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Alphabetical by first name; we each gave 100%. Martin Gargiulo and Ezra Zuckerman offered valuable comments, as did anonymous AMJ reviewers and Associate Editor Tim Pollock.

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Competitive Parity, Status Disparity, and Mutual Forbearance:

Securities Analysts' Competition for Investor Attention

Abstract

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 promoted 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, with notable implications for 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 the 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 actors' awareness of their relationships with one another. Absent attention to this awareness, our 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 across several domains, such as products or markets (e.g., Barnett, 1993; Baum & Korn, 1996). The theory predicts that when actors meet in multiple domains they can forbear from competition by permitting each other to dominate some domains, while maintaining a threat of competitive responses in the others, and escalating (and striking where it is most costly) if the rival makes an aggressive move (Wernerfelt, 1985; Karnani & Wernerfelt, 2006). 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 (Podolny, 1993; Magee & Galinsky, 2008; Benjamin & Podolny, 1999). 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 et al., 1994), higher prices (Hannan & Prager, 2006), and higher margins (Evans & Kessides, 1994), much of the evidence is derived from empirical settings in which the basis of competition are relatively stable over time. In such settings, multipoint contact serves to reduce risky behavior that might destabilize and escalate competition. We know little, however, about how multipoint contact affects competitor behavior in environments where 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 considered 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 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 they 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 against competition.

Our empirical setting is sell-side security analysts in the United States, and in particular the co-coverage 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, who each follow a portfolio of stocks largely comprised of companies operating within one or another widely accepted industry category (e.g., telecom, 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 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 co-coverage 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 – some preferred analysts and investors before others, mandating instead its public disclosure.[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 each actor such that their behavior can be identified and understood by competitors as well as by their audiences. Thus, for example, firms may focus on price competition, product differentiation, or market expansion because choices among these things are visible to their competitors and important to their customers. Analysts create two chief products based on their analysis: earnings estimates and recommendations. Both have investment value (Womack, 1996, Loh & Mian, 2006), but earnings estimates are prized among institutional investors 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.

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[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 (SEC, 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 favourable coverage and to force analysts to focus on their own analysis rather than serve as 'promoters' of the companies they covered (Eleswarapu, Thompson & Venkataraman 2004).

Estimates are understood by investors and other analysts as either being “in line” with estimates previously released by analysts, which provide confirmatory evidence but little new information, or by being bold, which provide 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 the consensus in the industry, is the reference point through which investors interpret subsequent analyst estimates (Reingold, 2006). The consensus estimate is not the same as an accurate estimate because analysts influence each other’s beliefs and can be collectively wrong about the securities they cover (Rao, Greve & Davis, 2001). Analysts issue estimates sequentially and observe each other’s estimates, so they know when their estimate is bold.

Bold estimates seek investor attention by being clearly and deliberately different from those issued by other analysts (Clement & Tse, 2005; Hong et al., 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 (1991: 102) observes, “imitation ensures a lack of competitive advantage and hence mediocre performance,” while differentiation moderates competition and improves performance. Differentiation based on either unique market positioning or resource endowments produces less 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 on the basis of the usefulness of the 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 a bold estimate must result from either the belief that they possess better or more comprehensive information than at least some other analysts, or 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). Consistent 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. There are also strong individual incentives available to analysts who differentiate themselves by issuing accurate bold earnings estimates (Kadous, Meyer & Thayer, 2008), but these incentives are countered by the career risks of being boldly wrong (Scharfstein & Stein, 1990; Hong & Kubik, 2003). Timid and herding estimates, in contrast, are unremarkable, providing no stimuli to investors, placing no competitive pressure on rivals, and avoiding risk for the 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 find 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 (Graham, 1999; Boyson, 2010) 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 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 effect of the portfolio embeds analysts within 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 with the multiple domains in which firms compete, the stocks analysts co-cover 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 (1955: 76) 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.” Simmel also predicted that the potential for cooperation among rivals increases when they interact across 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 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 sphere in which the other element is superordinate” (Simmel, 1950: 289). Such reciprocal dominance enables rivals to convey mutual threats, adding the risk of counter-attacks 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 to place her earnings estimate. Timidly higher than others, so she will be recognized by her own clients 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 counter-raids 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:

H1 *An analyst’s likelihood of issuing bold earnings estimates is lower on stocks where the analyst experiences high multipoint contact with other analysts.*

Competitive Parity

Mutual forbearance theory rests on several assumptions. First, in order to reduce competition, actors must recognize their multiple points of contact and the mutual dependence of their performance on each other's actions (Greve, 2008). This assumption is plausible in our empirical context because analysts who co-cover 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 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 is met only after Reg-FD is 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 – benefitted 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 non-corporate 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 rather than privileged access when determining earnings estimates (Mohanram & Sunder, 2006). Yet, expectations and reward structures for analysts remained unchanged: attract positive investor attention. Bold estimates remained an important way to accomplish this, but the basis for such estimates became centered on the analyst. 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, for example, by 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 differ substantially prior to Reg-FD, there is little incentive for advantaged analysts to enter into reciprocal dominance agreements and forbear from competition. They stand to gain much from the bold forecasts they make, and the likelihood that a less privileged analyst will make a bold – and accurate – estimate is low. This will be the case even if privileged analysts only occasionally gain 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 because there is no important news or the company decides to inform all analysts at once. If privileged access produces a competitive advantage that shifts across 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 unable to maintain mutual forbearance at all, or they may only be 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 following boundary condition on the emergence of mutual forbearance:

H2 *The effect in H1 is stronger under Reg-FD, and may be exclusive to this period.*

Status Disparity

A fourth assumption in mutual forbearance is that actors willingly enter into relations of reciprocal dominance and mutual forbearance. Research on multipoint contact, given its origin in strategy and economics (e.g., Wernerfelt, 1985; Bernheim & Whinston, 1990), has focused on competitive implications of multipoint contact when all actors are considered equal, and has not been concerned with the social structure of the market. Yet we know that many markets are hierarchically arranged such 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 and 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 the 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 the *Institutional Investor* magazine's annual All-American Research Team. Although there are several analyst rankings, including the *Wall Street Journal* and Thompson Reuters' StarMine analyst awards, the *Institutional Investor* All Star ranking is the most prestigious and long standing, and the ranking that analysts themselves care most about (Reingold, 2006; Kessler, 2003). The All Star ranking 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, as well as one to two analysts who receive "runner-up" status. 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). Receiving an All Star ranking of any type affects both analyst compensation and job opportunities (Groysberg, 2010), yet continued All Star ranking is 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 (Zhuang, 2011; Reingold, 2006).

