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Mutual Forbearance and Competition Among Security Analysts

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Research in industrial organization and strategic management has shown that rivals competing with each other in multiple markets are more willing to show each other mutual forbearance, i.e., compete less aggressively, within their spheres of influence, i.e., the markets in which each firm dominates. Sell-side equity analysts typically cover multiple stocks in common with their rivals. We examine the impact of this "multipoint contact" for mutual forbearance on two key dimensions of competition among security analysts: forecast accuracy and information leadership (issuing earnings forecasts or stock recommendations that influence rival analysts). We find that multipoint contact is associated with analysts exerting greater information leadership on stocks within their own spheres of influence. We also find greater forbearance related to information leadership under Regulation Fair Disclosure (Reg FD). In contrast, multipoint contact was not associated with greater forecast accuracy on stocks within analysts' spheres of influence, either before or under Reg FD. Our analysis is among the first to consider mechanisms of competition among securities analysts and also adds to the literature on Reg FD by demonstrating that the increased workload imposed on analysts after Reg FD fostered mutual forbearance as a response.

Keywords: mutual forbearance; multipoint contact; securities analysts; Regulation Fair Disclosure
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1. Introduction

Sell-side securities analysts are pivotal intermediaries in capital markets, and their performance and functioning have been a focus of extensive research in both accounting and finance. Studies of analyst functioning and performance have emphasized interactions among analysts, the firms whose stocks they cover, and their primary target audience, institutional investors (O'Brien and Bhushan 1990). Interactions among analysts themselves, in contrast, have received little attention beyond examinations of analyst herding behavior (Trueman 1994, Hong et al. 2000) and performance variation among analysts covering a given stock along dimensions such as forecast timeliness (Cooper et al. 2001, Loh and Stulz 2011), accuracy (Clement 1999), and the informativeness of research reports (Frankel et al. 2006). Yet, analysts typically cover a portfolio of stocks, bringing them into contact and competition with a variety of other analysts across multiple stocks. Thus far, the impact of this "multipoint contact" among security analysts on their competitive behavior has not been examined.

However, a large body of research in industrial organization and strategic management has shown that when firms compete with each other in multiple geographic or product markets, they are more willing to show each other mutual forbearance by competing less aggressively. Mutual forbearance theory (Edwards 1955, Porter 1980, Karnani and Wernerfelt 1985) posits that this occurs because firms competing simultaneously in multiple domains must weigh the prospect of an advantage at any given point of contact against the (potentially higher) cost of retaliation (now or in the future) by the same firms at another point (or points) of contact. When two firms meet in multiple domains, each has an incentive to stake out certain domains as its "sphere of influence" and to refrain from competing intensely in its rivals' spheres—as long as its own sphere is similarly respected (Baum and Greve 2001). To examine whether multipoint contact is associated with mutual forbearance among securities analysts, we test whether the extent of multipoint contact an analyst experiences covering a given stock is associated with greater forbearance on that stock toward the analyst if the stock falls within his or her sphere of influence.

We focus on analysts' accuracy and information leadership in both earnings forecasts and recommendations as possible competitive behaviors in which mutual forbearance may arise. Forecast accuracy is an important dimension along which analysts compete that is directly observable by investors and other analysts (Lys and Soo 1995), whereas information leadership captures the relative influence among analysts covering a given stock and is not tied to specific forecast or recommendation outcomes (Cooper et al. 2001, Loh and Stulz 2011). Therefore, our examination includes both direct and indirect analyst outcomes. In addition to seeking convergent findings across distinct dimensions of analyst competition, these aspects of analyst competition are of particular relevance to the study of forbearance. A focus on accuracy permits us to assess whether the weaker competition accompanying mutual forbearance is associated with analysts' reducing their effort or, instead, coordinating their joint efforts to minimize forecast error more effectively. Potential coordination across spheres of influence also suggests a link to information leadership, since mutual forbearance should present analysts with opportunities to exert leadership within their own spheres of influence while subordinating within their rivals' spheres. We predict that, rather than investing in accuracy and contesting for information leadership on all stocks they cover, when multipoint contact is high, analysts will exhibit greater forecast accuracy and information leadership on stocks *within their own* spheres of influence rather than on stocks *within their rivals'* spheres.

We also consider the impact of Regulation Fair Disclosure (Reg FD). Enacted in October 2000, Reg FD prohibited selective disclosure of information by publicly traded firms to preferred analysts and institutional investors. For analysts in particular, the U.S. Securities and Exchange Commission (SEC) anticipated that "the regulation will encourage competition [among securities analysts] because it places all analysts on equal competitive footing with respect to access to material information. Analysts will continue to be able to use and benefit from superior diligence or acumen, without facing the prospect that other analysts will have a competitive edge simply because they have been favored with selective disclosure" (U.S. Securities and Exchange Commission 2000, Section VI). Reg FD thus leveled the playing field in capital markets, which increased the time and effort required for analysts to compete effectively (Mohanram and Sunder 2006). Among securities analysts with extensive multipoint contact, mutual forbearance represents a practical response to the increased competition, information gathering, and analytical workload imposed by Reg FD. We therefore expect an increase in analysts' tendency toward mutual forbearance under Reg FD.

Our findings confirm the role of mutual forbearance in shaping information leadership among securities analysts. When multipoint contact is high, analysts exhibit greater information leadership for both earnings forecasts and recommendations on stocks *within their own* spheres of influence. Furthermore, this effect is more pronounced under Reg FD. In contrast, we find no evidence of mutual forbearance being associated with increased forecast accuracy within analysts' own spheres of influence, either before or under Reg FD. These results contribute to the literature on sell-side security analysts by presenting one of the first analyses to consider mechanisms of competition among analysts and in particular the role of mutual forbearance in shaping competition among them through multipoint contact. It also adds to the literature on Reg FD by demonstrating that the increased workload imposed on analysts after Reg FD fostered mutual forbearance as a response.

2. Theory and Hypotheses

2.1. Functioning of Securities Analysts

Securities analysts are key information intermediaries in contemporary capital markets and as such compete intensely for investor attention. Although analysts may compete on many dimensions, including optimism (McNichols and O'Brien 1997), boldness (Bowers et al. 2014), and portfolio choice (Barth et al. 2001), we focus on the accuracy of their forecasts as well as the timeliness of both their forecasts and stock recommendations, each of which has been shown to be an important indicator for investors as well as analyst careers.

Forecast accuracy is among the most studied analyst performance outcomes, as it is related to security returns (O'Brien 1988) and analyst employment outcomes (Mikhail et al. 1999). Although early studies of forecast accuracy suggested that individual analysts were unable to provide accurate forecasts over multiple years (Brown and Rozeff 1980), more recent evidence suggests that certain analysts are more consistently accurate (Sinha et al. 1997, Stickel 1992). Analysts' accuracy is the result of information and analysis, their two primary tools, but Lys and Soo (1995) find that, controlling for forecasting difficulty, accuracy increases with the number of analysts following a stock. Their result is consistent with two explanations. One is that analysts respond to increasing competition with more accurate forecasts. The other is that analysts learn from each other's forecasts, and the opportunities for information spillover increase with analyst following. The idea that analyst accuracy might be the result of analyst awareness of the efforts of other analysts is consistent with the literature on herding (Trueman 1994, Hong et al. 2000). None of these literatures focuses explicitly on how analysts compete, however, and so mutual forbearance offers one account of their competitive behavior.

