change.

Although prior research suggests that multipoint contact attenuates competition, as evidenced, for example, by lower failure rates (Barnett, Greve, & Park, 1994), higher prices (Hannan & Prager, 2006), and higher margins (Evans & Kessides, 1994) under conditions of multipoint contact, much of the evidence is derived from empirical settings in which the bases of competition are relatively stable over time. In such settings, multipoint contact serves to reduce risky behavior that might destabilize and escalate competition. Researchers know little, however, about how multipoint contact affects competitor behavior in environments in which the basis of competition is unstable and sources of competitive advantage may shift or disappear. Because mitigation of competitive pressure is beneficial to multipoint competitors in dynamic environments but also more difficult to sustain (Gimeno & Woo, 1996), it is important to theorize and empirically test this boundary condition of mutual forbearance.

Moreover, the role of status has not previously been examined either under conditions of regulatory change or in the presence of mutual forbearance. Status is a measure of quality in uncertain environments (Podolny, 1993). While high-status actors are generally seen to have advantages related to their position, little is known about how they respond when such advantages are altered or removed. Additionally, prior research on mutual forbearance has not addressed the role of such hierarchical relationships among multipoint competitors. Yet such orderings may materially influence the competitive responses of actors seeking either to maintain or improve their position and so influencing the intensity of competition (Fligstein, 1996).

In this study, we address these boundary conditions directly. We examine how actors change their competitive behavior when a critical source of competitive advantage is abruptly removed by a regulatory change. This event permits us to examine how the effect of multipoint contact varies with competitive conditions and also the conditions under which actors enter into mutual forbearance relationships in the first place. We predict that the effects of multipoint contact will be stronger, and status weaker, under conditions of *competitive parity*—that is, a situation in which no actor possesses an overwhelming competitive advantage because all actors have equal access to resources that yield competitive advantage. We also predict that multipoint contact effects will be stronger for high-status actors under conditions of *status disparity*, because they have incentives to stabilize the status order by forbearing from competition.

Our empirical setting is "sell-side" security analysts in the United States, and in particular the cocoverage contacts they develop when following the same stocks. Security analysts are key information intermediaries in contemporary capital markets and, as such, compete intensely for investor attention. Security analysts' primary competitive tools are information and analysis. The information advantage of company insiders relative to analysts is so great, however, that analysts who obtain preferential access to information from corporate management gain a competitive advantage (Cohen, Frazzini, & Malloy, 2010; Horton & Serafeim, 2009). Multipoint contact is basic to competition among security analysts, each of whom follows a portfolio of stocks largely comprised of companies operating within one or another widely accepted industry category (e.g., telecom, information technology [IT], retail) (Zuckerman, 2004). As a result, analysts tend to have extensive multipoint contact. Constraints on time, effort, and understanding make it difficult for each analyst to cover all the stocks in his/her portfolio comprehensively, creating a high potential for mutual forbearance to emerge among them. Status is also vital to securities analysts, who are divided into tiers by an annual "All-Star" analyst list published in the influential industry trade magazine *Institutional Investor*. The cocoverage structure is thus well suited for examining mutual forbearance effects under conditions of status disparity.

A further advantage of our empirical context is that it provides a natural experiment for testing the boundaries of mutual forbearance and status via a change in competitive parity (Davis, 2010; Grant & Wall, 2009). In October 2000, the US Securities and Exchange Commission (SEC) enacted Regulation Fair Disclosure (Reg-FD), which prohibited companies from "tipping off"—disclosing material information privately—to some preferred analysts and investors before others. The regulation instead mandates public disclosure of material information.[1] After enactment of Reg-FD, companies were required to make all material disclosures publicly to all investors and analysts at the same time, as well as to increase the number of public financial disclosures they made (Bailey, Li, Mao, & Zhong, 2003). This regulatory change reduced the ability of analysts to use social connections as a source of competitive advantage, forcing them to rely on analytical skills for conducting quantitative research on firms instead of privileged information access from corporate management, providing us with an opportunity to assess the role of competitive parity and status disparity as boundary conditions of multimarket contact.

THEORY AND HYPOTHESES

Bold Earnings Estimates and Analyst Competition for Investor Attention

An analysis of mutual forbearance requires an examination of the competitive actions available to actors that allow identification and understanding of their behavior by their competitors. Thus, for example, firms may focus on price competition, product differentiation, or market expansion because choices among these strategies are visible to their competitors and important to their customers. Analysts create two chief products using their analysis: earnings estimates and recommendations. Both have investment value (Loh & Mian, 2006; Womack, 1996), but institutional investors prize earnings estimates as providing more detailed and frequent information (Reingold, 2006). Because of this, and because firms issue financial information quarterly, analysts focus much of their effort on the creation of earnings estimates.

Investors and other analysts understand an analyst's estimates as either being in line with estimates previously released by analysts and so providing confirmatory evidence but little new information, or as being bold, and so providing new information to the market at large. A bold estimate for a given stock is one that is beyond a band set by the mean and standard deviation of preceding estimates for that stock. The mean of all outstanding estimates, called a *consensus estimate* in the industry, is the reference point through which investors interpret subsequent analyst estimates (Reingold, 2006). A consensus estimate is not the same as an accurate estimate because analysts influence each others' beliefs and can be collectively wrong about the securities they cover (Rao, Greve, & Davis, 2001). Analysts issue estimates sequentially and observe each others' estimates, so they know when their estimates are bold.

Bold estimates invite investor attention by being clearly and deliberately different from those issued by other analysts (Clement & Tse, 2005; Hong, Kubik, & Solomon, 2000). Boundedly rational investors cope with information overload by responding selectively to some analyst estimates and ignoring others. Because selective attention is driven in part by salience (Fiske & Taylor, 1991), bold estimates gain investor attention as well as attention from other analysts, since such estimates imply that prior estimates are incorrect in either magnitude or direction. They are also a sign of differentiation. As Porter observed, "imitation ensures a lack of competitive advantage and hence mediocre performance" (1991: 102), while differentiation moderates competition and improves performance. Differentiation based on either unique market positioning or resource endowments diminishes competition and may even result in local monopoly. In the competition among sell-side security analysts, bold earnings estimates play a leading role, particularly because of the way that institutional investors, the primary clients of equity analysts, allocate their trading activity. Many institutional investors work with a number of brokerage firms and their analysts and award trading activity to a given firm on the basis of the usefulness of its research coverage (Groysberg, 2010; Ljungqvist, Marston, Starks, Wei, & Yan, 2007). Analysts who receive attention for their reports receive more of their clients' trading activities, increasing trading commission revenue for their brokerage firm (Allen, 2012).

Because all analysts have access to public statements by the companies they cover, such as quarterly earnings releases, the willingness to issue bold estimates must result from either belief that they possess better or more comprehensive information than at least some other analysts, or belief

[1] Prior to Reg-FD, such private information release allowed some analysts and investors to anticipate market reactions and benefit from them financially. It also enabled companies to use private information as "currency" to obtain favorable coverage in exchange for early access (Securities and Exchange Commission, 2000). One interpretation of Reg-FD is that it was the SEC's response to the Internet-boom practice of companies releasing information to analysts who provided more favorable coverage, intended to force analysts to focus on their own analysis rather than serve as "promoters" of the companies they covered (Eleswarapu, Thompson, & Venkataraman, 2004).

that they are better able to integrate the various pieces of information they possess. Lieberman and Asaba's (2006) analysis, which accounts for imitation using uncertainty and information-based theories and differentiation using rivalry-based theories, is informative in conceptualizing analyst boldness. Uncertainty, which increases with the paucity of information, motivates analysts to seek social cues from reference groups, causing bandwagon and herding behavior (Haunschild & Miner, 1997; Haveman, 1993; Henisz & Delios, 2001). In keeping with this reasoning, herding is more common among inexperienced securities analysts, who mimic others' estimates to compensate for their limited expertise in the collection and analysis of information (Clement & Tse, 2005).

A bold estimate thus suggests not only that an analyst expects much greater (or worse) financial performance for a given stock, but also that others following the stock are mistaken in their beliefs. Strong individual incentives are available to analysts who differentiate themselves by issuing accurate bold earnings estimates (Kadous, Mercer, & Thayer, 2008), but the career risks of being boldly wrong counter these incentives (Hong & Kubik, 2003; Scharfstein & Stein, 1990). Timid and herding estimates, in contrast with bold estimates, are unremarkable, providing no stimuli to investors, placing no competitive pressure on rivals, and avoiding risk for an analyst. Therefore, in this context, bold estimates are competitive actions that threaten rivals, just as actions such as promotions and price cuts do in other contexts.

A range of evidence supports the view of analyst boldness as a form of competitive aggression. Prior studies show that analysts tend to herd even when they possess private information that justifies a bolder estimate (Trueman, 1994) or have information about the results of their prior herding (Welch, 2000). Analysts tend to issue bold estimates when they are unconcerned with reputational loss (Boyson, 2010; Graham, 1999) or employed by smaller brokerages that have more attention to gain and less to lose (Jegadeesh & Kim, 2010). The relation between competitive aggression and boldness suggests that it is worthwhile to focus on the influence of analyst multipoint contact and status among analysts on the boldness of their earnings estimates.

Analyst Multipoint Contact

Analysts work on portfolios of companies rather than individual companies, and this has implications for their competitive relations. Analysts use information from each of the stocks they cover to create forecasts on all of them. Limits on time and attention make it impossible to understand multiple industries and multiple firms within industries, leading analysts to cover portfolios of stocks that are related in such a way that information generated by investigating one stock will be useful for assessing other stocks in the portfolio (Zuckerman, 1999). Analysts also compete for investor attention on more than one stock at the same time. This portfolio effect embeds analysts in a structure of multiple contacts with other analysts who also cover the same stocks.

Mutual forbearance theory suggests that actors meeting in multiple domains can reduce their competition because their domain overlap enables them to recognize their mutual interdependence and to tailor their interactions to minimize risks of competitive retaliation and escalation. As do the multiple domains in which firms compete, the stocks analysts cocover affect their patterns of contact and thus their potential to coordinate in the competition for investor attention.