Although analyst accuracy can be measured, it is not a reliable indicator of analyst quality because, simply by carefully matching the consensus, an analyst has a good chance of being very accurate with little or no analytical work at all. The All Star 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, the All-Star ratings are a proxy for quality in a market where quality is not easily inferred. All Star 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 an All Star ranking.

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 the 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 (Graham, 1999; Boyson, 2010; 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 may 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 *Institutional Investor* magazine's All-Star Team (Zhuang, 2011). And if not, they face an increased risk of dismissal (Scharfstein & Stein, 1990; Hong & Kubik, 2003).

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:

H3 *All-star analysts 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 issuing them may 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 the competitive pressure and preserve the status structure, high-status analysts are more willing to enter into forbearance relationships. Thus:

H4 The effect in H1 is stronger for all-star analysts.

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; SEC 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, as 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 are employed by analysts 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 multi-point contact. These observations suggest that H1-4 will find greater support for analysts' *positive* bold earnings estimates.

Another aspect of boldness concerns whether an estimate is accurate, as it would be if the estimates is based on analysts' exclusive access to the source of information in the pre Reg-FD era or superior analysis in the post Reg-FD era. In addition to garnering investor attention, controlling for the accuracy of their estimates, analysts making bold forecasts are also more likely to move to prominent brokerage firms and be named members of Institutional Investor magazine's prestigious All-American Research Team (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 off some risk of inaccuracy for the sake of gaining attention. We cannot directly observe these tradeoffs, 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) for 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 and brokerage firm underwriting activity, as well as characteristics of the publicly-traded companies.

Our sample is constrained by the availability of historical data and the fiscal year ends of individual firms. Our observation period begins in 1995, which coincides with the first year for which IBES began updating analyst forecasts on a daily basis. Our start date of January 1, 1995 means that we include analyst estimates for firms that have 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-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 from their joint stock coverage. Co-coverage is examined over 12 month moving windows, which are updated quarterly so that each quarter's multipoint contact is constructed for each analyst 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 based on private information obtained directly from the company, the 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 and used as reference points analysts with co-coverage, 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 each analyst-stock estimate is unusually high or low relative to other analysts' estimates for that 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 the 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 the focal estimate. We set our dependent variables as *positive bold* estimates that were more than 1.5 standard deviations above the consensus, and *negative bold* estimates that were more than 1.5 standard deviations below the consensus estimate.

We also analyze the accuracy of bold estimates, which requires defining *accurate positive bold* as an estimate that is positive bold, as well as closer to the actual earnings than the analyst consensus. Analogously we define *accurate negative bold* as an estimate that is negative bold, and closer to the 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 are estimated as a system of equations. This allows a specification in which the 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 reserve several variables describing an analyst's past tendency to issue bold estimates for identification of the boldness regression, and thus do not enter them into the accuracy regression. We apply fixed effects for analyst-stock dyads, and we allow correlation of all variance/covariance terms, which is the most flexible correlation structure. The estimation is 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 the bold estimate 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 rejected the null hypothesis of weak instruments. The only problematic result was the Sargan test, which indicated that bold estimates are not a 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 use 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 applying a linear probability model in all four regressions. The linearity allows easier interpretation of interaction effects than a logit would, as marginal effects in linear models are equal to the coefficient estimates (Angrist & Pischke, 2008: 95-107; see also Waguespack & Sorenson, 2011). In preliminary analysis we also used logit regression as single regressions with fixed effects, and the results of that analysis corresponds 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 *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 across analysts (Baum & Korn, 1996). This measure is formally defined as follows:

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

where $MPC_{i,m}$ is analyst *i*'s multipoint contact for her analysis of corporation *m*, $D_{i.n}$ is equal to 1 if analyst *i* covers corporation *n* in her report, $D_{j.n}$ is equal to 1 if other analysts *j* covering corporation *m* covers corporation *n* in their reports, and N_m is the total number of analysts who cover corporation *m* in their reports. Multipoint contact was recomputed at the time of each estimate using the appropriate quarterly network. Higher values of multipoint contact indicate a greater proportional stock coverage overlap between the focal analyst and 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 zero otherwise. Although Reg-FD was announced in August 2000, it was not ratified until October 23, 2000 (SEC, 2000). We allow for an adjustment period, setting October 1, 2000 as the start of the Reg-FD period (Mohanram & Sunder, 2006).

In order to estimate the effects of *analyst status*, we use the data from an annual list of All-Star analysts published in the influential trade magazine *Institutional Investor*. Those who are listed as All Stars are considered to be of higher status than those who are not listed (e.g., Groysberg & Lee, 2010; Groysberg, Polzer & Elfenbein, 2011; Hayward & Boeker, 1999; Leone & Wu, 2002). Every year since 1972, *Institutional Investor* has conducted a survey asking buy-side analysts and portfolio managers at institutional investors to rate sell-side analysts' performance. Because a small fraction of analysts are ranked in the surveys, 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 analysts who co-cover stocks with them. Estimates issued by analysts who appear in the *Institutional Investor* All-Star list differ from those issued by other analysts in a sense that the former tends to be bolder than the latter.