Analysts also compete on the timeliness of their forecasts and recommendations, since timeliness helps shape market interpretations and investor behavior and plays a crucial role in the development of a consensus estimate. Cooper et al. (2001) advance the concept of information leadership to capture the ability of a given analyst's earnings forecast revisions to prompt other analysts to revise their own. They show that markets are much more likely to react to forecast revisions made by analysts whom they identify as information leaders, resulting in larger impacts on stock price and trading volume. Similarly, Clement and Tse (2003) find that investors positively weigh the forecast horizon and the number of days elapsed since the last forecast in their investment decisions, whereas Loh and Stulz (2011) show that timely recommendations are more likely to be influential. The latter is interesting because we cannot directly measure the accuracy of recommendations, and recommendations are not tied to specific deadlines such as earnings releases. More generally, trading volume is positively linked to analyst compensation and career outcomes (Groysberg et al. 2011, Zhang 2005); leadership is also directly linked to benefits for analysts themselves. Thus, although it is established that information leadership is impactful to analyst careers and investors and is a function of analysts' mutual awareness of each other's activities, prior work on information leadership has yet to examine the role of competition among analysts in the timing of their information sharing.

An understanding of analyst competition as it impacts metrics such as forecast accuracy and timing is also important because of potential trade-offs identified between these metrics. Prior research has shown that information leadership is associated with greater first-mover trading volume (Cooper et al. 2001). Analysts hence have a strong incentive to release earnings forecasts before their rivals, but may have less information with which to make their forecasts. In competition for investor attention, analysts thus face a potential trade-off between being timelier or more accurate with their forecasts. Analysts who revise their forecasts first after a public announcement or a long gap may sacrifice accuracy for the sake of information leadership (Brown and Hugon 2009). Yet, Mozes (2003) finds that forecasts with greater immediacy, where analysts respond quickly to a significant change in publicly available information, are more accurate than the consensus, and Cooper et al. (2001) report that information leaders also tend to be accuracy leaders. This potential trade-off suggests that research examining analyst competition should consider both dimensions.

2.2. Mutual Forbearance

Mutual forbearance theory offers one framework for examining the competitive interactions of analysts beyond simple herding effects. Rivals often engage each other in the same activity in more than one distinct geographic or product domain, giving rise to a web of multipoint contacts. Historically, there has been a widely held belief that such multipoint contact leads to mutual forbearance, that is, a willingness to compete less intensely.[1] One line of reasoning supporting the emergence of weaker competition in the presence of multipoint contact is that greater latitude exists for rivals both to reward one another for forbearing and to punish one another for competing (Karnani and Wernerfelt 1985). The prospect of an advantage at any given point of contact must be weighed against the cost of retaliation by the same rival at other points of contact (Porter 1980). The more domains in which a pair of firms meet, the more information they gain about each other's competitive behavior—which actions the other has undertaken, under what conditions, and to what effect—thereby increasing their ability to anticipate each other's competitive behavior (Boeker et al. 1997, Hughes and Oughton 1993). When two firms meet in multiple domains, each thus has an incentive to stake out certain domains as its sphere of influence and to refrain from competing intensely in its multipoint rival's sphere of influence as long as its own sphere is similarly respected. The outcome of a history of interactions across multiple domains is thus expected to be weaker competition in all domains in which multipoint rivals meet and more stable and predictable competitor behavior over time.

In broad support of the hypothesis, research has shown that multipoint contact among rivals is associated with higher prices, profits, and growth, as well as lower market entry and exit rates (Feinberg 1985, Gimeno and Woo 1996, Barros 1999, Barnett et al. 1994, Haveman and Nonnemaker 2000, Greve 2008). Studies show that mutual forbearance arises among multinational corporations in response to their contact across national markets (Gimeno and Woo 1996) and among single-product firms as a result of their contact across multiple geographic markets (e.g., hotel and motel chains (Ingram and Baum 1997, Kalnins 2004) and airlines (Baum and Korn 1996)).

The concept of mutual forbearance is not limited to firms. Simmel (1950, p. 286–291), writing about social relations in general, argued that the potential for cooperation among actors increases when they compete in multiple domains, since each will gain by allowing the other to be "superordinate" in some domains in exchange for similar treatment in other

[1] Although analysts vary in the degree of autonomy they have in choosing the stocks they cover, deliberate choice is not necessary for mutual forbearance to emerge. For example, Korn and Baum (1999) show that multipoint contact among commuter airlines results mainly from uncoordinated geographic market (i.e., city-pair) choices and imitation of each other's market choices and only secondarily as a result of purposive choice.

domains. Simmel's reciprocal subordination hypothesis suggests, identically to Edwards' (1955) mutual forbearance hypothesis, that because the *potential* for competition is greater among actors who meet in multiple domains than among actors who meet in a single domain, *realized* competition among multipoint rivals is weaker. In order for mutual forbearance to occur, actors must have an incentive to forbear. What is required is the ability for actors to cause each other harm—in terms of profitability or otherwise—and for expected gains from competitive moves to be small relative to future losses resulting from competitive escalation.

2.3. Mutual Forbearance Among Securities Analysts

Although the equivalence of "multi-stock securities analysts" and multi-product firms can be problematic, the correspondence with multi-location, single-product firms is quite plausible (Bowers et al. 2014). Among securities analysts, incentives to reduce competition are related to compensation, reputation, and employment, each of which depends on the intensity with which competing analysts vie for investor attention and influence. For deterrence to emerge among multipoint analysts, they must believe that their rivals have both the ability and opportunity to retaliate in ways that can harm them, and that relative to competition on a single stock, the ability of analysts to retaliate across multiple stocks implies larger future losses from competitive escalation than immediate gains on a particular stock. Deterrent effects are amplified if multipoint contact permits analysts to retaliate on stocks in which a response is less costly or more convenient for them (i.e., stocks peripheral to their own portfolios but central to a rival's), making retaliation more likely. Competitive actions open to analysts include increased effort in their coverage of particular stocks, including frequency, timeliness, and accuracy of forecasts or recommendations, as well as initiating or ceasing coverage on the stock. Such actions have a disciplining effect because they can result in losses in investor attention and trading volume for an analyst's brokerage. Analysts are motivated by increased investor attention and trading volume on the stocks they cover because each is positively correlated with their compensation and reputation and negatively correlated with loss of their employment (Groysberg 2010, Mikhail et al. 1999).[2]

[2] Increased effort on the buy-side is also possible and, while less transparent to rivals, is likely detectable. Indeed, through contacts with common investors, analysts often become aware of rivals' activities on the buy-side of their jointly covered stocks. In a series of informational interviews we conducted with both buy- and sell-side analysts, each side indicated that buy-siders mentioned the work of rivals to other sell-siders.