Indeed, although theory and empirical evidence regarding mutual forbearance appear primarily in the industrial organization and strategic management literatures, and mutual forbearance arguments are most commonly applied to firms, Simmel's (1950: 286–291) early analysis of the construct emphasized conflict among individuals as a socially binding force. Simmel views individuals as being able to develop mutual restriction of competitive means, which occurs when "a number of competitors voluntarily agree to renounce certain practices of outdoing one another" (1955: 76). Simmel also predicts that the potential for cooperation among rivals increases when they interact in multiple domains. This is because each rival ("social element," in his terminology) can gain by allowing the other to be dominant in some domains, or "sphere of influence," in exchange for similar treatment in others. To let rivals dominate some domains in exchange for one's own dominance in other domains is effective and rewarding when "the sphere within which one social element is superordinate is very precisely and clearly separated from those spheres in which the other element is superordinate" (Simmel, 1950: 289). Such reciprocal dominance enables rivals to convey mutual threats, adding the risk of counterattacks to the intrinsic risk of making bold and incorrect estimates.

For an analyst who believes that a firm will have (say) higher earnings than other analysts have estimated, the strategic choice lies in *how much higher* than other analysts have done to place an earnings estimate. Timidly higher than others, so that the analyst's own clients will recognize him/her as having been right if the earnings are indeed higher? Or boldly higher than other analysts, so that their clients will also notice? Of course, being boldly higher also carries a greater risk of overshooting, which can result in the other analysts being more accurate after all. Bold estimates are thus risky under any circumstance. What multipoint contact adds is the potential to tailor such interactions to minimize risks of competitive retaliation by enabling the emergence of reciprocal dominance that distinguishes spheres of influence, as well as communication of mutual threats. As a result, client raids in a rival analyst's sphere of influence are likely to provoke the rival to launch counterraids in the attacking analyst's sphere, given that investors award brokerage business to those who provide valuable information (Green, Jame, Markov, & Subasi, 2012; Groysberg, 2010), and this changes the cost and benefit calculation enough to make a rational analyst provide fewer bold estimates. Thus we predict:

> *Hypothesis 1. An analyst's likelihood of issuing bold earnings estimates on a stock is lower if the analyst experiences high multipoint contact with other analysts.*

Competitive Parity

Mutual forbearance theory rests on several assumptions. First, to reduce competition, actors must recognize their multiple points of contact and the mutual dependence of their performance on each others' actions (Greve, 2008). This assumption is plausible in our empirical context, because analysts who cocover stocks learn about each other in multiple venues (Groysberg & Lee, 2008; Horton & Serafeim, 2009). Second, retaliation against rivals' competitive moves in their sphere of influence requires actors to coordinate activities across different domains. This assumption is also plausible, since such coordination is easier for individuals than for firms, which often require cooperation among multiple subunits spanning multiple activities (Yu, Subramaniam, & Cannella, 2009).

A third assumption is competitive parity: that no actor possesses an initial overwhelming competitive advantage and all actors initially have equal opportunities to gain access to resources that give competitive advantage. In our empirical context, competitive parity was met only after Reg-FD was enacted. Under Reg-FD, analysts who had neither been recipients of privileged information nor occupied industry positions that afforded rapid access to such information—even analysts who previously had no access to company information beyond press releases and government-mandated quarterly earnings reports—benefited from timely access to material information regarding the companies whose stocks they covered. By eliminating analysts' access to privileged information about corporate developments, Reg-FD effectively removed preferential access to idiosyncratic information as a source of competitive advantage.

The shift to disclosure and circulation of company information through public announcements and conference calls compelled previously privileged analysts to expend greater time and effort gathering and analyzing information to sustain their advantage (Bailey et al., 2003), while greatly improving the circumstances of more peripheral analysts. The result was increased difficulty in forecasting, along with increased competition among analysts for rigorous analysis, as evidenced by reduced accuracy and fewer reports (Bagnoli, Watts, & Zhang, 2008; Mohanram & Sunder, 2006).

In the post-Reg-FD competitive environment, with advantages from corporate relations diminished and public information disclosure requirements leveling the competitive playing field, we expect analysts to seek mitigation of the intensified competition. Although analysts were not precluded from social contacts with noncorporate actors such as other analysts and institutional investors, analyst workload increased after Reg-FD since each analyst had to rely more on information gathering and analytical abilities than on privileged access when determining earnings estimates (Mohanram & Sunder, 2006). Yet expectations and reward structures for analysts still encouraged the attraction of positive investor attention. Bold estimates remained an important way to accomplish this, but the basis for such estimates became centered on analysts. After Reg-FD came into effect, bold estimates were not only more difficult to make, requiring greater time and effort in both information gathering and analysis, but also riskier. Among securities analysts, mutual forbearance represented a useful adaptation to the heavy information gathering and analytical workload imposed by Reg-FD, with coordination of spheres of influence permitting each analyst to invest more in becoming leader in the coverage of certain stocks, while following in others.

In the pre-Reg-FD era, by contrast, analysts with privileged access to private corporate information had a competitive advantage that let them dominate others by, for example, issuing low-risk bold estimates based on advance knowledge of earnings-related information, without resorting to mutual forbearance (Baum & Korn, 1999). As a result, multipoint contact is likely to be explanatory of analyst boldness only after the enactment of Reg-FD weakened the information advantages of corporate-connected analysts and eliminated the opportunity for companies to tip off preferred analysts to encourage favorable coverage. Mutual forbearance, as a result of multipoint contact, should thus emerge among securities analysts after implementation of Reg-FD, as public information circulation puts analysts on a more equal footing and limits the ability of particular analysts to dominate particular stocks by virtue of preferential corporate relations.

Indeed, if analysts' competitive advantages differed substantially prior to Reg-FD, there was little incentive for advantaged analysts to enter reciprocal dominance agreements and forbear from competition. They stood to gain much from the bold forecasts they made, and the likelihood that a less privileged analyst would make a bold—and accurate—estimate was low. This would be the case even if privileged analysts only occasionally gained preferential access to inside information. This matters because preferential access may be on average beneficial, but in any given time period may not yield an advantage, either because there is no important news, or because the company decides to inform all analysts at once. If privileged access produces a competitive advantage that shifts among analysts over time, it is individually rational for the actor with the best information to use it immediately (e.g., by issuing a bold earnings estimate), even though such actions increase competitive pressures. Thus, even if multipoint contact is high, prior to Reg-FD, analysts may be observed to have been unable to maintain mutual forbearance at all, or as only able to maintain it at low level. Under Reg-FD, however, with advantages of privileged corporate access removed and all material information circulating publicly, mutual forbearance becomes feasible—even desirable.

Reg-FD thus satisfies the three conditions for causal inference from a natural experiment (Shadish, Cook, & Campbell, 2002): (1) there is an exogenous change of context, (2) the change affects actors unequally (due to different multipoint contact and access to information), and (3) actors cannot self-select into the groups that are differentially affected by the change of context. In meeting these conditions, the enactment of Reg-FD affords an effective test of the effect of following boundary condition on the emergence of mutual forbearance:

Hypothesis 2. The effect stated in Hypothesis 1 is stronger under Reg-FD and may be exclusive to the period after its enactment.

Status Disparity

A fourth assumption in mutual forbearance is that actors willingly enter relations of reciprocal dominance and mutual forbearance. Research on multipoint contact, given its origin in strategy and economics (e.g., Bernheim & Whinston, 1990; Wernerfelt, 1985), has focused on competitive implications of multipoint contact when all actors are considered equal and has not been concerned with the social structure of markets. Yet we know that many markets are hierarchically arranged in such a way that some participants have greater status than others (Podolny, 1993, 1994). This is particularly true in professional markets, where quality is often difficult to observe (Hayward & Boeker, 1998; Phillips & Zuckerman, 2001), and status is used to infer quality instead. In such markets, status is a signal that participants can use to reduce uncertainty about performance, since status is correlated with quality (Castellucci & Ertug, 2010; Podolny, 1993). Higher status gives greater credibility in the eyes of audiences, which in turn yields financial rewards that create an incentive for high-status actors to protect and enhance their standing (Podolny, 1993, 1994). This protective desire is particularly important when a status order is unstable—that is, when high-status actors remain unsure that their status will endure (Jordan, Sivanathan, & Galinsky, 2011).

A primary determinant of analyst status is *Institutional Investor*'s (*II*'s) annual ranking, the All-American Research Team (the "All-Stars"). Although there are several analyst rankings, including the *Wall Street Journal*'s ranking and Thomson Reuters StarMine analyst awards, the *II* ranking is the oldest and most prestigious of these rankings, and the one that analysts themselves care most about (Kessler, 2003; Reingold, 2006). It is based on an annual survey of institutional investors' ratings of analysts' service and insight and results in numbered placements of the top three analysts in each industry and in runner-up status for one to two more analysts. According to the director of research at the now-defunct Shearson Lehman Brothers, "Before *II*, you didn't know who the best analysts were. . . . *II* had an unbelievable effect. It started knighting people as *the* experts. . . . You could be seventh best in the United States and you're nothing. It's either one, two, three, runner-up or nothing" (Groysberg, 2010: 44). Being ranked affects both analyst compensation and job opportunities (Groysberg, 2010), yet continued awards are not guaranteed, since institutional investors are surveyed each year. As a result, analysts choose actions that they believe will increase their odds of becoming ranked or protect their current rank. Garnering positive investor attention is critical, since institutional investors control the voting (Reingold, 2006; Zhuang, 2011).

Although analyst accuracy can be measured, it is not a reliable indicator of analyst quality because, simply by carefully matching the consensus estimate on a stock, an analyst has a good chance of being very accurate with little or no analytical work at all. The *II* rankings are based on service to investors, not necessarily accuracy, for the former reason but also because institutional investors value timely and novel information in addition to accurate forecasts. Thus, *II* ranking is a proxy for quality in a market where quality is not easily inferred. These rankings involve subtle performance differences in the sense that a seventh-best analyst is probably very close to an All-Star analyst in actual performance, but low performance is not compatible with maintaining ranking as an All-Star.

We predict that status is a second boundary that determines whether an actor will be willing to enter into forbearance relationships. In particular, under conditions of *status disparity*, we expect that, because high-status individuals have more to gain than low-status individuals from maintaining the status quo through mutual forbearance, the negative effects of mutual forbearance on analyst boldness strengthen with analyst status and thus will be more applicable to high- than low-status analysts.