To measure an analyst's status, we consider the analyst's history of All Star rankings in the *Institutional Investor* since 1990. Our measure accounts both for how recently an analyst was an All Star as well as how many awards s/he has received. Specifically, we summed each year an analyst had been listed as an All Star, weighted by its recency; that is 1/($year_t$ – year of the award). This measure gives more weight to recent All Star rankings to account for the enduring, but weakening, effect of being ranked.[2] To assess the effect of analyst status on mutual forbearance, this weighted All Star measure was interacted 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, Kubik & Solomon, 2000). This is because more experienced analysts have established relationships with corporate management of the stocks they follow, and thus obtain preferential access to material information. We therefore controlled for each analyst's experience by counting the number of days between the current stock estimate and the analyst's earliest recorded earnings estimate on any stock.[4] We divided the number of days by 365.25 to obtain a measure of

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[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 the *Institutional Investor*. This suggests that neither analysts nor their customers rely on such fine-grained rankings when attributing status. This 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

years of experience. We also controlled for an analyst's *focal stock experience* measured as the number of days between the current stock estimate and the analyst's earliest recorded earnings estimate on that stock, again dividing by 365.25.

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

Analysts whose earnings estimates are closely followed by other analysts may also differ in their boldness. We control for this possibility using the analyst's *leader-follower ratio (LFR)* (Cooper et al., 2001; Loh & Stulz, 2011; Schroff et al., 2004). To compute an analyst's LFR we divided the sum of the number days of between the analyst's current estimate 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 literature. (Extending the number of estimates beyond a horizon of two increases the number of analysts needed to cover a stock in order to compute the measurement.) An LFR greater than one suggests the 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 the focal stock and other stocks s/he covered. We distinguished between positive and negative bold estimates since analysts may be more likely to issue bold estimates in one direction over 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

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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.

total number of negative bold estimates the analyst issued for the focal stock during the past 180 days and the mean number of bold estimates the analyst issued on all the other stocks s/he covered over the same time horizon, respectively. We calculated analogous variables for positive bold estimates. These variables are entered 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, 1999; Michaely & Womack, 1999), we also controlled for the underwriting activity by 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 the analyst issues the current estimate. First, we controlled for the total number of *analysts following the focal stock* by summing the number of other analysts with outstanding estimates on the stock on the date of the analyst's current estimate. In addition, using the CRSP database, we measured *focal stock size* as the company's *total assets*. These variables were also logged to reduce skew. Additionally, we controlled for the *standard deviation of the consensus estimate* for the focal stock on the date of the analyst's estimate. This control accounts for variation in stock uncertainty, as well as the analyst awareness of prior estimates leading 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* variable was coded 1 if a company released a quarterly or annual earnings report within a three day window of the 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* variable was coded 1 if a company issued earnings guidance within a three day window of the 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, or 42% 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 the average analyst following the 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 the leader-follower ratio (LFR). LFRs serve as good (albeit imperfect) indicators of reciprocal dominance among analysts. Although one or a few estimates may achieve leadership because of good information content rather than analyst dominance, averaging LFRs

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[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, *Ln stocks covered by the analyst's brokerage* (14.8) and *Ln total analysts following the focal stock* (13.2), were the only variables above the standard threshold of 10 (Besley, Kuh, & Welsch, 1980). Excluding the first of these gives identical results and no VIF statistics over 10. In the models reported we therefore include the full set of controls.

across many estimates and checking their dispersion within a given stock will smooth out the variation and distinguish stock where there are clear leaders and followers, and more competitive stocks where 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 having above-median multipoint contact in the upper panel and markets stocks having below-median multipoint contact in the lower panel. In both graphs there is an increase in multipoint contact after Reg-FD, suggesting some effort 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.

===== INSERT FIGURES 1-2 ABOUT HERE =====

To confirm that the increased LFR dispersion under Reg-FD observed in Figure 1 is not driven by certain analysts who dominate high multipoint contact stocks, we also compare, in Figure 2, the pattern of within-analyst LFR dispersion for high and low multipoint contact stocks in the analyst's portfolio. For each quarter, we split analyst-stocks above and below the median multipoint contact and then graph 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

[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 x intervals, respectively, where intervals are equal to upper quartile – lower quartile.

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 of the overall accuracy and the effect of multipoint competition are shown. The other coefficients show only minor variations in these regressions (the 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 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 reduces boldness, also as one would expect from the banning of selective 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 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 significantly below 0.5. Analyst experience increases accuracy, as does focal stock size and the number of analysts following.

===== INSERT TABLES 1-4 ABOUT HERE =====

Table 3 has Model 2 with the main effects and Model 3 with the full set of interactions, respectively. In Model 2, the coefficients for analyst multipoint contact are negative and significant, supporting Hypothesis 1, which predicted 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, $p <$

0.001).[8] Given the many studies that have found 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 x multipoint contact interaction supports Hypothesis 2, which predicted that multipoint contact would be 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. Consistent 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 Reg-FD (the sum of coefficients before and after is not significantly different from zero).

Hypothesis 4, which predicted 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 there is a positive effect for negative bold estimates. This means that prior to Reg-FD analysts issued more negative bold estimates on stocks where they experienced high multipoint contact, suggestive of 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

[8] The tests of coefficient estimate differences use the Stata *test* statement to give standard χ^2 tests for expressions of multiple coefficients.

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 bold, 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 estimates. 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 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 conduct separate analyses for the pre and post Reg-FD periods in Table 4. 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 is constructed as follows. The probability at the mean level of the variable on the horizontal axis is set equal to the probability of a (positive or negative) bold estimate in the focal period. Each variable is varied two standard deviations around the mean (axis labels show actual values), and the predicted probability is calculated 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 one or below zero, 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 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 visualize their strength relative to the baseline probability. Clearly, these estimates represent sizable effects.