A possible outcome of analysts' competitive interactions across multiple stocks is thus reduced competition among analysts. Analysts may refrain from competitive actions (e.g., striving to minimize forecast error, pursuing timing advantages, or initiating coverage) when covering stocks on which they face multipoint competitors. They may also tacitly evolve coordination norms, adopting "live-and-let-live" policies under which they divide jointly covered stocks among themselves into "spheres of influence" and grant each other primacy on one or more stocks within these spheres in exchange for similar treatment in their own sphere (Simmel 1950, Edwards 1955). Although research offers evidence of mutual forbearance among analysts, for example, that multipoint contact led analysts to refrain from issuing bold estimates, particularly when the analysts were equal competitors or of high status (Bowers et al. 2014), studies have yet to examine the role of such spheres of influence and thus the direction of deference; that is, who forbears to whom.

As Edwards (1955) originally observed, behavior controlled by such multipoint deterrence may be detrimental for the market at large. Although analysts may wish to convey new information to the market, for example, they may hesitate to do so to avoid appearing overly aggressive (e.g., challenging the superordinate analyst on a stock by being first to the market with new information) and thus restricting information available to investors, or they may simply reduce their effort in response to the mutual competitive restraint. Yet, such reciprocal subordination may improve market outcomes (Gimeno 1999). A division of labor would permit analysts to coordinate their investment in developing specialized expertise in gathering information and analyzing particular stocks within their own spheres of influence while deferring to rival analysts' insight and expertise on stocks within their spheres. In this regard, the choice of forecast accuracy and information leadership for our empirical tests is particularly germane: a focus on accuracy permits an assessment of whether multipoint contact leads analysts to coordinate their efforts to minimize forecast accuracy more effectively or, alternatively, to simply reduce their effort; focusing on information leadership permits an assessment of whether multipoint contact is associated with analysts yielding to their rivals' influence on some stocks in exchange for similar treatment on others.

2.4. Securities Analysts' Spheres of Influence: Who Forbears to Whom?

Over time, the analysts co-covering a group of stocks become familiar with one another and, through their ongoing interactions, come to know whose work can be trusted, what stocks each analyst really cares about and will (and can) defend vigorously, which stocks they can aim to establish dominance on, and which stocks they ought to subordinate to rivals in return. Anecdotal evidence indeed indicates that analysts pay greater attention to their coverage of particular stocks and that these preferences are well-known to other analysts. For example, in his memoir *Confessions of a Wall Street Analyst*, Daniel Reingold explained how Jack Grubman competed intensely on AT&T and retaliated against analysts who challenged him. Although Reingold did not cease coverage of AT&T, he claims that he competed less intensely as a result of Grubman's actions.

A test of the deterrence effects of mutual forbearance on analyst accuracy and information leadership requires us to specify the stocks on which particular analysts are likely to establish spheres of influence and those on which they are not. Although we cannot observe analysts' spheres of influence directly, we can gauge their likely locations. We can do this by identifying a "focal point" or "convention" on the basis of which analysts can be expected to coordinate their mutual forbearance behavior. Focal points represent each actor's "expectation of what the other expects him to expect to be expected to do" (Schelling 1960, p. 57), serving as a basis of coordination that actors use in the absence of direct communication (because it seems natural, special, or relevant to them) and aligns their behavior and expectations. Focal points are shaped by interactions among actors and adopted in response to pressures to comply with convergent expectations that solve the problem of coordinating. The existence of focal points suggests that simply examining the presence of multipoint contact, which creates conditions sufficient enough for mutual forbearance to emerge, is incomplete; rather, we must simultaneously examine the level of multipoint contact of the analyst and the importance of a particular stock to the analyst.

One such focal point around which securities analysts' expectations are likely to converge is stock-specific coverage experience, which reflects an analyst's expertise in, reputation for, and size of investor following on, as well as his or her likely commitment to maintaining and defending a coverage position on that stock. Long-standing coverage of a stock affords deeper understanding of the firm and factors affecting its earnings. Moreover, over time, analysts develop relationships with the management of firms they follow, which may also afford privileged access to idiosyncratic firm information, particularly prior to Reg FD (Cohen et al. 2010). As a result, analysts possessing greater stock-specific experience tend to release more informative and accurate earnings forecasts (Lamont 2002, Mikhail et al. 1997) and exhibit greater information leadership (Cooper et al. 2001, Shroff et al. 2014).

A second focal point around which securities analysts' expectations regarding spheres of influence may cohere is portfolio size. The size of the portfolio an analyst covers reflects the same factors—expertise, reputation, investor following, commitment to maintaining and defending a position—but at the analyst rather than analyst-stock level. The size of the stock portfolio a given analyst covers thus captures the analyst's predominance among analysts covering stocks within a particular industry or sector.

2.5. Hypotheses

In equilibrium, analysts can benefit from such coordination by avoiding the need to divide their effort over all the stocks they cover. Rather than *lowering* their effort in response to the competitive restraint that results from this coordination, analysts can *focus* and *specialize* their effort on stocks that fall within their spheres of influence and defer to their rivals who are specialized in other stocks. Under conditions favoring mutual forbearance among analysts, that is, when multipoint contact among them is high, analysts may thus yield forecast accuracy and information leadership advantages on stocks within their multipoint rivals' spheres of influence in exchange for reciprocal treatment on stocks within their own spheres. We therefore expect the effects of multipoint contact on forecast accuracy and information leadership to depend on whether or not a stock is within an analyst's own or a rival's sphere of influence; as a corollary, we expect that analysts will forbear from competition with their more experienced multipoint rivals, particularly those who cover large stock portfolios:

Hypothesis 1 (H1). *On stocks where they experience high multipoint contact, analysts issue* more accurate earnings forecasts *for stocks within their own spheres of influence than for stocks within their rivals' spheres.*

Hypothesis 2 (H2). *On stocks where they experience high multipoint contact, analysts exercise* greater information leadership *in* earnings forecasts *on stocks within their own spheres of influence than on stocks within their rivals' spheres.*

Hypothesis 3 (H3). *On stocks where they experience high multipoint contact, analysts exercise* greater information leadership *in* recommendations *on stocks within their own spheres of influence than on stocks within their rivals' spheres.*

The potential for mutual forbearance among securities analysts has important implications for the efficacy of regulatory efforts. Consequently, we consider the impact of the SEC's enactment of Reg FD on competition among analysts. Reg FD was enacted to level the playing field in capital markets by prohibiting publicly traded firms from selectively disclosing material information to preferred analysts and investors (U.S. Securities and Exchange Commission 2000, Section VI). The intention of this regulation was to prohibit preferential access to information to certain analysts, a prohibition the SEC anticipated would encourage competition among securities analysts by placing them on "equal footing with respect to access to material information" (U.S. Securities and Exchange Commission 2000, Section VI). Evidence indeed suggests that analysts have faced difficulties adapting to the loss of advantages from close relations with corporate management (Cohen et al. 2010) and the competitive challenges of the more level playing field created by public information disclosure requirements (Bagnoli et al. 2008, Mohanram and Sunder 2006). Evidence also suggests that Reg FD fostered mutual forbearance among analysts, with bold estimates less likely to be issued under the regulation (Bowers et al. 2014).