Low-status actors allocate more attention and resources to competing against high-status actors than vice versa, and as a result, high-status actors receive more critical scrutiny and greater competitive challenges from low-status actors. For a low-status analyst, issuing bold estimates when available information supports them represents an opportunity to disrupt the status order. Prior research suggests that analysts tend to issue bold estimates when they are unworried by the potential loss of status and so have more to gain than lose (Boyson, 2010; Graham, 1999; Jegadeesh & Kim, 2010). Although low-status analysts may lose their clients as a result of inaccurate estimates, the stakes are lower for low-status analysts in that, if their estimates are inaccurate, they do not have to worry about losing status in addition to everything else that could occur because they made a wrong call. In addition, because clients' expectations for analyst accuracy is lower for low-status analysts, low accuracy is less damaging. Low-status analysts thus have an incentive to compete fully and to issue bold estimates whenever they have information to support them. There is, however, the caveat that the (prior to Reg-FD) information disadvantage of low-status analysts might result in erroneous estimates. Consequently, they must hope that their boldness turns out to be correct enough, often enough, to gain positive investor attention and increase their chances of being named to an *II* All-Star Team (Zhuang, 2011). And if not, they face an increased risk of dismissal (Hong & Kubik, 2003; Scharfstein & Stein, 1990).

High-status actors, in contrast, are averse to status loss: "The distress of losing a position to an inferior exceeds the pleasure of gaining the position of a superior" (Bothner, Kang, & Stuart, 2007: 214). This has two implications. First, high-status actors will behave differently when they have a competitive advantage over low-status actors and when the competitive field is level. In our context, the potential of losing status through inaccurate bold predictions will affect the competitive behavior of high-status analysts. Before Reg-FD, they held an information-based competitive advantage over low-status analysts and would have been able to preempt or react to competitive attacks through making bold and accurate predictions. With Reg-FD removing such advantages, greater competitive parity exposed high-status analysts to increased competitive pressure from low-status analysts, and their lack of unique information from network connections made aggressive moves through bold estimates a high-risk strategy. Instead, they would have been more interested in reducing the competitive pressure through engaging in fewer aggressive actions after Reg-FD. Thus, we predict:

Hypothesis 3. Analysts with Institutional Investor's *ranking are less likely to issue bold estimates after Reg-FD.*

Second, concerned with maintaining their privileged position, high-status analysts should prefer to stabilize the status order by forbearing from competition when the opportunity arises. In doing so, they avoid the risk that the bold estimates they have information to support are mistaken and thus that issuing them will result in downward adjustment of their status. Although low-status analysts may issue more bold estimates in general because they are willing to take risks to gain investor attention and improve their status position, when multipoint contact presents an opportunity to reduce competitive pressure and preserve the existing status structure, high-status analysts are more willing to enter into forbearance relationships. Thus:

Hypothesis 4. The effect stated in Hypothesis 1 is stronger for analysts with II *ranking.*

The Direction and Accuracy of Boldness

Prior studies of mutual forbearance typically focus on straightforward competitive actions for which there is only one interpretation, such as pricing. Yet some actions that can be taken in competitive environments, such as research and development spending, may have differential impact depending on how they are made, in addition to the fact that they are made at all. Prior studies of analyst boldness have focused on boldness without reference to its direction, but we believe it informative to distinguish between *positive* and *negative* bold estimates because they may provoke distinct reactions that affect an analyst's willingness to issue them. Specifically, negative bold estimates may anger executives of the firms that analysts rely on for information (McNichols & O'Brien, 1997; Securities and Exchange Commission, 2000), suggesting caution in issuing such estimates, particularly prior to Reg-FD. In the pre Reg-FD era, negative bold estimates enable analysts to attract client attention and place competitive pressures on rivals, particularly if their estimates turn to be correct. However, analysts with privileged information access to a firm are unlikely to issue a negative bold earnings estimate, even when in possession of information and analysis to support it, because their competitive advantage relies on continued information access from their corporate contacts. This is especially likely if these analysts lack overall status, which an All-Star analyst would have, and thus are strongly dependent on the firm.

Positive bold estimates, in contrast, may have an ingratiation effect on corporate executives, and so analysts use such estimates to vie for privileged access to information from executives (Westphal & Clement, 2008). Thus, prior to Reg-FD, negative and positive boldness are influenced by both analyst-firm and analyst-client relations. The ingratiation effect is likely to dominate, however, because it also affects analysts without information access who seek to obtain it. The reduction in bold negative estimates from fear of angering executives leaves little room for further reduction as a result of multipoint contact. These observations suggest that tests of Hypotheses 1–4 will show greater support for analysts' *positive* bold earnings estimates.

Another aspect of boldness concerns whether an estimate is accurate, as it would be if based on an analyst's exclusive access to a source of information in the pre-Reg-FD era or on superior analysis in the post-Reg-FD era. If the accuracy of estimates is controlled for, analysts making bold forecasts, in addition to garnering investor attention, are also more likely to move to prominent brokerage firms and be ranked as *II* All-Stars (Zhuang, 2011). When analysts compete fully, they thus have a strong incentive to issue bold estimates to attract investor attention and may be willing to trade some risk of inaccuracy for a gain in attention. We cannot directly observe these trade-offs, but we can examine them indirectly by incorporating a model of accuracy into our model of boldness so that we can observe whether bold estimates are on average likely to be accurate. Multipoint contact reduces competition, for example, but is not enough to deter an analyst with unusually good information from publishing a bold estimate. Thus, we should observe that multipoint competition increases the accuracy of bold estimates as a result of the heightened threshold for boldness.

The accuracy analysis provides a test of our premise that boldness before Reg-FD is driven by inside information to a greater extent than boldness after Reg-FD, which implies a drop in accuracy after Reg-FD. Because multipoint contact should lead to greater reluctance to issue bold estimates, we should also observe that the bold estimates that do occur for stocks with high multipoint contact are more accurate. We do not hypothesize these relations explicitly but rather use them to examine the plausibility of the theoretical mechanisms underlying our predictions.

DATA AND METHODS

Our data, compiled from Thomson's IBES database, includes information on the activities and employers (i.e., brokerage firms) of all securities analysts who issued earnings estimates for publicly traded companies in the United States between January 1, 1995, and December 31, 2007. We augment these data with information on analyst reputations, brokerage firm underwriting activity, and characteristics of the publicly traded companies.

The availability of historical data and the fiscal year-ends of individual firms constrain our sample. Our observation period begins in 1995, which coincides with the first year for which IBES began updating analyst forecasts daily. Our start date of January 1, 1995, means that we include analyst estimates for firms that had not released annual earnings as of January 1, 1995, which includes firms with fiscal year-ends from September 1, 1994, and later. Our end date of December 31, 2007, means that, given reporting and delays in the release of annual earnings, we analyze analyst estimates covering earnings releases for firms with fiscal year ends up to September 30, 2007. Because the identity of analysts is critical to our analysis, we exclude all estimates issued by unnamed analysts. The final sample included 1,229,872 estimates: 473,649 issued by 4,784 analysts covering 1,824 stocks prior to Reg-FD (January 1, 1995, to September 30, 2000) and 756,223 issued by 6,670 analysts for 1,439 stocks under Reg-FD (October 1, 2000, to December 31, 2007).

Multipoint Contact

Following earlier research on equity analysts (e.g. Zuckerman, 1999, 2004), we define an analyst's multipoint contact in terms of joint stock coverage. Cocoverage is examined over 12-month moving windows, which are updated quarterly so that construction of each quarter's multipoint contact for each analyst is based on all analyst joint stock coverage in the prior 12 months. So, for example, the quarter for April 1, 1999, to June 30, 1999, is constructed using information on all joint stock coverage among analysts between March 31, 1998, and March 31, 1999. We adopted 12-month windows for two reasons. First, analysts vary in the frequency in which they issue estimates on stocks they cover. A shorter window would not capture information on analysts who cover a stock but issue estimates for it infrequently. Second, a 12-month window captures analysts who may normally actively cover a stock but may be precluded from doing so for a period of time, for example, by regulatory quiet periods surrounding underwriting or other financial transactions (Michaely & Womack, 1999).

Co-coverage influences analysts' estimates by serving as a basis for mutual monitoring. Reingold (2006) provides several illustrations of these mechanisms. In one, when an analyst who covered WorldCom observed a rival lower his estimate of WorldCom, possibly on the basis of private information obtained directly from the company, the first analyst initiated a search for information to account for the lower estimate. In a second example, when an analyst well known for being aggressively negative with AT&T upgraded it to a "strong buy" without any apparent change in AT&T's outlook, another analyst covering AT&T received inquiries and comments from clients, such as "I smell a deal," prompting him to initiate further search. These incidents, which occurred prior to Reg-FD, suggest that analysts obtained private corporate information during this period, monitored analysts with cocoverage and used them as reference points, and sought additional information in response to rival analysts' bold estimates.

Dependent Variables and Method

Our unit of analysis is the analyst-stock estimate, and our first dependent variable measures whether a given analyst-stock estimate is unusually high or low relative to other analysts' estimates for the given stock. The boldness of analyst estimates is a qualitative distinction. Therefore, following prior work (e.g., Rao et al., 2001; Clement & Tse, 2005; Zhuang, 2011), we created a dummy variable coded 1 for analyst estimates that differed from the current mean, or consensus, estimate for a stock by more than 1.5 standard deviations and 0 otherwise. We used the standard deviation of analyst estimates rather than a numeric distinction (e.g., twice or half the consensus estimate, as in Rao et al. [2001]) to capture boldness more consistently across stocks and estimates over time. We calculated the consensus estimate for each stock by averaging all active earnings estimates for that stock the day prior to a focal estimate. We labeled our dependent variables *analyst positive boldness* for estimates that were more than 1.5 standard deviations above the consensus and *analyst negative boldness* for estimates that were more than 1.5 standard deviations below the consensus estimate.

We also analyzed the accuracy of bold estimates, which required defining *accurate positive boldness* for estimates that have positive boldness and are closer to actual earnings than the analyst consensus. Analogously, we define *accurate negative boldness* for estimates that have negative boldness and are closer to actual earnings than the analyst consensus.

We employed a simultaneous regression approach in which models for positive boldness, accuracy of positive boldness, negative boldness, and accuracy of negative boldness were estimated as a system of equations. This allowed a specification in which accuracy is a function of some of the same covariates as boldness, as well as actual boldness as an endogenous effect. This specification is useful if we suspect that information or context that influences the choice of boldness simultaneously influences accuracy, so that there will be some correlation among these outcomes. We reserved several variables describing an analyst's past tendency to issue bold estimates for identification of the boldness regression and thus did not enter them into the accuracy regression. We applied fixed effects for analyst-stock dyads and allowed correlation of all variance-covariance terms, thus employing the most flexible correlation structure. The estimation was implemented using three-stage least squares (3SLS).