===== INSERT FIGURE 3 AND TABLE 5 ABOUT HERE =====

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 either 'offensive' or 'defensive' in nature. Analysts are most likely to have established strongholds on stocks where they exhibit both high LFR and multipoint contact; that is, where 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 on stocks where they exhibit low LFR and high multipoint contact; that is, where 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 where 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 low LFR, offensive moves to develop a leadership position.

In Table 5, we checked the proportion of bold estimates broken down by the leader-follower ratio (LFR) of the analyst and the multipoint contact of the 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. We already know that markets low multipoint contact will have more bold estimates. What we do not know is whether this is driven primarily by more offensive moves by less dominant analysts or by more defensive moves by dominant analysts. 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 in based on the subsample of analysts who were active in both time periods are the same as Model 3. Second, although we consider bold estimates to be those more than 1.5 standard deviations away from the consensus estimate, the choice of cutoff point was guided solely by the idea that only rare, and hence salient, estimates should be deemed bold. We re-estimated 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. Estimates using the 1.0 standard deviation cutoff differ from Model 3 in that the interaction of multipoint contact and Reg-FD is significant and positive for positive bold. The 1.0 standard deviation cutoff, which classifies 38% of the estimates as bold (compared to 20% and 14% 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 (SUR) estimations in which dependent variables from some equations can be repressors in other equations.

DISCUSSION AND CONCLUSION

Our investigation showed that changes in the regulatory environment impacts actors' competitive responses unevenly. Specifically we find that mutual forbearance occurs among actors engaged in competition across multiple markets, in this setting in the form of 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 it as offering support to core assumptions of the basic theory. Mutual forbearance only occurs when the 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 subtler implications. One might envision forbearance arising even when actors gained competitive advantage from unique information, but if the advantage is large enough, and even if temporary, 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 the information was restricted, which is a full reversal of the result when information circulated publically. Other competitive actions (positive bold estimates) were less strongly suppressed than under full information circulation. This finding extends our understanding of factors that moderate mutual forbearance (Baum & Korn, 1999; Greve, 2008; Yu et al., 2009) by making one of the premises in the theory more explicit: equal footing. If an actor possesses a substantial competitive advantage from resources or market power, structural conditions that would otherwise facilitate mutual forbearance do not in fact foster it. Relatively similar actors 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 the investment banking market studied by Podolny (1993, 1994), low-status actors did not appear to reciprocate 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). The difference can be understood from the different costs and incentives, as low-status analysts do not have cost disadvantages over 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 it 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 (private disclosure of information by companies 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 the multipoint contact swung from being especially competitive prior 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 policymakers 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 such as the NTSB) 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 for 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, and certainly in the form of regulation, we speculate that industry deregulation, as well as transitions from dominant designs to technological ferment, will lead to less information being available about alternative actions, as well as greater heterogeneity in competitive strength.

Second, competitive aggression or forbearance is not just seen in behavior within each 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. There are also observable outcomes of multipoint contact other than boldness such as the accuracy of estimates, as we showed, or in 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 supplementary analysis, which we do not report here to conserve space, we find 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 of trial-and-error learning (Korn & Baum, 1999), learned quickly how to compete under conditions of competitive parity. Future research is needed to explore the micro-cognitive processes through which actors learn to compete under novel conditions (Greve, 2006).

Discovering how the structure of markets affect 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 see 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 the regulatory change, we see our work as at least as important in suggesting that there are still major opportunities for theoretical progress in this area of work.

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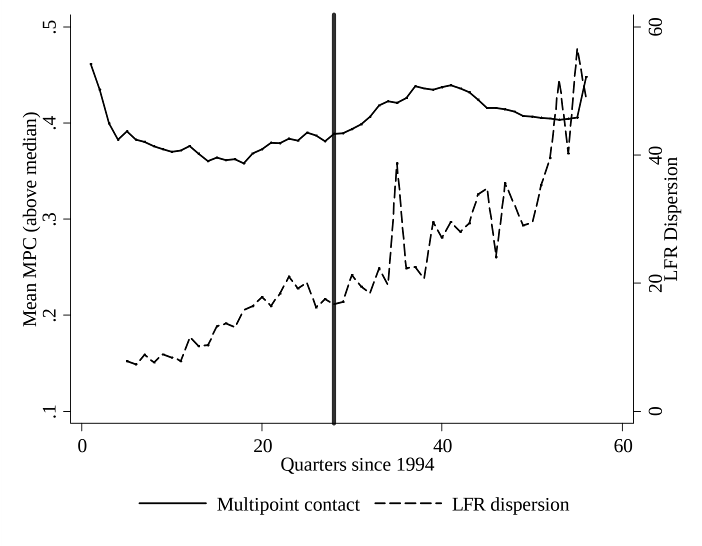
Figure 1: Multipoint contact and LFR dispersion