By enabling each analyst to invest more in reducing forecast error and establishing information leadership in the coverage of stocks falling within their spheres of influence while following on stocks within their rivals' spheres, mutual forbearance, facilitated by the multipoint contact arising naturally among analysts, affords a practical and viable response to the competitive challenges posed by Reg FD. We therefore expect the enactment of Reg FD to increase analysts' incentive to mitigate competitive pressures and thus the tendency of multipoint contact to foster mutual forbearance relationships. Accordingly, we predict:

Hypothesis 4 (H4). *The prediction in* H1 *is stronger following the enactment of Reg FD.*

Hypothesis 5 (H5). *The prediction in* H2 *is stronger following the enactment of Reg FD.*

Hypothesis 6 (H6). *The prediction in* H3 *is stronger following the enactment of Reg FD.*

3. Data and Methods

3.1. Sample

We collect data for all analysts' annual earnings estimates released to Thomson's Institutional Brokers' Estimate System (IBES) database during the period from January 1, 1990, to December 31, 2013. We restrict the sample to analyst forecasts and recommendations with necessary information required to compute our measure of information leadership, the leader-follower ratio (*LFR*) (Cooper et al. 2001, Loh and Stulz 2011). Moreover, since we are interested in assessing analysts' information leadership, it is also important to exclude any forecasts or recommendations they issue for a stock at the same time the firm releases information, rendering information leadership moot. We use data from COMPUSTAT to identify quarterly earnings release dates (RDQ) and exclude any analyst estimates issued within three days of earnings announcement dates. In Table 1, panel 1A summarizes the sample selection procedure.

Given these restrictions, there were 2,399,938 distinct analyst earnings forecasts with data available to calculate our measures of forecast accuracy, information leadership, and multipoint contact. However, because each analyst issues multiple forecasts in a given stock-year, these are not independent observations. We therefore aggregate the data, averaging at the analyst-stock-year level. This aggregation results in 686,844 analyst-stock-year observations, reduced to 510,363 by data requirements for the control variables. Finally, to control for persistence in analyst performance due to unobserved heterogeneity in analysts' advantages, we include lagged forecast accuracy and information leadership in our models (Heckman and Borjas 1980, Jacobson 1990), which further reduces the sample as the lag consumes the first year of the sample and all observations where an analyst does not follow a given stock in the prior year. The final sample consists of 307,335 analyst-stock-years, comprising 11,167 distinct analysts and 6,930 unique stocks. Recommendation data covers only a subset of this period, becoming available only in 1993, and the subset of analysts who issue stock recommendations. After annual aggregation, exclusion of observations because of data requirements, and inclusion of lagged variables, recommendation data are available for 8,000 distinct analysts who cover 5,244 unique stocks, and the subsample includes 100,672 analyst-stock-year observations.

3.2. Dependent Variables

Our analysis focuses on three measures of analyst performance: forecast accuracy (H1 and H4) and two aspects of information leadership (H2, H3, H5, and H6). We measure forecast accuracy, *ACC*, as the negative of absolute forecast error scaled by stock price at the time of the forecast (Lang and Lundholm 1996). More formally, $ACC = -|EPS_{\text{actual}} - EPS_{\text{forecast}}|/PRICE$. We multiply *ACC* by 100 to allow for the intuitive interpretation of *ACC* as a percentage of the stock price.

We measure information leadership using the *LFR* proposed by Cooper et al. (2001). Our first measure, *FLFR*, focuses on information leadership in earnings forecasting. *FLFR* captures the interplay between a given analyst's forecasts for a given stock and the forecasts of rival analysts also covering the same stock. For each earnings forecast an analyst issues on a given stock, we calculate the ratio of the cumulative number of days by which the preceding two forecasts on that stock lead the forecast of interest to the cumulative number of days by which the subsequent two

Table 1 Sample Selection and Distribution

Panel 1A: Sample selection criteria

Criterion	Forecasts	Analyst-stock-years	Unique stocks	Unique analysts
Data from IBES for 1990–2013 for U.S. firms with one-year ahead EPS forecasts, valid PRICE on date of forecast from CRSP, forecast not within three days of firm-issued earnings, guidance, or conference calls	2,399,938			
Forecasts averaged by analyst-stock-year		686,844	12,220	16,805
Availability of forecasts to compute *FLFR*		555,357	9,828	16,304
Availability of control variables		510,363	8,881	16,040
Availability of lagged *FLFR* and lagged *ACC*		307,335	6,930	11,167

Criterion	Recommendations	Analyst-stock-years	Unique stocks	Unique analysts
Data from IBES for 1993–2013 for U.S. firms with recommendation not within three days of firm-issued earnings, guidance, or conference calls	663,947			
Recommendations averaged by analyst-stock-year		474,307	18,300	16,224
Availability of recommendations to compute *RLFR*		386,651	11,602	14,999
Availability of control variables		242,778	7,566	12,366
Availability of lagged *RLFR* and lagged *ACC*		100,672	5,244	8,000