To validate the specification, we conducted the following tests: A Durbin-Wu-Hausman test confirmed our assumption that boldness was indeed endogenous to the accuracy regression, supporting our simultaneous equation approach. An Anderson canonical correlation test for underidentification confirmed that we had enough variables in the boldness regression to identify it in the accuracy regression. The Stock and Yogo (2005) test permitted rejection of the null hypothesis of weak instruments. The only problematic result was the Sargan test, which indicated that bold estimates were not fully exogenous in the regression for accuracy. This indicates potential bias in the accuracy regression but is not problematic for the boldness regression, which we used for testing our hypotheses. These tests were conducted using the "ivreg2" routines of Stata on pairwise regressions of positive and negative boldness, respectively, on positive and negative accuracy.

Each regression is linear, which means that we applied a linear probability model in all four regressions. The linearity allows easier interpretation of interaction effects than a logit analysis would, as marginal effects in linear models are equal to coefficient estimates (Angrist & Pischke, 2008: 95–107; see also Waguespack & Sorenson, 2011). In a preliminary analysis, we also used logit in single regressions with fixed effects, and the results of that analysis correspond well with the full models presented here. We are thus able to reproduce these results across analytical approaches that differ in both functional form and assumptions regarding the interdependence of outcomes.

Independent Variables

Our measure of *analyst multipoint contact* captures the extent to which an analyst covering a stock jointly with other analysts also covers other stocks jointly with those analysts. Thus, multipoint contact is specific to a particular analyst-stock pair. To compute the measure, for each stock an analyst covered, we calculated the proportion of the portfolio of stocks the analyst covered that were covered jointly by each other analyst who also covered the focal stock and then computed the average proportional overlap among analysts (Baum & Korn, 1996). This measure is formally defined as follows:

$$MPC_{i,\ m} = \frac{(\Sigma_{i \neq j}\, D_{i,\ n} \times D_{j,\ n})/(\Sigma\ D_{i,\ n} + 1)}{N_m - 1},$$

where $MPC_{i,\ m}$ is analyst i's multipoint contact for analysis of corporation m, $D_{i,\ n}$ is equal to 1 if analyst i covers corporation n in a report, $D_{j,\ n}$ is equal to 1 if other analysts j covering corporation m cover corporation n in their reports, and N_m is the total number of analysts who cover corporation m in their reports. We recomputed multipoint contact at the time of each estimate using the appropriate quarterly network. Higher values of multipoint contact indicate a greater proportional stock coverage overlap between a focal analyst and his/her alters on a given stock (and thus a greater potential for mutual forbearance on the focal stock).

To examine the effect of the shift to competitive parity, multipoint contact was interacted with *Reg-FD*, a dichotomous variable coded 1 for all dates after October 1, 2000, and 0 otherwise. Although Reg-FD was announced in August 2000, it was not ratified until October 23, 2000 (Securities and Exchange Commission, 2000). We allowed for an adjustment period, setting October 1, 2000, as the start of the Reg-FD period (Mohanram & Sunder, 2006).

To estimate the effects of *analyst status*, we used annual *Institutional Investor* lists. As noted above, those listed are considered to be of higher status than those who are not (e.g., Groysberg & Lee, 2008; Groysberg, Polzer, & Elfenbein, 2011; Hayward & Boeker, 1998; Leone & Wu, 2007). Because a small fraction of analysts are ranked this ranking represents an elite professional accomplishment with substantial impact on analysts' credibility and visibility. In addition, because of the wide prevalence of this observable ranking system, analysts recognize status differences among other analysts who cocover their stocks. Estimates issued by ranked analysts list differ from those issued by other analysts in the sense that the former tend to be bolder.

To measure an analyst's status, we considered his/her history of *II* rankings since 1990. Our measure accounts both for how recently an analyst was an All-Star as well as how many such rankings he or she has received. Specifically, we summed each year an analyst had been listed as an All-Star, weighted by its recency (i.e., 1/(year$_t$ − year of listing). This measure gives more weight to recent rankings to account for the enduring, but weakening, effect of being ranked.[2] To assess the effect of analyst status on mutual forbearance, we interacted this weighted All-Star measure with multipoint contact.[3]

Control Variables

We controlled for a number of characteristics of analysts, their employers (i.e., brokerage firms), and the stocks they cover that may influence the likelihood of an analyst issuing a bold estimate. All variables are updated at the time of each estimate unless otherwise indicated. Because we include analyst-stock dyad fixed effects, we only enter covariates that vary over time.

Analyst controls. Research suggests that *analyst experience* increases the likelihood of issuing bold estimates (Hong et al., 2000), because more experienced analysts have established relationships with corporate management of the firms whose stocks they follow and thus obtain preferential access to material information. We therefore controlled for each analyst's years of experience by counting the number of days between a current stock estimate and the analyst's earliest recorded earnings estimate on any stock[4] and dividing by 365.25 to obtain a measure of years of experience. We also controlled for an analyst's *focal stock experience*, measured as the number of days between the analyst's current and earliest recorded earnings estimate on that stock, divided by 365.25.

We also controlled for an analyst's *stock portfolio size*, measuring it as the number of stocks the analyst followed at the time of each estimate (logged to reduce skew). Prior research shows lower rates of issuing of bold estimates for analysts covering larger numbers of firms (Clement & Tse, 2005), a result likely due to the reduced attention that an analyst can give to each stock he or she follows.

Analysts whose earnings estimates are closely followed by other analysts may also differ in their boldness. We controlled for this possibility using an analyst's *leader-follower ratio (*LFR; Cooper, Day, & Lewis, 2001; Loh & Stulz, 2011; Schroff, Venkataraman, & Xin, 2004). To compute an analyst's LFR, we divided the sum of the number of days between the date of the analyst's current estimate for a stock and the dates of the preceding two estimates for the stock by the sum of the number of days between the current estimate and the two following estimates for the stock, following prior research. (Extending the number of estimates beyond a horizon of two increases the number of analysts needed to cover a stock to compute the measurement.) An LFR greater than 1 suggests an analyst's estimate was more quickly followed by other analysts than it followed others.

Lastly, we controlled for each analyst's tendency to issue bold estimates, both for a focal stock and other stocks he or she covered. We distinguished between estimates with positive and negative boldness since analysts may be more likely to issue bold

[2] We are grateful to Tim Pollock for suggesting this measurement approach.

[3] In additional analyses, we examined specific numerical rankings but found better fit with a dichotomous measure that indicates only whether or not an analyst was ranked in *Institutional Investor*. This finding suggests that neither analysts nor their customers rely on such fine-grained rankings when attributing status, as is substantiated by anecdotal accounts of equity analysts (Kessler, 2003; Reingold, 2006).

[4] Consistent data on the dates of analyst estimates are not available prior to January 1, 1990. As a result, that is the first date on which we can observe an analyst's earliest estimate. Because we do not include estimates prior to 1995 in the analysis, the histories for analysts issuing estimates before 1995 are left-censored. We therefore estimated models including a dummy variable coded 1 for analysts who issued an estimate before 1995 and 0 otherwise. The variable was not significant and did not alter the findings.

estimates in one direction than another, and there may be time-dependent effects at the stock level (e.g., issuing a positive bold estimate lowers the likelihood of a negative bold estimate on the same stock for a period of time). The variables *prior negative bold estimate* (*focal stock*) and *prior negative bold estimate* (*portfolio*) were defined as the total number of negative bold estimates an analyst issued for a focal stock during the past 180 days and the mean number of bold estimates the analyst issued on all the other stocks he/she covered over the same time horizon, respectively. We calculated analogous variables for positive bold estimates. We entered these variables only in the boldness regressions in order to identify the systems of equations.

Brokerage firm controls. We controlled for several characteristics of the brokerage firm that employed an analyst. First, we controlled for *brokerage size*, indexed by the number of stocks covered by analysts working for the firm. Since underwriting relationships between brokerage firms and issuing companies have been shown to impact analyst recommendation activity (e.g., Hayward & Boeker, 1998; Michaely & Womack, 1999), we also controlled for the underwriting activity of the brokerage. We obtained data on all new issues for publicly traded US firms using the SDC Platinum database and matched them with the IBES analyst data. We controlled for the brokerage's *total underwriting activity* with a cumulative count of all *new issues underwritten* by the firm since 1990. We also controlled for the cumulative number of times (also since 1990) the brokerage had participated in *focal stock underwriting activity*. Each of these variables was logged to reduce skew.

Stock controls. We used several measures to account for characteristics of the stock for which an analyst issued a current estimate. First, we controlled for the total number of *analysts following a focal stock* by summing the number of other analysts with outstanding estimates on the stock on the date of a focal analyst's current estimate. In addition, using the CRSP database, we measured *focal stock size* as a company's *total assets*. These variables were also logged to reduce skew. Additionally, we controlled for the standard deviation of the consensus estimate for a focal stock on the date of the analyst's estimate (*consensus estimate, focal stock, s.d.)*. This control accounts for variation in stock uncertainty and for analyst awareness of prior estimates, which may lead to herding.

Finally, since information released by corporate management may influence the likelihood of bold estimates being issued, we included two dummy variables, focal stock earnings release and focal stock guidance release, using data from FirstCall. The *earnings release, focal stock,* variable was coded 1 if a company released a quarterly or annual earnings report within a three-day window of an analyst's current estimate and 0 otherwise. In addition to earnings reports, companies also issue earnings guidance, often to help analysts reduce their earnings expectations (Cotter, Tuna, & Wysocki, 2006). The *guidance release, focal stock,* variable was coded 1 if a company issued earnings guidance within a three-day window of an analyst's current estimate and 0 otherwise.

Other controls. We controlled for temporal effects using a *time trend* variable that counted the number of days since January 1, 1995, divided by 365.25.