a: Above median multipoint contact



1b: Below median multipoint contact

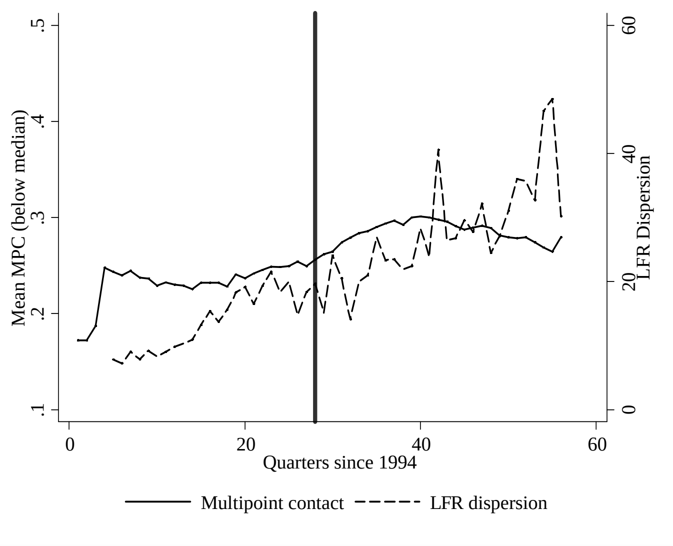
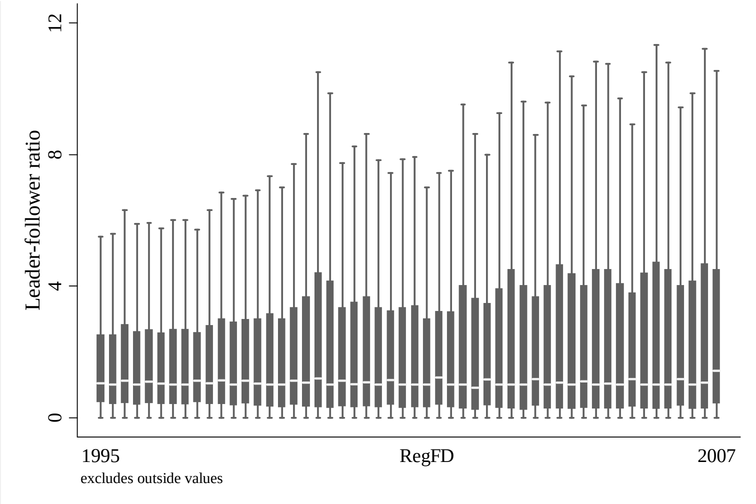


Figure 2: Box Plots of Leader-Follower Ratio (LFR) Dispersion by High and Low Multipoint Contact (MPC)

2a: Above Median Multipoint Contact



2b: Below Median Multipoint Contact

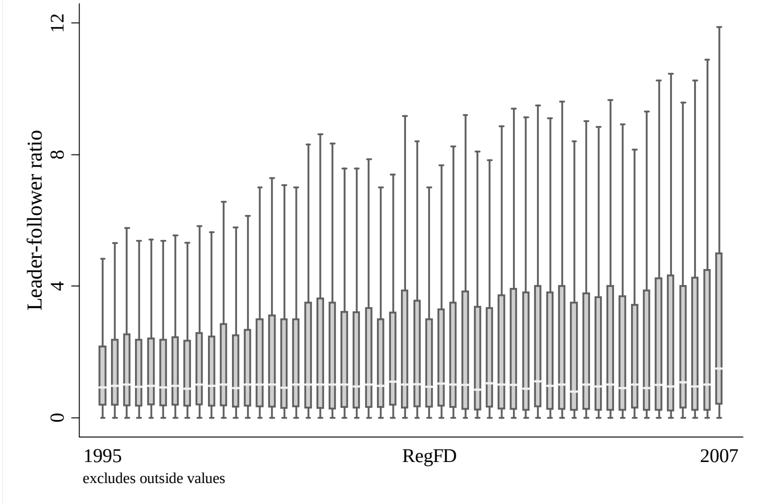
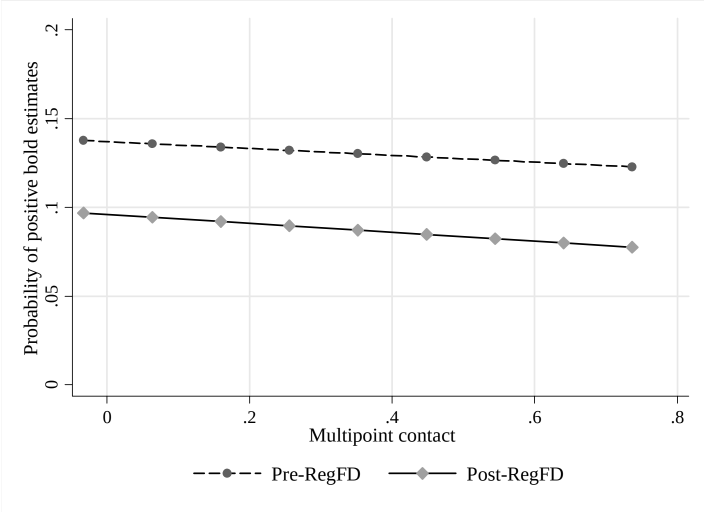
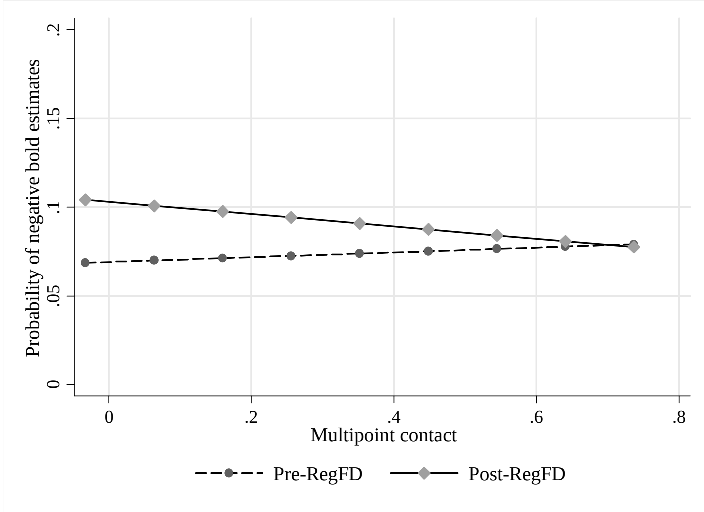