Panel 1B: Time trends in mean *ACC, FLFR, MPC, and RLFR*

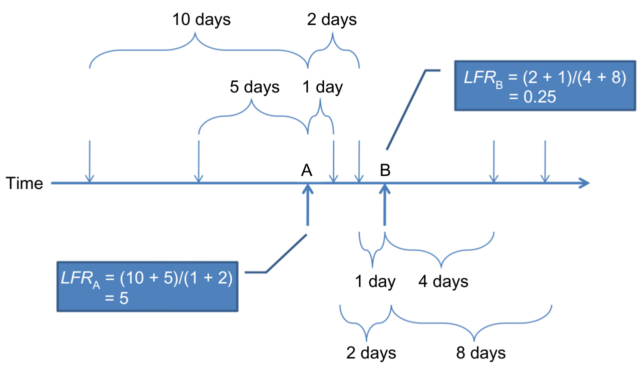
Year	*N*	*ACC*	*FLFR*	*MPC*	N_{RLFR}	*RLFR*
1990	7,577	−2.287	2.157	0.277		
1991	9,471	−1.655	2.340	0.304		
1992	9,795	−1.355	2.410	0.301		
1993	10,121	−1.082	2.486	0.283	2,668	1.942
1994	9,938	−0.879	2.543	0.273	4,451	1.440
1995	9,702	−1.066	2.306	0.295	4,041	1.780
1996	11,821	−1.024	2.672	0.286	3,907	1.773
1997	11,981	−0.858	2.984	0.288	3,712	1.873
1998	12,434	−1.155	3.343	0.283	4,056	1.982
1999	12,520	−1.318	3.833	0.296	4,220	2.058
2000	11,990	−1.376	3.970	0.302	3,668	2.231
2001	11,307	−1.487	3.769	0.310	3,721	2.095
2002	11,767	−1.318	4.142	0.333	5,617	2.004
2003	12,810	−1.116	4.482	0.348	4,950	1.842
2004	14,853	−0.830	4.652	0.353	4,883	1.964
2005	16,581	−0.958	4.703	0.339	4,447	2.001
2006	17,684	−0.982	4.796	0.334	4,683	1.944
2007	18,913	−1.391	4.852	0.322	4,970	2.048
2008	12,277	−3.106	3.211	0.324	5,853	1.785
2009	13,403	−3.056	3.050	0.336	6,544	1.767
2010	14,522	−1.586	3.208	0.339	6,136	1.943
2011	15,965	−1.644	3.162	0.350	6,751	1.942
2012	17,301	−1.881	3.105	0.356	7,127	1.950
2013	12,602	−1.030	3.307	0.364	4,267	2.122
Annual trend		−0.022	0.063	0.003		0.008
(*t*-statistic)		(−1.20)	(2.81)	(8.03)		(1.36)

forecasts on that stock follow the focal forecast.[3] An *FLFR* greater than one means that the analyst's estimates are more rapidly followed by estimates from rival analysts, i.e., the analyst in question is an information leader. The closer the *FLFR* is to zero, in contrast, the longer it takes for rival analysts to follow the analyst in question, i.e., the analyst is less influential. Following Loh and Stulz (2011), our second measure, *RLFR*, is computed in the same way but based on recommendations rather than forecasts. Figure 1 illustrates computation of analyst-stock *LFR* for two hypothetical forecasts (recommendations), one by an information leader (forecast A) and one by a follower (forecast B).[4]

[3] Following Cooper et al. (2001), when calculating lead- and follow-times for a given analyst, we exclude any additional forecasts (recommendations) made by that analyst in the pre- and post-release periods and count multiple forecasts (recommendations) issued on the same day as a single forecast.

[4] Prior research also has employed relative measures for forecast accuracy by considering the distribution of *ACC* across analysts.

Figure 1 (Color online) Calculation of the Leader-Follower Ratio (LFR)



Note. A and B indicate the timing of forecasts (recommendations) issued by two analysts, A and B, for a stock that they co-cover.

All three measures, *ACC*, *FLFR*, and *RLFR*, are averaged across all relevant forecasts or recommendations in a year for each analyst-stock combination. Given this aggregation, we control for forecast horizon (*HORIZON*) measured as the log of one plus the number of days between the date the forecast is issued and the end of the fiscal period for the forecast, averaged across all forecasts in a year for a given analyst-stock combination. As analysts obtain more information, including the realization of quarterly earnings over time, we expect *HORIZON* to be negatively related to forecast accuracy. In contrast, as influential analysts are timelier, we expect *HORIZON* to be positively related to information leadership. As *HORIZON* is measured at the forecast level, we average it across all forecasts in a given year for a given analyst-firm combination. [5]

3.3. Multipoint Contact

Our measure of multipoint contact, *MPC*, gauges the extent to which an analyst, when covering a given stock with rival analysts, also covers other stocks jointly with those rival analysts (Baum and Korn 1996). We define an analyst as following a given stock if the analyst issues at least one earnings forecast in the prior 12 months. To compute the measure, for each stock an analyst covered, we calculate the proportion of other stocks in the analyst's portfolio that are covered jointly by each rival analyst also covering the focal stock and then compute the average proportional overlap across rival analysts (Baum and Korn 1996). Formally:

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

where $MPC_{i\cdot m}$ is analyst i's multipoint contact for stock m, $D_{i\cdot n}$ is equal to 1 if analyst i covers stock n, $D_{j\cdot n}$ is equal to 1 if other analysts j covering stock m also cover stock n, and N_m is the total number of analysts covering stock m. *MPC* is computed at the time of each forecast and then averaged across all forecasts in a year for each analyst-stock pair. This is necessary since the number of analysts covering a stock, as well as the portfolio of stocks they cover, can vary through the year due to coverage changes or events such as quiet periods during which analysts cannot release information. Higher levels of overlap across analyst portfolios result in higher values of *MPC*. *MPC* equals one when an analyst's rivals on a particular stock all cover stock portfolios identical to the focal analyst's and zero when the analyst's rivals cover no other stocks in common. Figure 2 provides a hypothetical example showing computation of analyst-stock *MPC*.

Panel 1B in Table 1 presents time trends in the cross-sectional means of our three dependent variables (*ACC*, *FLFR*, and *RLFR*) as well as multipoint contact (*MPC*). While no distinct trend appears for *ACC* and *RLFR*, we see increasing trends for both *FLFR* and *MPC*.

3.4. Variables for Sphere of Influence Interactions

As noted above, a test of our hypotheses requires specification of analysts' spheres of influence. Although we cannot observe analysts' spheres of influence directly, we can gauge their likely locations using focal points (Schelling 1960) on which we expect analysts to coordinate their forbearance behavior. We identify two such focal points. The first is analyst stock-specific coverage experience, *STKEXP*, measured as the number of years between the analyst's earliest estimate on the stock recorded in the IBES database and the current year, logged to reduce skewness. A second focal point around which securities analysts' expectations may converge is analyst portfolio size. We define *PORTF* as the number of stocks an analyst covers in a given year, logged to reduce skewness.

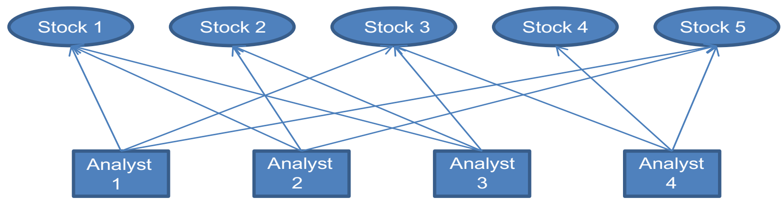
3.5. Control Variables

We control for analyst-specific and stock-specific factors that may influence an analyst's forecast accuracy and ability to exert information leadership using variables motivated by prior research. Given findings in Cooper et al. (2001), Mozes (2003), and Brown and Hugon (2009) suggesting that analysts may face a

The advantage of this approach is that it avoids the need for a detailed control variable specification. However, intertemporal trends cannot be analyzed using relative measures. Given our interest in trends in analyst forecast accuracy and information leadership pre- and post-Reg FD, we do not employ relative measures.

[5] Recommendations do not have a horizon per se, since they do not correspond to a fiscal period as do forecasts. Nonetheless, we include *HORIZON* in the *RLFR* regressions as a measure of a given analyst's timeliness. Results are unaltered by exclusion of this variable.