Descriptive Statistics

Means, standard deviations, and correlations are given in Table 1.[5] In general, the statistics are unremarkable and suggest little potential collinearity. A small number of correlations are moderately strong (i.e., above .65, indicating 42 percent shared variance), including the correlation between the time trend and Reg-FD variables and the correlations between both these variables and the number of stocks analysts covered. The first of these correlations is obvious, and the latter correlations correspond to the observed decline in the number of stocks covered by an average analyst following enactment of Reg-FD (Mohanram & Sunder, 2006).[6]

RESULTS

We begin with a descriptive analysis examining how multipoint contact developed before and after Reg-FD, along with changes in leader-follower ratios. LFRs serve as good (albeit imperfect) indicators of

[5] We computed descriptive statistics for the sample used to estimate each dependent variable. However, because the means, standard deviations, and correlations are similar, we present descriptive statistics for the "all bold" sample as representative.

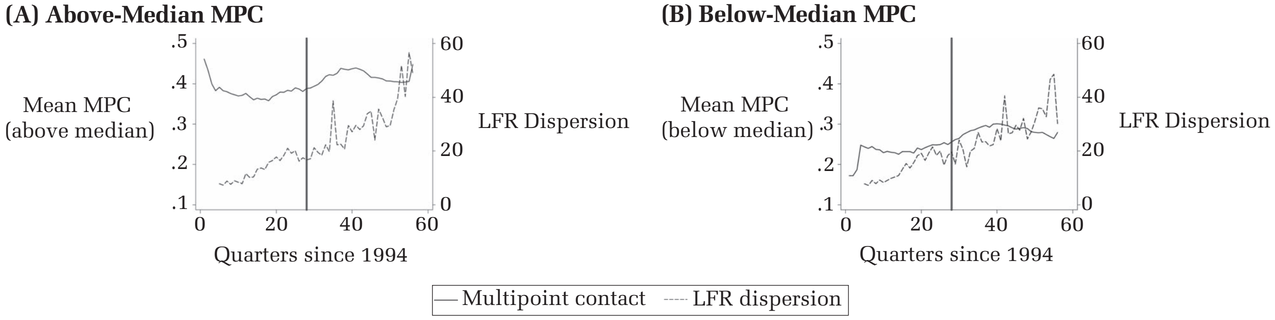
[6] As a further collinearity check, we computed variance inflation factors (VIFs). Two controls, both logged, *stocks covered by analyst's brokerage* (14.8) and *total analysts following focal stock* (13.2), were the only variables above the standard threshold of ten (Belsey, Kuh, & Welsch, 1980). Excluding the first of these gives identical results and no VIF statistics over ten. In the models reported we therefore include the full set of controls.

TABLE 1
Descriptive Statistics and Correlations[a]

Variable	Mean	s.d.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1. Analyst positive boldness	0.11	0.32																							
2. Analyst negative boldness	0.09	0.28	−.11																						
3. Accurate positive boldness	0.06	0.23	.69	−.08																					
4. Accurate negative boldness	0.03	0.18	−.07	.59	−.05																				
5. Time trend	11.33	3.74	−.06	.04	−.12	−.05																			
6. Analyst experience[b]	5.80	3.89	−.01	.01	−.02	.00	.17																		
7. Analyst focal stock experience[b]	6.37	1.06	−.02	.00	−.01	.01	.15	.52																	
8. Analyst portfolio size[b]	2.62	1.01	.04	−.04	.10	.04	−.64	.12	.10																
9. Analyst prior negative bold, focal stock	0.08	0.22	.03	.15	−.02	.11	.06	.00	−.02	−.05															
10. Analyst prior negative bold, portfolio	0.09	0.13	.01	.09	−.02	.06	.07	.02	.00	−.04	.12														
11. Analyst prior positive bold, focal stock	0.11	0.26	.15	.02	.14	−.01	−.07	−.02	−.02	.06	−.07	.01													
12. Analyst prior positive bold, portfolio	0.11	0.14	.07	.02	.07	.00	−.11	−.02	−.02	.12	.02	−.04	.11												
13. Brokerage total underwriting[b]	5.42	2.22	−.02	.01	−.01	.01	.20	.15	.12	−.05	.01	.02	−.02	−.03											
14. Brokerage size[b]	5.50	1.32	.01	−.02	.06	.03	−.31	.06	.05	.48	−.03	−.02	.02	.05	.55										
15. Brokerage focal stock underwriting	0.16	0.36	−.01	.00	−.01	.00	.05	.05	.00	.01	−.01	−.01	−.01	−.02	.24	.13									
16. Analyst leader-follower ratio	4.89	17.86	.01	.01	.00	−.01	.07	.01	.01	−.04	.00	.01	.00	.01	.04	.01	.02								
17. Analysts following focal stock[b]	3.53	1.15	−.01	−.01	.03	.02	−.08	.08	.07	.21	−.01	−.01	.00	.01	.67	.92	.16	.03							
18. Focal stock size[b]	7.59	2.02	−.04	−.04	−.01	−.01	.15	.13	.25	−.05	−.05	−.05	−.05	−.07	.10	.10	−.13	−.04	.14						
19. Focal stock, consensus estimate, s.d.	0.20	5.29	−.01	−.01	−.01	.00	−.01	.00	−.01	.00	−.01	.00	−.01	−.01	.00	.01	.00	.00	.01	.00					
20. Focal stock, earnings release	0.22	0.41	.02	.02	.01	−.02	.15	.01	.01	−.10	.01	.03	.01	.01	.08	−.01	.03	.09	.03	−.04	−.01				
21. Focal stock, guidance release	0.09	0.29	.01	.03	−.01	.01	.16	.07	.08	−.10	.03	.04	.00	.00	.07	.00	−.03	.06	.03	.09	−.01	.22			
22. Analyst multipoint contact	0.35	0.19	−.04	−.02	−.02	.00	.12	−.10	.01	−.23	−.02	−.04	−.04	−.07	.18	.13	−.03	−.01	.22	.30	.01	.00	.03		
23. Reg-FD	0.60	0.49	−.06	.06	−.14	−.04	.87	.15	.12	−.66	.08	.12	−.09	−.12	.19	−.30	.04	.06	−.09	.15	.00	.14	.17	.13	
24. Analyst status	0.51	1.13	−.01	−.01	.01	.01	−.10	.35	.24	.21	−.02	−.02	−.01	−.01	.28	.36	.09	.01	.39	.16	.00	.00	.03	.10	−.07

[a] $n = 960{,}080$; 112,894 groups.
[b] Logarithm.

FIGURE 1
Multipoint Contact and Leader-Follower Ratio Dispersion[a]



[a] "MPC" is multipoint contact; "LFR" is leader-follower ratio.

reciprocal dominance among analysts. Although one or a few estimates may achieve leadership because of good information content rather than analyst dominance, averaging LFRs across many estimates and checking their dispersion within a given stock will smooth out variation and distinguish stocks for which there are clear leaders and followers as well as more competitive stocks for which analysts vie for leadership. The behavioral expectation is that if multipoint contact enables dominance, it should also lead to greater dispersion in LFRs. If dominance is the result of some other factor, such as privileged information access, the two should not be related.

Figure 1 shows mean multipoint contact as a function of time, with the vertical line marking the enactment of Reg-FD. For clarity, the graph is split into two, with stocks for which multipoint contact is above the median in the left panel and stocks for which multipoint contact is below the median in the right panel. In both graphs multipoint contact increases after Reg-FD, suggesting some effort among analysts to initiate multipoint contact, perhaps with the intent of mutual forbearance. Although the magnitude is not great and the increase is not systematic, this is not surprising considering the coordination that would be needed for a rapid increase in multipoint contact. However, the LFR dispersion, indicating change in behaviors, moves much more quickly. The rapid increase, especially under Reg-FD, suggests much stronger alignment between multipoint contact and mutual forbearance as information access became more even; this accords well with our expectations.

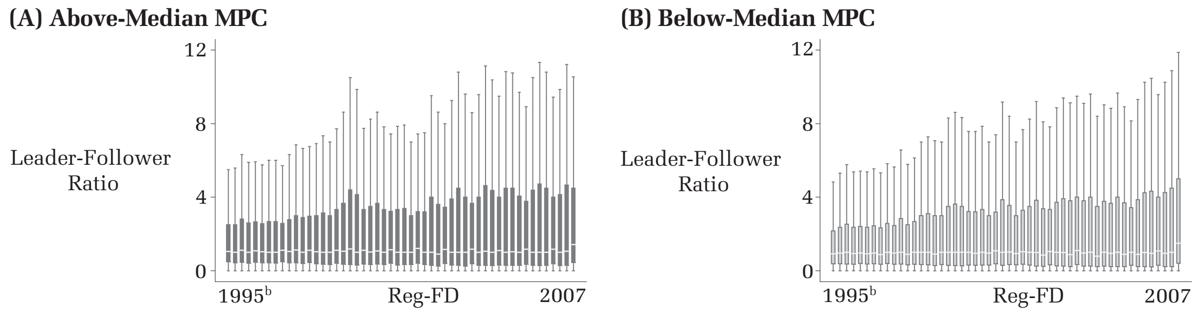
To confirm that the increased LFR dispersion under Reg-FD observed in Figure 1 is not driven by certain analysts' domination of stocks for which multipoint contact is high, we also compare, in Figure 2, the pattern of within-analyst LFR dispersion for high and low multipoint contact stocks in an analyst's portfolio. For each quarter, we split analyst-stocks above and below the median multipoint contact and then graphed dispersion of LFR for each group of observations with box plots.[7] As the figure shows, it is not the case that analyst LFR dispersion is low for high multipoint contact stocks or that certain analysts who always dominate high multipoint contact stocks underlie the patterns evident in Figure 1.

The regressions are displayed in Tables 2 through 4. Table 2 shows all the coefficient estimates. Tables 3 and 4 show all coefficient estimates for the boldness regressions, but in the accuracy regressions only the coefficient estimates that are informative as to overall accuracy and the effect of multipoint competition are shown. The other coefficients show only minor variations in these regressions (full results are available from the authors).

Table 2 shows the full system of equations for the control variables. The estimates match expectations, as more experienced analysts and analysts with a record of bold estimates are more likely to be bold. There is less boldness on large stocks and stocks followed by many analysts, as one would expect given the greater availability of information for such stocks. Reg-FD reduced boldness, also as one would expect from the banning of selective

[7] The upper and lower boxes represent 75th and 25th percentiles, respectively. The middle bars indicate medians. The upper and lower adjacent lines indicate upper quartile plus and minus 1.5 intervals, respectively, where intervals are equal to upper quartile minus lower quartile.