Figure 3: Estimated Probability of Bold Estimates

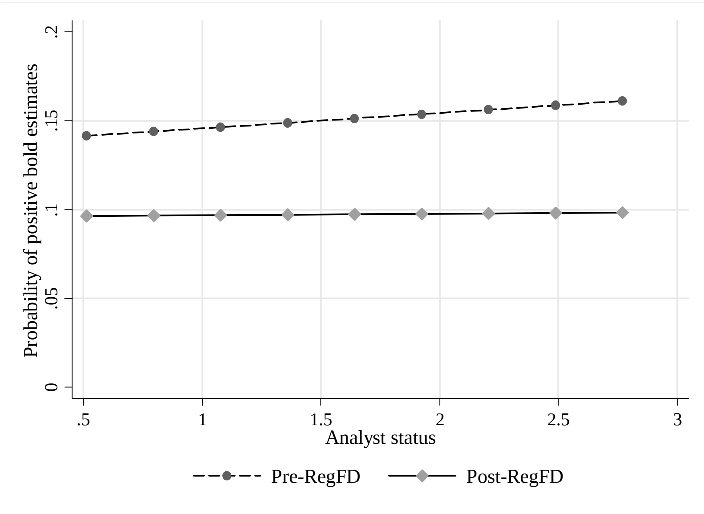
3a: Positive Bold Estimates



3c: Negative Bold estimates



3b: Positive Bold Estimates



3d: Negative Bold Estimates

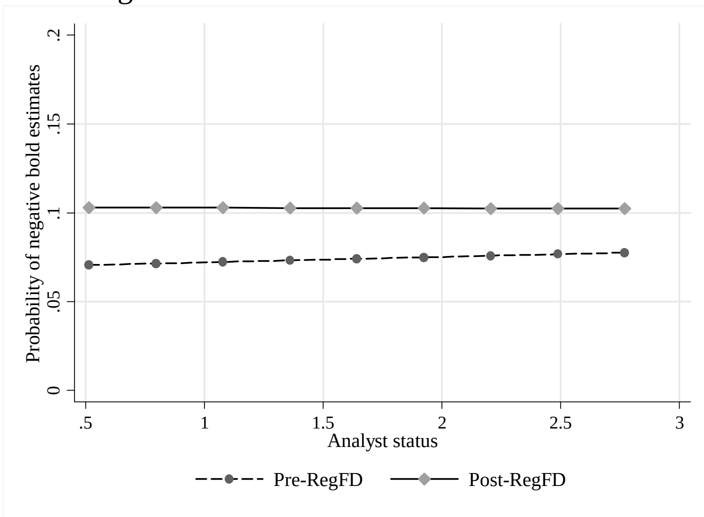


Table 1: Descriptive Statistics and Correlations

	Variable	Mean	SD	1	2	3	4	5
1	Analyst positive boldness	.11	.32	1				
2	Analyst negative boldness	.09	.28	-.11	1			
3	Analyst positive boldness accuracy	.06	.23	.69	-.08	1		
4	Analyst negative boldness accuracy	.03	.18	-.07	.59	-.05	1	
5	Time trend	11.33	3.74	-.06	.04	-.12	-.05	1
6	Ln analyst experience	5.80	3.89	-.01	.01	-.02	.00	.17
7	Ln analyst focal stock experience	6.37	1.06	-.02	.00	-.01	.01	.15
8	Ln analyst stock portfolio size	2.62	1.01	.04	-.04	.10	.04	-.64
9	Analyst negative bold 180 days focal stock	.08	.22	.03	.15	-.02	.11	.06
10	Analyst negative bold 180 days portfolio	.09	.13	.01	.09	-.02	.06	.07
11	Analyst positive bold 180 days focal stock	.11	.26	.15	.02	.14	-.01	-.07
12	Analyst positive bold 180 days portfolio	.11	.14	.07	.02	.07	.00	-.11
13	Ln issues analyst’s brokerage has underwritten	5.42	2.22	-.02	.01	-.01	.01	.20
14	Ln stocks covered by analyst’s brokerage	5.50	1.32	.01	-.02	.06	.03	-.31
15	Ln issues analyst’s brokerage has underwritten focal stock	.16	.36	-.01	.00	-.01	.00	.05
16	Analyst leader-follower ratio focal stock	4.89	17.86	.01	.01	.00	-.01	.07
17	Ln analysts following focal stock	3.53	1.15	-.01	-.01	.03	.02	-.08
18	Ln total assets focal stock	7.59	2.02	-.04	-.04	-.01	-.01	.15
19	Standard deviation of estimates focal stock	.20	5.29	-.01	-.01	-.01	.00	-.01
20	Stock earnings release focal stock	.22	.41	.02	.02	.01	-.02	.15
21	Stock guidance release focal stock	.09	.29	.01	.03	-.01	.01	.16
22	Analyst multipoint contact	.35	.19	-.04	-.02	-.02	.00	.12
23	Reg-FD	.60	.49	-.06	.06	-.14	-.04	.87
24	Analyst status	.51	1.13	-.01	-.01	.01	.01	-.10

	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
6	1																	
7	.52	1																
8	.12	.10	1															
9	.00	-.02	-.05	1														
10	.02	.00	-.04	.12	1													
11	-.02	-.02	.06	-.07	.01	1												
12	-.02	-.02	.12	.02	-.04	.11	1											
13	.15	.12	-.05	.01	.02	-.02	-.03	1										
14	.06	.05	.48	-.03	-.02	.02	.05	.55	1									
15	.05	.00	.01	-.01	-.01	-.01	-.02	.24	.13	1								
16	.01	.01	-.04	.00	.01	.00	.01	.04	.01	.02	1							
17	.08	.07	.21	-.01	-.01	.00	.01	.67	.92	.16	.03	1						
18	.13	.25	-.05	-.05	-.05	-.05	-.07	.10	.10	-.13	-.04	.14	1					
19	.00	-.01	.00	-.01	.00	-.01	-.01	.00	.01	.00	.00	.01	.00	1				
20	.01	.01	-.10	.01	.03	.01	.01	.08	-.01	.03	.09	.03	-.04	-.01	1			
21	.07	.08	-.10	.03	.04	.00	.00	.07	.00	-.03	.06	.03	.09	-.01	.22	1		
22	-.10	.01	-.23	-.02	-.04	-.04	-.07	.18	.13	-.03	-.01	.22	.30	.01	.00	.03	1	
23	.15	.12	-.66	.08	.12	-.09	-.12	.19	-.30	.04	.06	-.09	.15	.00	.14	.17	.13	1
24	.35	.24	.21	-.02	-.02	-.01	-.01	.28	.36	.09	.01	.39	.16	.00	.00	.03	.10	-.07

N = 960,080; 112,894 groups.