Figure 2 **(Color online) Calculation of Multipoint Contact (MPC)**



Focal analyst	Focal stock	Focal analyst co-covers focal stock with rival analysts	Other stocks focal analyst covers	Other stocks focal analyst co-covers with rival analysts co-covering focal stock	Focal analyst coverage overlap with rival analysts co-covering focal stock	Focal analyst multipoint contact (MPC) on focal stock
A1	S3	A3, A4	S1, S5	S1 w/A3 S5 w/A4	A3 = 1/2 = 0.5 A4 = 1/2 = 0.5	(0.5 + 0.5)/2 = 0.5
A2	S2	A3	S4, S5	None w/A3	A3 = 0/2 = 0	0/1 = 0
A3	S1	A1	S2, S3	S3 w/A1	A1 = 1/2 = 0.5	0.5/1 = 0.5
A4	S5	A1, A2	S3, S4	S3 w/A1 None w/A2	A1 = 1/2 = 0.5 A2 = 0/2 = 0	(0.5 + 0)/2 = 0.25

Notes. Hypothetical example in which four analysts (A1–A4) each cover a subset of five stocks (S1–S5). Lines link analysts to the stocks they are assumed to cover in the calculations given.

trade-off along these two facets of competition, we use a similar set of control variables in analyses of both forecast accuracy and information leadership. Control variables are measured either annually or, in the case of variables that vary within-year, are converted to yearly means.

3.5.1. Lagged Dependent Variables. Previous research indicates that prior analyst forecast accuracy is one of the most important determinants of current analyst forecast accuracy. Furthermore, analyst information leadership is likely to persist if it affords increased information and experience advantages. We therefore include the lagged values of *ACC* and the *LFR* variables (computed as analyst-stock-year means) as control variables in the analysis. Including these lagged values also helps account for the possibility that our empirical models suffer specification bias due to unobserved heterogeneity in analysts' advantages (Heckman and Borjas 1980, Jacobson 1990). Additionally, given evidence that analysts make a trade-off between being timely and accurate (e.g., Brown and Hugon 2009), *ACC* and *LFR* are likely to be correlated. Consequently, we also include lagged values of *ACC* in our *FLFR* and *RLFR* regressions and *FLFR* in our *ACC* regressions.[6]

3.5.2. Analyst-Level Controls. As analysts tend to be industry experts, prior research has found that analysts who cover firms from fewer industries are more likely to perform better. We thus control for the yearly mean number of distinct industries, measured at the two-digit Standard Industrial Classification (SIC) code level, across the firms that a given analyst follows. To reduce any influence of outliers, we transform each variable by taking the log of one plus the unadjusted variable. We define *NIND* as natural log of one plus the number of industries followed.

3.5.3. Stock-Level Controls. As large firms attract more analyst coverage for their stocks, they may also have different patterns of information leadership. Furthermore, large firms may also provide better disclosure, leading to more accurate forecasts. We control for the number of analysts by including the natural log of the number of distinct analysts following a firm in a given year (*NANL*). We control for firm size as the natural logarithm of total assets (*SIZE*) at the time of the last annual report. We also control for return volatility, which measures any idiosyncratic volatility that might make the task of analysts following a given firm more difficult. Return volatility is measured as the standard deviation of daily returns measured over the prior fiscal year (*STDRET*). Finally, following more intangible-intensive firms might pose additional challenges for analysts. We measure intangible intensity as *RD*, defined as annual R&D expense scaled by total assets, measured over the prior fiscal year. *RD* and *STDRET* are multiplied by 100 to express them as percentages.

3.6. Estimation

We regress our variables of interest (*ACC*, *FLFR*, and *RLFR*) on lagged values of these variables, the independent variables of interest, and the control variables

[6] We do not include lagged *RLFR* in the *ACC* regressions because more than half the observations would be lost.

using year-by-year regressions. Our regression specifications are as below.[7]

$$\begin{aligned} ACC_t = {} & \alpha_1 + \beta_1 ACC_{t-1} + \beta_2 FLFR_{t-1} + \beta_3 MPC \\ & + \beta_4 NIND + \beta_5 PORTF + \beta_6 STKEXP \\ & + \beta_7 NANL + \beta_8 HORIZON + \beta_9 SIZE \\ & + \beta_{10} STDRET + \beta_{11} RD + \varepsilon, \end{aligned} \tag{2a}$$

$$\begin{aligned} FLFR_t = {} & \alpha_1 + \beta_1 ACC_{t-1} + \beta_2 FLFR_{t-1} + \beta_3 MPC \\ & + \beta_4 NIND + \beta_5 PORTF + \beta_6 STKEXP \\ & + \beta_7 NANL + \beta_8 HORIZON + \beta_9 SIZE \\ & + \beta_{10} STDRET + \beta_{11} RD + \varepsilon, \end{aligned} \tag{2b}$$

$$\begin{aligned} RLFR_t = {} & \alpha_1 + \beta_1 ACC_{t-1} + \beta_2 RLFR_{t-1} + \beta_3 MPC \\ & + \beta_4 NIND + \beta_5 PORTF + \beta_6 STKEXP \\ & + \beta_7 NANL + \beta_8 HORIZON + \beta_9 SIZE \\ & + \beta_{10} STDRET + \beta_{11} RD + \varepsilon. \end{aligned} \tag{2c}$$

Our predictions pertain to how the association of multipoint contact (*MPC*) with our variables of interest varies depending on the likelihood that a stock falls within their sphere of influence. We do this by partitioning our sample on the basis of each of our proxies for analysts' spheres of influence: analyst portfolio size (*PORTF*) and analyst stock-specific experience (*STKEXP*). We expect *MPC* to be more strongly associated with greater forecast accuracy and greater information leadership for the subgroups of analysts covering larger portfolios and with greater stock-specific experience, i.e., β_3 increases as the sphere influence increases.