FIGURE 2
Box Plots of Leader-Follower Ratio Dispersion by High and Low Multipoint Contact[a]



[a] "MPC" is multipoint contact.
[b] Excludes outside values.

information transfers. Analyst status has a small effect, but this result is not informative because the status effect is likely to differ before and after Reg-FD. The accuracy regressions show an overall high accuracy of bold estimates. Using a 0.5 likelihood of a bold estimate being correct as a baseline (an arbitrary but intuitive threshold that corresponds to the likelihood of flipping a coin), the accuracy of positive bold estimates is significantly above 0.5, while for negative bold estimates, accuracy is

TABLE 2
3SLS Fixed-Effect Simultaneous Regression Models of Bold Estimates, Model 1[a]

Variables	Positive Boldness		Accurate Positive Boldness		Negative Boldness		Accurate Negative Boldness	
Time trend	−0.002***	(0.0002)	0.001***	(0.0002)	−0.001***	(0.0002)	−0.002***	(0.0001)
Analyst experience[b]	0.0002*	(0.0001)	−0.0004***	(0.0001)	0.0003**	(0.0001)	−0.0004***	(0.0000)
Analyst prior experience, focal stock[b]	−0.0006	(0.0004)	0.002***	(0.0002)	0.002***	(0.0003)	0.003***	(0.0002)
Analyst portfolio size[b]	−0.0013*	(0.0006)	0.003***	(0.0003)	−0.0009†	(0.0005)	0.002***	(0.0003)
Analyst prior negative bold, focal stock	0.048***	(0.001)			0.189***	(0.001)		
Analyst prior negative bold, portfolio	0.022***	(0.002)			0.137***	(0.002)		
Analyst prior positive bold, focal stock	0.174***	(0.001)			0.029***	(0.001)		
Analyst prior positive bold, portfolio	0.115***	(0.002)			0.025***	(0.002)		
Brokerage total underwriting, issues[b]	−0.001***	(0.0002)	0.001***	(0.0001)	0.001***	(0.0002)	0.001***	(0.0001)
Brokerage stocks covered	0.003**	(0.001)	−0.004***	(0.001)	−0.001	(0.001)	−0.003***	(0.000)
Brokerage total underwriting, focal stock[b]	−0.007***	(0.001)	0.001*	(0.000)	−0.006***	(0.001)	0.000	(0.000)
Analyst leader-follower ratio	0.0001***	(0.00002)	−0.00002*	(0.00001)	−0.000	(0.000)	−0.00003***	(0.00001)
Analysts following focal stock[b]	−0.004***	(0.001)	0.005***	(0.001)	0.001	(0.001)	0.004***	(0.000)
Focal stock size[b]	−0.003***	(0.0002)	0.004***	(0.0001)	−0.005***	(0.0001)	0.002***	(0.0002)
Focal stock, consensus estimate, s.d.	−0.0004***	(0.00001)	−0.0000	(0.0000)	−0.0002***	(0.00001)	0.00006*	(0.00003)
Focal stock, earnings release	0.016***	(0.001)	0.004***	(0.000)	0.002**	(0.001)	−0.007***	(0.000)
Focal stock, guidance release	0.011***	(0.001)	−0.004***	(0.001)	0.018***	(0.001)	−0.001**	(0.001)
Reg-FD	−0.020***	(0.001)	−0.051***	(0.001)	0.026***	(0.001)	−0.016***	(0.001)
Analyst status	−0.0002	(0.0003)	−0.0003†	(0.0002)	−0.0005†	(0.00003)	0.0003	(0.0002)
Positive boldness			0.595***	(0.004)				
Negative boldness							0.455***	(0.003)
χ^2	30,502.3***		67,024.8***		33,035.0***		25,448.4***	

[a] Standard errors are in parentheses.
[b] Logarithm.
† $p < .10$
* $p < .05$
** $p < .01$
*** $p < .001$

TABLE 3
3SLS Fixed-Effect Simultaneous Regression Models of Bold Estimates, Models 2 and 3[a]

Variables	Model 2				Model 3			
	Positive Boldness		Negative Boldness		Positive Boldness		Negative Boldness	
Time trend	−0.002***	(0.0002)	−0.001***	(0.0002)	−0.002***	(0.0002)	−0.001***	(0.0002)
Analyst experience[b]	0.000	(0.000)	0.000	(0.000)	0.0002†	(0.0002)	0.0002†	(0.0001)
Analyst prior experience, focal stock[b]	−0.000	(0.000)	0.002***	(0.0003)	−0.000	(0.0004)	0.002***	(0.0003)
Analyst portfolio size[b]	−0.003***	(0.001)	−0.002***	(0.001)	−0.003***	(0.001)	−0.002***	(0.001)
Analyst prior negative bold, focal stock	0.047***	(0.001)	0.189***	(0.001)	0.047***	(0.001)	0.188***	(0.001)
Analyst prior negative bold, portfolio	0.021***	(0.002)	0.136***	(0.002)	0.020***	(0.002)	0.134***	(0.002)
Analyst prior positive bold, focal stock	0.174***	(0.001)	0.029***	(0.001)	0.173***	(0.001)	0.029***	(0.001)
Analyst prior negative bold, portfolio	0.114***	(0.002)	0.025***	(0.002)	0.112***	(0.002)	0.023***	(0.002)
Brokerage total underwriting, issues[b]	−0.001***	(0.000)	0.001***	(0.000)	−0.001***	(0.000)	0.001**	(0.000)
Brokerage stocks covered	0.003***	(0.001)	−0.001	(0.001)	0.004***	(0.001)	−0.001	(0.001)
Brokerage total underwriting, focal stock[b]	−0.007***	(0.001)	−0.007***	(0.001)	−0.007***	(0.001)	−0.006***	(0.001)
Analyst leader-follower ratio	0.00009***	(0.00002)	−0.00000	(0.00002)	0.00009***	(0.00002)	−0.00000	(0.00002)
Analysts following focal stock[b]	−0.003**	(0.001)	0.002*	(0.001)	−0.003**	(0.001)	0.002†	(0.001)
Focal stock size[b]	−0.002***	(0.000)	−0.005***	(0.000)	−0.003***	(0.000)	−0.005***	(0.000)
Focal stock, consensus estimate, s.d.	−0.0004***	(0.0001)	−0.0002***	(0.0001)	−0.0004***	(0.0001)	−0.0002**	(0.0001)
Focal stock, earnings release	0.016***	(0.001)	0.0019**	(0.0007)	0.015***	(0.001)	0.0014*	(0.0007)
Focal stock, guidance release	0.011***	(0.001)	0.017***	(0.001)	0.011***	(0.001)	0.018***	(0.001)
Reg-FD	−0.020***	(0.001)	0.026***	(0.001)	−0.013***	(0.002)	0.045***	(0.002)
Analyst status	0.000	(0.000)	−0.000	(0.000)	0.009***	(0.001)	0.003***	(0.001)
Analyst multipoint contact	−0.027***	(0.002)	−0.018***	(0.002)	−0.019***	(0.003)	0.014***	(0.003)
Reg-FD × analyst multipoint contact					−0.006†	(0.003)	−0.048***	(0.003)
Reg-FD × analyst status					−0.008***	(0.001)	−0.003***	(0.001)
Analyst multipoint contact × analyst status					−0.011***	(0.002)	−0.004**	(0.002)
Effects on accuracy								
Analyst multipoint contact	0.008***	(0.001)	0.013***	(0.001)	−0.003	(0.002)	0.011***	(0.001)
Reg-FD × analyst multipoint contact					0.019***	(0.002)	0.004*	(0.002)
Positive boldness	0.597***	(0.004)			0.598***	(0.004)		
Negative boldness			0.457***	(0.003)			0.458***	(0.003)
χ^2	30,713.7***		33,160.3***		30,977.5***		33,479.4***	

[a] Standard errors are in parentheses.
[b] Logarithm.
† $p < .10$
* $p < .05$
** $p < .01$
*** $p < .001$

significantly below 0.5. Analyst experience increases accuracy, as does focal stock size and the number of analysts following a stock.

Table 3 presents model 2, with main effects, and model 3, with the full set of interactions. In model 2, the coefficients for analyst multipoint contact are negative and significant, supporting Hypothesis 1, which predicts that analysts are less likely to issue bold estimates when multipoint contact is high. The finding is consistent across positive and negative bold estimates, but as expected it is stronger for positive bold estimates (the coefficients are significantly different at $p < .001$).[8] Given the many studies that have shown that multipoint contact attenuates competitive aggressiveness, this finding supports our conceptualization of analysts' boldness as a key element of their competitive behavior.

Model 3 includes the interactions and thus provides tests of Hypotheses 2, 3, and 4. The significant negative coefficients for the Reg-FD times multipoint contact interaction support Hypothesis 2, which predicts that multipoint contact is more strongly related to mutual forbearance under competitive parity (i.e., under Reg-FD). The interaction of status and Reg-FD tests Hypothesis 3 regarding the attenuation of the effect of status on competition under regulation. Consistently with the prediction, high-status analysts were more likely to issue bold estimates before Reg-FD (presumably as a result of being tipped off more often), but had the same likelihood as low-status analysts under

[8] The tests of coefficient estimate differences use the Stata "test" statement to give standard chi-square tests for expressions of multiple coefficients.