Table 2: 3SLS Fixed-Effect Simultaneous Regression Models of Bold Estimates

Model 1	Positive Bold	Positive Bold Accuracy	Negative Bold	Negative Bold Accuracy
Time trend	-0.002***	0.001***	-0.001***	-0.002***
	(0.0002)	(0.0002)	(0.0002)	(0.0001)
Ln analyst experience	0.0002*	-0.0004***	0.0003**	-0.0004***
	(0.0001)	(0.0001)	(0.0001)	(0.0000)
Ln analyst focal stock experience	-0.0006	0.002***	0.002***	0.003***
	(0.0004)	(0.0002)	(0.0003)	(0.0002)
Ln analyst stock portfolio size	-0.0013*	0.003***	-0.0009+	0.002***
	(0.0006)	(0.0003)	(0.0005)	(0.0003)
Analyst negative bold 180 days	0.048***		0.189***	
focal stock	(0.001)		(0.001)	
Analyst negative bold 180 days	0.022***		0.137***	
portfolio	(0.002)		(0.002)	
Analyst positive bold 180 days	0.174***		0.029***	
focal stock	(0.001)		(0.001)	
Analyst positive bold 180 days	0.115***		0.025***	
portfolio	(0.002)		(0.002)	
Ln issues analyst's brokerage	-0.001***	0.001***	0.001***	0.001***
has underwritten	(0.0002)	(0.0001)	(0.0002)	(0.0001)
Ln stocks covered by analyst's	0.003**	-0.004***	-0.001	-0.003***
brokerage	(0.001)	(0.001)	(0.001)	(0.000)
Ln issues analyst's brokerage	-0.007***	0.001*	-0.006***	0.000
has underwritten focal stock	(0.001)	(0.000)	(0.001)	(0.000)
Analyst leader-follower ratio	0.0001***	-0.00002*	-0.000	-0.00003***
	(0.00002)	(0.00001)	(0.000)	(0.00001)
Ln analysts following focal stock	-0.004***	0.005***	0.001	0.004***
	(0.001)	(0.001)	(0.001)	(0.000)
Ln total assets focal stock	-0.003***	0.004***	-0.005***	0.002***
	(0.0002)	(0.0001)	(0.0001)	(0.0002)
Standard deviation of estimates	-0.0004***	-0.0000	-0.0002***	0.00006*
focal stock	(0.00001)	(0.0000)	(0.00001)	(0.00003)
Stock earnings release focal stock	0.016***	0.004***	0.002**	-0.007***
	(0.001)	(0.000)	(0.001)	(0.000)
Stock guidance release focal	0.011***	-0.004***	0.018***	-0.001**
stock	(0.001)	(0.001)	(0.001)	(0.001)
Reg-FD	-0.020***	-0.051***	0.026***	-0.016***
	(0.001)	(0.001)	(0.001)	(0.001)
Analyst status	-0.0002	-0.0003+	-0.0005+	0.0003
	(0.0003)	(0.0002)	(0.00003)	(0.0002)
Analyst positive bold estimate		0.595***		
		(0.004)		
Analyst negative bold estimate				0.455***
				(0.003)
x^2	30502.3***	67024.8***	33035.0***	25448.4***

Standard errors in parentheses. + p<.10; * p<0.05; ** p<0.01; *** p<0.001

Table 3: 3SLS Fixed-Effect Simultaneous Regression Models of Bold Estimates

	Model 2		Model 3	
	Positive Bold	Negative Bold	Positive Bold	Negative Bold
Time trend	-0.002***	-0.001***	-0.002***	-0.001***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Analyst experience	0.000	0.000	0.0002+	0.0002+
	(0.000)	(0.000)	(0.0002)	(0.0001)
Ln analyst focal stock experience	-0.000	0.002***	-0.000	0.002***
	(0.000)	(0.0003)	(0.0004)	(0.0003)
Ln analyst stock portfolio size	-0.003***	-0.002***	-0.003***	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
Analyst negative bold 180 days focal stock	0.047***	0.189***	0.047***	0.188***
	(0.001)	(0.001)	(0.001)	(0.001)
Analyst negative bold 180 days portfolio	0.021***	0.136***	0.020***	0.134***
	(0.002)	(0.002)	(0.002)	(0.002)
Analyst positive bold 180 days focal stock	0.174***	0.029***	0.173***	0.029***
	(0.001)	(0.001)	(0.001)	(0.001)
Analyst positive bold 180 days portfolio	0.114***	0.025***	0.112***	0.023***
	(0.002)	(0.002)	(0.002)	(0.002)
Ln issues analyst's brokerage has underwritten	-0.001***	0.001***	-0.001***	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
Ln stocks covered by analyst's brokerage	0.003***	-0.001	0.004***	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Ln issues analyst's brokerage underwritten focal stock	-0.007***	-0.007***	-0.007***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
Analyst leader-follower ratio	0.00009***	-0.00000	0.00009***	-0.00000
	(0.00002)	(0.00002)	(0.00002)	(0.00002)
Ln analysts following focal Stock	-0.003**	0.002*	-0.003**	0.002+
	(0.001)	(0.001)	(0.001)	(0.001)
Ln total assets focal stock	-0.002***	-0.005***	-0.003***	-0.005***
	(0.000)	(0.000)	(0.000)	(0.000)
Standard deviation of estimates focal stock	-0.0004***	-0.0002***	-0.0004***	-0.0002**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Stock earnings release focal stock	0.016***	0.0019**	0.015***	0.0014*
	(0.001)	(0.0007)	(0.001)	(0.0007)
Stock guidance release focal stock	0.011***	0.017***	0.011***	0.018***
	(0.001)	(0.001)	(0.001)	(0.001)
Reg-FD	-0.020***	0.026***	-0.013***	0.045***
	(0.001)	(0.001)	(0.002)	(0.002)
Analyst status	0.000	-0.000	0.009***	0.003***
	(0.000)	(0.000)	(0.001)	(0.001)
Analyst multipoint contact	-0.027***	-0.018***	-0.019***	0.014***
	(0.002)	(0.002)	(0.003)	(0.003)
Reg-FD X Analyst multipoint contact			-0.006+	-0.048***
			(0.003)	(0.003)
Reg-FD X Analyst status			-0.008***	-0.003***
			(0.001)	(0.001)
Analyst multipoint contact X Analyst status			-0.011***	-0.004**
			(0.002)	(0.002)
Effects on accuracy				
Analyst multipoint contact	0.008***	0.013***	-0.003	0.011***
	(0.001)	(0.001)	(0.002)	(0.001)
Reg-FD X Analyst multipoint contact			0.019***	0.004*
			(0.002)	(0.002)
Analyst bold positive estimate	0.597***		0.598***	
	(0.004)		(0.004)	
Analyst bold negative estimate		0.457***		0.458***
		(0.003)		(0.003)
*x*2	30713.7***	33160.3***	30977.5***	33479.4***