In addition, we also test whether the impact of multipoint contact on our measures is stronger under Reg FD. We create an indicator variable, *POSTFD* that equals one for the years 2001 and later and zero for the years 2000 and prior, and interact *POSTFD* with *MPC* in our regressions. Our modified regression specifications are as below.

$$\begin{aligned} ACC_t = {} & \alpha_1 + \alpha_2 POSTFD + \beta_1 ACC_{t-1} + \beta_2 FLFR_{t-1} \\ & + \beta_3 MPC + \beta_{31} MPC \times POSTFD \\ & + \beta_4 NIND + \beta_5 PORTF + \beta_6 STKEXP \\ & + \beta_7 NANL + \beta_8 HORIZON + \beta_9 SIZE \\ & + \beta_{10} STDRET + \beta_{11} RD + \varepsilon, \end{aligned} \tag{3a}$$

$$\begin{aligned} FLFR_t = {} & \alpha_1 + \alpha_2 POSTFD + \beta_1 ACC_{t-1} + \beta_2 FLFR_{t-1} \\ & + \beta_3 MPC + \beta_{31} MPC \times POSTFD \\ & + \beta_4 NIND + \beta_5 PORTF + \beta_6 STKEXP \\ & + \beta_7 NANL + \beta_8 HORIZON + \beta_9 SIZE \\ & + \beta_{10} STDRET + \beta_{11} RD + \varepsilon, \end{aligned} \tag{3b}$$

$$\begin{aligned} RLFR_t = {} & \alpha_1 + \alpha_2 POSTFD + \beta_1 ACC_{t-1} + \beta_2 RLFR_{t-1} \\ & + \beta_3 MPC + \beta_{31} MPC \times POSTFD \\ & + \beta_4 NIND + \beta_5 PORTF + \beta_6 STKEXP \\ & + \beta_7 NANL + \beta_8 HORIZON + \beta_9 SIZE \\ & + \beta_{10} STDRET + \beta_{11} RD + \varepsilon. \end{aligned} \tag{3c}$$

In these regressions, the main effect (β_3) estimates the effect of multipoint contact prior to Reg FD, the interaction term (β_{31}) estimates the *incremental* effect of multipoint contact under Reg FD, and $\beta_3 + \beta_{31}$ gives the total effect of multipoint contact in the post Reg FD period.

To limit the impact of outliers on our estimation, we follow Leone et al. (2014) recommendation to estimate robust regressions, which they find superior to more *ad hoc* methods including truncation and winsorization based on an analysis of outliers.[8] In addition, to correct for effects of cross-section and time-series dependence, all reported t-statistics are adjusted for two-way clustering by firm (CUSIP) and time (years) (Petersen 2009, Gow et al. 2010).

3.7. Descriptive Statistics and Correlations

Table 2 presents the descriptive statistics related to forecast accuracy (*ACC*), the two information leadership measures (*FLFR* and *RLFR*), multipoint contact (*MPC*), and the control variables. Panel 2A presents the descriptive statistics for the entire sample. The mean of *ACC* indicates a mean absolute forecast error of 1.43% of price. The mean of *FLFR* is 3.53, substantially above one, suggesting a strong tendency toward stocks having clearly established information leaders. The mean of *RLFR* is lower at 1.92, which may be related to the relative infrequency in updating recommendations. The mean of *MPC* suggests that the average analyst has slightly more than 32% coverage

[7] As discussed earlier, each regression includes lagged dependent variables, the independent variable of interest (*MPC*) and control variables. To control for the simultaneity and interdependence between information leadership and accuracy, we include lagged values of both measures in the regression. We do not include lagged measures of recommendation information leadership in the first two equations, as these data are available only for a small subset of the entire sample.

[8] Leone et al. (2014) show that robust regression offers an approach to address potential concerns with outliers based on statistical theory that outperforms standard approaches to influential observations. We implement this approach using the ROBUSTREG procedure in SAS utilizing the MM method. Robust regression iteratively down-weights influential observations and re-estimates the regression until further adjustments do not influence the estimates materially. Robust regression is thus a compromise between including all the data and treating all observations equally as under ordinary least squares (OLS) and altering or excluding observations from the analysis on an ad hoc basis (i.e., winsorizing or truncating the data).

Table 2 Sample Descriptive Statistics

Panel 2A: Descriptive statistics for entire sample (1991–2013; 1994–2013 for *RLFR*)

Variable	Mean	SD	1st percentile	25th percentile	Median	75th percentile	99th percentile
ACC_t	−1.43	3.11	−20.00	−1.23	−0.43	−0.15	0.00
$FLFR_t$	3.53	4.59	0.04	0.78	1.75	4.29	25.00
$RLFR_t$	1.92	3.23	0.05	0.51	0.99	1.93	20.77
MPC	0.32	0.17	0.02	0.19	0.30	0.42	0.84
NIND	1.30	0.52	0.00	0.69	1.39	1.61	2.64
PORTF	2.55	0.56	0.69	2.30	2.56	2.89	3.93
STKEXP	1.75	0.52	0.69	1.39	1.96	2.10	2.64
NANL	2.72	0.62	1.10	2.30	2.77	3.19	3.83
HORIZON	5.17	0.40	3.65	5.05	5.22	5.36	5.82
SIZE	7.99	1.90	4.01	6.64	7.92	9.30	12.62
STDRET	2.65	1.45	0.88	1.67	2.29	3.21	7.68
RD	3.73	10.91	0.00	0.00	0.00	3.14	61.82

Panel 2B: Pre- (1991–1999; 1994–1999 for *RLFR*) and post- (2001–2013) Reg FD periods

Variable	Pre-FD mean	Post-FD mean	Post − Pre	*p*-value
ACC_t	−1.23	−1.54	−0.31	<0.01
$FLFR_t$	2.77	3.92	1.15	<0.01
$RLFR_t$	1.83	1.94	0.12	<0.01
MPC	0.29	0.34	0.05	<0.01
NIND	1.40	1.25	−0.16	<0.01
PORTF	2.56	2.56	0.00	0.644
STKEXP	1.72	1.75	0.03	<0.01
NANL	2.67	2.75	0.08	<0.01
HORIZON	5.12	5.19	0.08	<0.01
SIZE	7.52	8.26	0.74	<0.01
STDRET	2.52	2.62	0.10	<0.01
RD	3.36	3.90	0.54	<0.01

Panel 2C: Across-analyst spreads in *ACC*, *FLFR*, and *RLFR* in low-*MPC* and high-*MPC* stock-years

	Low *MPC* mean	High *MPC* mean	High − Low	*p*-value
$\max(ACC_t) - \min(ACC_t)$	1.03	1.41	0.38	<0.01
$\max(FLFR_t) - \min(FLFR_t)$	7.38	8.48	1.10	<0.01
$\max(RLFR_t) - \min(RLFR_t)$	2.47	3.74	1.27	<0.01

Notes. Panel A: Sample consists of 307,335 analyst-stock-year observations. Recommendation data (*RLFR*) are available for a subset of 100,672 observations. Panel B: Pre-Reg FD sample includes 105,360 analyst-stock-year observations for 1991–1999 (27,055 for *RLFR* for 1994–1999), and the post-Reg FD sample includes 189,985 observations for 2001–2013 (69,949 for *RLFR*); observations for year 2000 are excluded. Panel C: Low (high) multipoint firm-years have mean *MPC* below (above) the annual median. *p*-Values are for two-tailed difference of means tests. See the appendix for variable definitions.

overlap with other analysts following a given stock. The mean of *NIND* is 1.30, which corresponds to an average of 2.7 industries covered (i.e., $e^{1.30} - 1$). The mean of *PORTF* is 2.55, which corresponds to an average of 11.8 firms followed (i.e., $e^{2.55} - 1$). The mean of *STKEXP* is 1.75, which corresponds to an average experience of around five years (i.e., $e^{1.75} - 1$). The mean of *HORIZON* is 5.17, which corresponds to an average horizon of 176 days (i.e., $e^{5.17}$). Given that we average forecasts across the year for a given analyst-stock combination, it is not surprising that mean *HORIZON* is slightly under one-half year. The mean of *SIZE* is 7.99, which corresponds to an average market capitalization of approximately \$2.95 billion. The average stock has a mean daily return volatility of 2.65% and R&D intensity of 3.73%.