TABLE 4
3SLS Fixed-Effect Simultaneous Regression Models of Pre- and Post-Reg-FD Bold Estimates[a]

	Pre-Reg-FD Estimates				Post-Reg-FD Estimates			
Variables	Positive Boldness		Negative Boldness		Positive Boldness		Negative Boldness	
Time trend	−0.009***	(0.0004)	0.003***	(0.0002)	−0.000	(0.000)	−0.002***	(0.0002)
Analyst experience	0.0005†	(0.0002)	−0.000	(0.000)	0.000	(0.000)	0.0002**	(0.00006)
Analyst prior experience, focal stock[b]	0.002**	(0.001)	0.005***	(0.001)	−0.000	(0.000)	0.000	(0.000)
Analyst portfolio size[b]	−0.004***	(0.001)	−0.002*	(0.001)	−0.004***	(0.001)	−0.004***	(0.001)
Analyst prior negative bold, focal stock	−0.050***	(0.003)	0.218***	(0.002)	0.096***	(0.002)	0.165***	(0.002)
Analyst prior negative bold, portfolio	−0.067***	(0.005)	0.184***	(0.004)	0.046***	(0.003)	0.109***	(0.003)
Analyst prior positive bold, focal stock	0.151***	(0.002)	−0.017***	(0.001)	0.179***	(0.002)	0.092***	(0.002)
Analyst prior positive bold, portfolio	0.112***	(0.004)	−0.018***	(0.003)	0.095***	(0.003)	0.057***	(0.003)
Brokerage total underwriting issues[b]	0.002***	(0.000)	0.001***	(0.000)	−0.002***	(0.0003)	0.000	(0.000)
Brokerage stocks covered[b]	0.008***	(0.002)	−0.002*	(0.001)	0.003**	(0.001)	0.005***	(0.001)
Brokerage total underwriting, focal stock	−0.005**	(0.002)	−0.001	(0.001)	−0.006***	(0.001)	−0.008***	(0.001)
Analyst leader-follower ratio	0.0003***	(0.0000)	0.00008*	(0.00003)	0.00004†	(0.00002)	−0.000	(0.000)
Analysts following focal stock[b]	−0.001	(0.002)	0.005***	(0.001)	−0.005***	(0.001)	−0.004**	(0.001)
Focal stock size[b]	0.002***	(0.000)	−0.003***	(0.000)	−0.006***	(0.000)	−0.005***	(0.000)
Focal stock, consensus estimate, s.d.	−0.0004***	(0.0001)	−0.000	(0.000)	−0.0003***	(0.0001)	−0.0003***	(0.0001)
Focal stock, earnings release	0.024***	(0.002)	−0.010***	(0.001)	0.009***	(0.001)	0.008***	(0.001)
Focal stock, guidance release	−0.007*	(0.003)	0.028***	(0.002)	0.016***	(0.001)	0.013***	(0.001)
Reg-FD	0.007***	(0.001)	0.002**	(0.001)	−0.000	(0.001)	0.001	(0.001)
Analyst status	−0.039***	(0.004)	0.004	(0.003)	−0.014***	(0.002)	−0.032***	(0.002)
Analyst multipoint contact	−0.021***	(0.003)	−0.005**	(0.002)	−0.003	(0.002)	−0.005*	(0.002)
Effects on accuracy								
Multipoint contact	0.015***	(0.002)	0.013***	(0.002)	0.010***	(0.001)	0.002*	(0.001)
Positive boldness	0.889***	(0.006)			0.395***	(0.004)		
Negative boldness			0.849***	(0.005)			0.251***	(0.004)
χ^2	10,456.4***		15,960.3***		20,885.7***		18,368.4***	

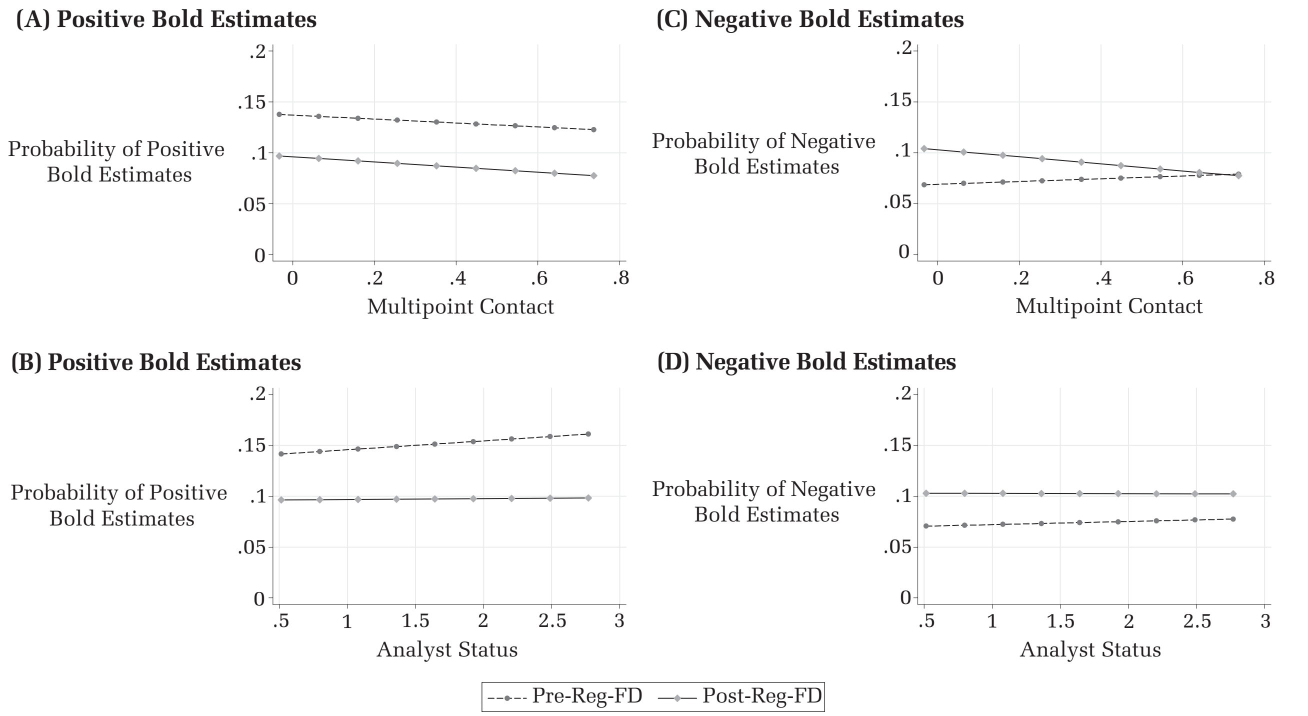
[a] Standard errors are in parentheses.
[b] Logarithm.
† $p < .10$
* $p < .05$
** $p < .01$
*** $p < .001$

Reg-FD (the sum of coefficients before and after is not significantly different from zero).

Hypothesis 4, which predicts that the negative effect of analyst multipoint contact on the issue of bold earnings estimates is stronger for high-status analysts, is also supported in this analysis, as the interaction is negative and significant for both high- and low-status analysts. Thus, the main effect of multipoint contact remains negative for positive bold estimates with the interaction included, but a positive effect is observed for negative bold estimates. This means that prior to Reg-FD, analysts issued more negative bold estimates on stocks for which they experienced high multipoint contact, suggesting their inability to engage in mutual forbearance under conditions of unequal information access. The sum of the main effect and the interaction with Reg-FD is negative and significant, indicating that equalization of analysts' competitive strength also promoted mutual forbearance conditions for negative bold estimates. These estimates fully support our contention that competitive parity is a boundary condition for mutual forbearance, as the negative bold estimates show a breakdown of mutual forbearance, while the positive bold estimates show a weakening, before Reg-FD prevented preferential release of information.

In models 2 and 3, we show only selected estimates on accuracy to conserve space. The key estimates are the effects of bold estimates and the effects of multipoint contact. The latter also support our theory, as a higher threshold is seen through positive and significant coefficient estimates. The only nonconforming coefficient is the main effect for positive boldness, suggesting that prior to Reg-FD high-status analysts (who may have had preferential access to privileged information) did not hold back from issuing positive bold esti-

FIGURE 3
Estimated Probability of Bold Estimates



mates. The difference between this and the negative bold positive effect may reflect an ingratiation effect prior to Reg-FD, as it suggests reluctance to issue negative bold estimates but not positive bold estimates. Under Reg-FD there is no difference, as can be seen by comparing the sum of the main effect and interaction (0.019 − 0.003 relative to 0.011 + 0.004).

Finally, we conducted separate analyses for the pre- and post-Reg-FD periods; Table 4 presents results. The merit of this analysis is that it lets the accuracy regressions differ before and after Reg-FD, giving us an opportunity to examine whether accuracy declined after preferential information release ceased. The estimates strongly support this prediction. The pre-Reg-FD estimates display uncanny accuracy, with both positive and negative bold estimates above 0.8. Under Reg-FD, they drop to 0.395 and 0.251 for positive and negative estimates, respectively, far below a coin toss threshold of accuracy (i.e., 0.5). For the hypothesis-testing variables, the estimates in the split period regressions correspond to the findings in the full regression with one exception: the interaction of multipoint contact and status (Hypothesis 4) falls below standard significance levels for positive boldness under Reg-FD.

Figure 3 shows the estimated probability of positive and negative bold estimates as a function of multipoint contact before and after Reg-FD. Each panel in the figure was constructed as follows: The probability at the mean level of the variable on the horizontal axis was set equal to the probability of a (positive or negative) bold estimate in a focal period. Each variable was varied two standard deviations around the mean (axis labels show actual values), and we calculated the predicted probability holding all other variables constant. Because the model contains main effects of Reg-FD and interaction effects, the lines in each graph have different levels and slopes. The graphs thus show how Reg-FD affected the magnitude of the effects of multipoint contact and analyst status.

Panel 3A shows that multipoint contact reduced positive boldness before and after Reg-FD, and the effect was marginally stronger after Reg-FD. As the vertical axis shows, the effect in each period is substantively large, but not unrealistic (the linear probability model can predict probabilities above 1 or below 0 but does not do so for our regressions). Panel 3B shows that status increased boldness before Reg-FD, and again the effect was substantively strong but had practically no effect under Reg-FD. Panel 3C shows that multipoint contact increased

TABLE 5
Boldness Estimates by Multipoint Contact and Leader-Follower Ratio[a]

			Pre-Reg-FD Estimates				Post-Reg-FD Estimates			
	Behavior		Positive Boldness		Negative Boldness		Positive Boldness		Negative Boldness	
LFR Level	Low MPC	High MPC	Low MPC	High MPC	Low MPC	High MPC	Low MPC	High MPC	Low MPC	High MPC
Low	Offensive move, no stronghold	Offensive move in other's stronghold	13.44%	12.03%	7.03%	7.17%	11.76%	9.81%	12.49%	10.11%
High	Defensive move, no stronghold	Defensive move in own stronghold	15.79%	14.21%	7.15%	7.21%	10.97%	8.83%	11.53%	9.29%

[a] "MPC" is multipoint contact, and "LFR" is leader-follower ratio. "High" and "low" are defined as top quartile and bottom quartile, respectively, of the observations for multipoint contact and leader-follower ratio. The table shows the ratios of the number of boldness estimates in each cell to the total number of estimates in each cell. The same patterns are visible but attenuated when the top and bottom halves of the observations are used.

negative bold estimates before Reg-FD but reduced them after Reg-FD's enactment. Panel 3D shows that status increased bold estimates before Reg-FD but had little effect afterward. Status was clearly important for competition before Reg-FD and led to more aggressive competition—a result that makes sense if high-status analysts had an informational advantage that made them more confident in their estimates. Multipoint contact led to weaker competition in nearly all contexts, the sole exception being pre-Reg-FD for negative estimates. These effects can be read directly from the regressions, but the graphs help make visible their strength relative to the baseline probability. Clearly, these estimates represent sizable effects.