Standard errors in parentheses. * p<0.05; ** p<0.01; *** p<0.001

Table 4: 3SLS Fixed-Effect Simultaneous Regression Models of Bold Estimates

	Pre Reg-FD		Post Reg-FD	
	Positive Bold	Negative Bold	Positive Bold	Negative Bold
Time trend	-0.009***	0.003***	-0.000	-0.002***
	(0.0004)	(0.0002)	(0.000)	(0.0002)
Analyst experience	0.0005+	-0.000	0.000	0.0002**
	(0.0002)	(0.000)	(0.000)	(0.00006)
Ln analyst focal stock experience	0.002**	0.005***	-0.000	0.000
	(0.001)	(0.001)	(0.000)	(0.000)
Ln analyst stock portfolio size	-0.004***	-0.002*	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Analyst negative bold 180 days focal stock	-0.050***	0.218***	0.096***	0.165***
	(0.003)	(0.002)	(0.002)	(0.002)
Analyst negative bold 180 days portfolio	-0.067***	0.184***	0.046***	0.109***
	(0.005)	(0.004)	(0.003)	(0.003)
Analyst positive bold 180 days focal stock	0.151***	-0.017***	0.179***	0.092***
	(0.002)	(0.001)	(0.002)	(0.002)
Analyst positive bold 180 days portfolio	0.112***	-0.018***	0.095***	0.057***
	(0.004)	(0.003)	(0.003)	(0.003)
Ln issues analyst's brokerage has underwritten	0.002***	0.001***	-0.002***	0.000
	(0.000)	(0.000)	(0.0003)	(0.000)
Ln stocks covered by analyst's brokerage	0.008***	-0.002*	0.003**	0.005***
	(0.002)	(0.001)	(0.001)	(0.001)
Ln issues analyst's brokerage underwritten focal stock	-0.005**	-0.001	-0.006***	-0.008***
	(0.002)	(0.001)	(0.001)	(0.001)
Analyst leader-follower ratio	0.0003***	0.00008*	0.00004+	-0.000
	(0.0000)	(0.00003)	(0.00002)	(0.000)
Ln analysts following focal Stock	-0.001	0.005***	-0.005***	-0.004**
	(0.002)	(0.001)	(0.001)	(0.001)
Ln total assets focal stock	0.002***	-0.003***	-0.006***	-0.005***
	(0.000)	(0.000)	(0.000)	(0.000)
Standard deviation of estimates focal stock	-0.0004***	-0.000	-0.0003***	-0.0003***
	(0.0001)	(0.000)	(0.0001)	(0.0001)
Stock earnings release focal stock	0.024***	-0.010***	0.009***	0.008***
	(0.002)	(0.001)	(0.001)	(0.001)
Stock guidance release focal stock	-0.007*	0.028***	0.016***	0.013***
	(0.003)	(0.002)	(0.001)	(0.001)
Reg-FD	0.007***	0.002**	-0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Analyst status	-0.039***	0.004	-0.014***	-0.032***
	(0.004)	(0.003)	(0.002)	(0.002)
Analyst multipoint contact	-0.021***	-0.005**	-0.003	-0.005*
	(0.003)	(0.002)	(0.002)	(0.002)
Effects on accuracy				
Multipoint contact	0.015***	0.013***	0.010***	0.002*
	(0.002)	(0.002)	(0.001)	(0.001)
Analyst bold positive estimate	0.889***		0.395***	
	(0.006)		(0.004)	
Analyst bold negative estimate		0.849***		0.251***
		(0.005)		(0.004)
*x*2	10456.4***	15960.3***	20885.7***	18368.4***

Standard errors in parentheses. * $p<0.05$; ** $p<0.01$; *** $p<0.001$

Table 5: Bold Estimates by Multipoint Contact (MPC) and Leader-Follower Ratio (LFR)

			Pre Reg-FD				Post Reg-FD			
	Behavior		Positive bold estimates		Negative bold estimates		Positive bold estimates		Negative bold estimates	
	Low MPC	High MPC	Low MPC	High MPC	Low MPC	High MPC	Low MPC	High MPC	Low MPC	High MPC
Low LFR	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 LFR	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%

Note: High and Low are defined as top quartile and bottom quartile of the observations for MPC (multipoint contact) and LFR (leader-follower ratio). The table shows the ratios of the number of bold estimates in each cell to the number of estimates in each cell. The same patterns are visible but attenuated when the top and bottom half of the observations are used.

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