To provide further insight into the mechanisms underlying our findings, we consider the intent of analysts' bold estimates—specifically, whether they are likely to be offensive or defensive. Analysts are most likely to have established strongholds in regard to stocks for which they exhibit both high LFR and multipoint contact—that is, for which they both show leadership and experience potential forbearance. Bold estimates issued under such conditions are thus likely to be defensive actions intended to maintain a stronghold. In contrast, analysts are unlikely to have established strongholds in regard to stocks for which they exhibit low LFR and high multipoint contact—that is, those for which they do not demonstrate leadership despite the presence of potential forbearance. Bold estimates issued by such analysts are therefore likely to signify offensive moves intended to challenge a rival's stronghold. Although stocks for which analysts experience low multipoint contact do not afford potential forbearance, bold estimates issued by analysts who exhibit high LFR are likely defensive moves to protect their leadership position, and bold estimates issued by analysts with low LFR are likely offensive moves intended to develop a leadership position.

Table 5 presents the proportion of bold estimates broken down by analyst LFR and the multipoint contact on a given stock. We focus on the post-Reg-FD period in the interpretation of this table, as this is when the competitive advantage has been lost and mutual forbearance becomes especially important, but we also show the pre-Reg-FD period. When conducting this analysis, we already knew that markets in which multipoint contact is low will have more bold estimates. What we did not know was whether more offensive moves by less dominant analysts or more defensive moves by dominant analysts were the primary driver. The table for positive boldness shows that less dominant (low-LFR) analysts issue more bold estimates, and thus offensive use of boldness is more prevalent. However, the difference is small. For negative bold estimates, we see the same (weak) relation: low-LFR analysts issue a greater proportion of bold estimates. Thus, under Reg-FD, we see a mixture of offensive and defensive moves, almost equally balanced. Before Reg-FD, high-LFR analysts tended to be bolder, but only in a positive direction, which is consistent with their having preferential access to corporate information—and wishing to maintain it.

We also conducted several robustness checks, which we summarize here (full results are available from the authors). First, we examined whether the findings result from analyst turnover or changed behavior among analysts who issued estimates both before and after Reg-FD was enacted. Estimates based on the subsample of analysts who were active in both time periods were the same as those in model 3. Second, although we considered bold estimates to be those more than 1.5 standard deviations away from the consensus estimates for the stocks, the choice of cutoff point was guided solely by the idea that only rare, and hence salient, estimates should be deemed bold. We reestimated model 3 using 2.0 and 1.0 standard deviations from consensus as boldness cutoff points. Estimates using the 2.0 standard deviation cutoff are the same as model 3's. Estimates using the 1.0 standard deviation cutoff differ from model 3's in that the interaction of multipoint contact and Reg-FD is significant and positive for positive boldness. The 1.0 standard deviation cutoff, which classifies 38 percent of the estimates as bold (compared to 20 and 14 percent for the 1.5 and 2.0 cutoffs respectively), seems less consistent with the rareness and salience of bold estimates. However, our other findings are robust to the choice of the boldness cutoff point. Finally, we find that the results of our hypothesis testing remain unchanged even when using seemingly unrelated regression estimations in which dependent variables from some equations can be repressors in other equations.

DISCUSSION AND CONCLUSION

Our investigation showed that changes in regulatory environment impact actors' competitive responses unevenly. Specifically we find that mutual forbearance occurs among actors engaged in competition in multiple markets, in this setting in the form of their making timid rather than aggressive and attention-seeking bold estimates. A key contribution is that we also showed boundary conditions of this finding. Under conditions of competitive disparity, as when some analysts had access to superior firm information, mutual forbearance was significantly weakened; indeed we saw more aggressive competition. In markets with status disparity, mutual forbearance was more important to high-status actors than to low-status actors. We are unaware of other evidence of such boundary effects, and we see our finding as offering support to core assumptions of the basic theory. Mutual forbearance only occurs when actors are sufficiently similar to each other that they cannot easily find ways to individually benefit from full competition, and actors with a stronger vested interest in maintaining the status quo are more likely to forbear.

Our finding that under some conditions multipoint contact strengthened rather than weakened competition when actors had informational advantages has important but more subtle implications. One might envision forbearance arising even when actors gain competitive advantage from unique information, but if an advantage—even if temporary—is large enough, it is not clear why an actor would refrain from using it. Our investigation of bold estimates shows that multipoint contact sharpened certain competitive actions (negative bold estimates) when information was restricted, which is a full reversal of the result we found when information circulated publicly. Other competitive actions (positive bold estimates) were less strongly suppressed than under full information circulation. This finding extends understanding of factors that moderate mutual forbearance (Baum & Korn, 1999; Greve, 2008; Yu et al., 2009) by making one theoretical premise more explicit: equal footing. If an actor gains a substantial competitive advantage from resources or market power, structural conditions that would otherwise facilitate mutual forbearance do not in fact foster it. Actors relatively similar in competitive strength, however, do tend to mutually forbear from aggressive behavior when multipoint contact is higher. The difference between the competitive actions, in turn, is likely explained by how positive and negative estimates affect the relation between analyst and firm, which is a separate concern from that of the analyst and client (investor) relation.

For status, we showed behaviors consistent with status maintenance by high-status actors, who were more likely to limit their competitive actions when engaged in multipoint competition. However, along with this finding come some interesting puzzles. Unlike actors in the investment banking market studied by Podolny (1993, 1994), low-status actors here did not appear to reciprocate forbearance by market-stabilizing actions. Instead, low-status analysts maintained some likelihood of issuing bold estimates in markets with multipoint contact (though less so than in markets without it). The difference can be understood from the different costs and incentives, as low-status analysts do not have cost disadvantage relative to high-status ones and have more to gain if they are boldly accurate. The observed instability in the analyst rankings after Reg-FD (e.g., Bagnoli et al., 2008) is likely a result of this asymmetry. It implies that firm status heterogeneity may break mutual forbearance.

One might ask how a regulatory change could be sufficiently strong to totally obviate informational advantages and change competitive patterns so strongly. Information flows can be concealed in ways that make a regulatory change unenforceable. Perhaps information leaks occurred during our investigation period, but we did not find evidence of them in the analysts' estimates. We think this is consistent with the public nature of earnings estimates: issuing highly accurate earnings estimates consistently is very visible and arouses suspicion. For example, Jack Grubman's uncanny accuracy on WorldCom stock made some institutional investors nervous about breaking the law rather than eager to make trades (Reingold, 2006). If private information is being disclosed, companies have an incentive to do so quietly. Although we cannot rule out quiet releases of material information, we do find our evidence of adherence to Reg-FD in the public work of issuing reports and estimates plausible given the superior opportunities for misconduct in other areas of behavior.

An interesting implication of our findings is that a regulatory crackdown on one form of collusion (companies' private disclosure of information to preferred analysts) was effective in its own right but led to an increase in another form of collusion (mutual forbearance among analysts linked by multipoint contact). The finding is particularly interesting because multipoint contact swung from being especially competitive prior to Reg-FD to being less competitive afterward. Notably, the rise in mutual forbearance suggests that market information may not be conveyed as directly or efficiently as actors focus on each other as sources of competitive advantage, rather than individual skill. It is a conventional observation that regulation has consequences beyond the intended ones, but the effect shown here might surprise the policy makers who drafted and passed Reg-FD.

The scope of our work has limitations that suggest several promising directions for further research. We can discern a trend toward public information circulation in safety-intensive industries such as airlines, railroads, and nuclear power plants, in which legislation requires operators (and public oversight agencies) to publicly disclose all safety-related reports to create opportunities for operators to learn from one another's experience. In addition to safety-intensive sectors, the development of fair competition regulations, together with sophisticated information technology, has mandated public information circulation in a range of other industries. There are thus ample opportunities to investigate the effects of public information circulation on competition, as well as the frequency with which those conditions obtain. More generally, our findings raise the question of what would happen if an industry characterized by relative homogeneity in competitive strength becomes more heterogeneous. In other words, what are the effects of the reverse of the process we study here? While movement from public to private information circulation is harder to find examples of, especially in the form of regulation, we speculate that industry deregulation, as well as transitions from dominant designs to technological ferment, will lead both to less information being available about alternative actions and to greater heterogeneity in competitive strength.

Second, competitive aggression and forbearance are seen not just in behavior in a market, but also in entry and exit behaviors (Greve & Baum, 2001). Analysts' expansion and contraction of coverage are promising research possibilities and offer a chance to test findings from firm-level analyses of multipoint contact (e.g., Baum & Korn, 1996, 1999) in the context of individuals competing for attention. Observable outcomes of multipoint contact other than boldness exist, such as the accuracy of estimates, as we showed, and their timeliness. While we encourage future research examining such alternative outcomes, we chose boldness because our theoretical analysis suggested that it would reflect both mutual forbearance and status effects.

Third, additional boundary conditions likely affect mutual forbearance. In a supplementary analysis, which we do not report here to conserve space, we found that analysts changed their behavior shortly after the enactment of Reg-FD, suggesting the possibility that they understood the new rules of the game imposed by this regulation from the start and shared interpretations of the changing roles of multipoint contact extensively. This is interesting but leads to a question about how analysts, without accumulating trial-and-error learning (Korn & Baum, 1999), learned quickly how to compete under conditions of competitive parity. Future research is needed to explore the microcognitive processes through which actors learn to compete under novel conditions (Greve, 2006).

Discovering how the structure of markets affects the behavior of market participants has been a central research theme in management, economics, and sociology for some time now, and one might think that little remains to be done. In fact, we have shown that work so far has failed to reveal important contingencies in how a major theory—mutual forbearance—predicts market behaviors. Our findings, that competitive parity and status disparity, themselves major research areas, act as boundary conditions, show that one can place research at the intersection of these three major research traditions and develop new theory and evidence. Although we were aided in making our empirical case by the natural experiment of a regulatory change, we see our work as at least as important in suggesting that major opportunities for theoretical progress in this area of work still exist.

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