Panel 2B compares the sample across the pre- and post-Reg FD periods. After Reg FD, mean forecast accuracy (*ACC*) drops significantly from −1.23 to −1.54. Mean information leadership in forecasting (*FLFR*) increases significantly from 2.77 to 3.92. Mean information leadership in recommendations (*RLFR*) also increases significantly although more modestly from 1.83 to 1.94. The extent of multipoint contact also increases, with mean *MPC* increasing from 0.29 to 0.34. We observe significant changes in some of the control variables as well, which suggests that the stock portfolios covered by analysts shifted under Reg FD. In particular, we see a reduction in the number of industries covered (*NIND*) and a small increase in analyst stock-specific experience (*STKEXP*). This is indicative of analysts narrowing coverage and becoming industry

Table 3 Correlations

Variable	ACC_t	$FLFR_t$	$RLFR_t$	*MPC*	*NIND*	*PORTF*	*STKEXP*	*NANL*	*HORIZON*	*SIZE*	*STDRET*	*RD*
ACC_t		0.01***	−0.01	−0.02***	0.03***	0.04***	0.08***	**0.18*****	−0.05***	**0.12*****	**−0.41*****	−0.04***
$FLFR_t$	−0.02***		0.06***	−0.01*	0.01	0.01	0.02***	−0.03***	0.04***	−0.05***	0.02***	0.01***
$RLFR_t$	0.00	0.06***		0.01***	−0.01	0.00	0.01***	0.02***	0.00	0.01	0.01**	0.01
MPC	−0.02***	0.04***	0.02***		**−0.41*****	**−0.34*****	0.05***	**0.20*****	0.02**	**0.26*****	**−0.13*****	−0.09***
NIND	0.03	0.00	0.00	**−0.40*****		**0.41*****	0.04***	**−0.12*****	−0.03***	**−0.15*****	0.00	−0.11***
PORTF	0.02***	0.02***	0.00	**−0.25*****	**0.35*****		**0.14*****	0.04***	0.00	0.08***	**−0.12*****	−0.06***
STKEXP	0.08***	0.02***	0.00	0.06***	0.06***	**0.17*****		**0.26*****	−0.01*	**0.22*****	**−0.16*****	−0.06***
NANL	**0.20*****	−0.01	0.01	**0.23*****	**−0.13*****	0.03***	**0.18*****		0.07***	**0.55*****	**−0.19*****	0.00
HORIZON	−0.06***	0.01	0.00	0.00	−0.04***	−0.02***	−0.04***	0.07***		0.05***	−0.01	0.02***
SIZE	**0.17*****	−0.01***	0.00	**0.28*****	**−0.16*****	0.09***	**0.23*****	**0.57*****	0.04***		**−0.50*****	**−0.23*****
STDRET	**−0.40*****	0.03***	0.01	**−0.15*****	0.04***	**−0.12*****	**−0.19*****	**−0.17*****	−0.02**	**−0.54*****		**0.29*****
RD	0.05***	−0.01	0.00	**−0.11*****	0.00	**−0.11*****	−0.02*	**0.11*****	0.05***	**−0.18*****	**0.21*****	

Notes. Sample consists of 307,355 analyst-stock-year observations and 100,672 for *RLFR*. The table presents average annual correlations for the 23-year period from 1991 to 2013 (20-year period from 1994 to 2013 for *RLFR*). Figures above/below diagonal are Pearson/Spearman correlations. Two-tailed significance levels, computed from the distribution of annual correlations, are *** (1%), ** (5%), * (10%); correlations with absolute value greater than 0.1 are in boldface. See the appendix for variable definitions.

experts, consistent with the evidence in Mohanram and Sunder (2006). Finally, the shakeout that occurred in the capital markets after the collapse of the technology bubble in the late 1990s is reflected in the composition of firms in the pre- and post-Reg FD periods, with firms being larger and having lower R&D intensity post-Reg FD.

Panel 2C compares our sample stocks partitioned by the level of multipoint contact. For each stock-year, we average *MPC* across all analysts covering the stock and then split the sample based on whether the average *MPC* is below the median for all stocks in the same year. We then compare the distribution of forecast error and analyst leadership across these stocks. If increased multipoint contact facilitates information leadership and concomitantly followership, one would expect a larger spread in both measures on stocks where analysts experience greater *MPC*. Panel 2C is consistent with this conjecture. The spread in *ACC* increases significantly from 1.03 for analyst low-*MPC* stocks to 1.41 for analyst high-*MPC* stocks. Similarly, the spread between minimum and maximum *FLFR* increases significantly from 7.38 for stocks where analyst average *MPC* is low to 8.48 for stocks where analyst average *MPC* is high. Finally, the spread in *RLFR* increases significantly from 2.47 for analyst low-*MPC* stocks to 3.74 for analyst high-*MPC* stocks.

Table 3 presents the correlations among the variables, computed as the average of annual cross-sectional correlations (Pearson above the diagonal, Spearman below). *ACC* and both measures of *LFR* are weakly correlated. *ACC* and *MPC* are negatively correlated, while analyst *FLFR* and *RLFR* are weakly correlated with *MPC*. *ACC* is weakly correlated with analyst coverage and analyst stock-specific experience (*NIND*, *PORTF*, *STKEXP*). *ACC* is negatively correlated with stock return volatility (*STDRET*) as well as *HORIZON*, indicating a tendency of forecasts to be made earlier and for volatile stocks to be less accurate. *ACC* is positively correlated with stock size (*SIZE*) and analyst following (*NANL*), indicating a tendency of forecasts made for larger and more extensively covered stocks to be more accurate. *FLFR* is positively correlated with the coverage variables (*NIND*, *PORTF*, *STKEXP*). *FLFR* is also positively correlated with *HORIZON.*

4. Results

Our hypotheses pertain to how multipoint contact influences analysts' coverage behavior on stocks within their spheres of influence. We estimate the impact of multipoint contact (*MPC*) on analyst forecast accuracy (*ACC*), forecast information leadership (*FLFR*), and recommendation information leadership (*RLFR*), conditioning on analyst stock-specific experience and portfolio size (our proxies for analysts' spheres of influence) to test our hypotheses. As discussed earlier, we run pooled robust regressions with two-way clustered *t*-statistics.

4.1. Mutual Forbearance Hypothesis Tests (H1, H2, and H3)

Our first two hypotheses predict that in the presence of multipoint contact, when covering stocks within their spheres of influence, analysts will issue more accurate forecasts (H1) and achieve greater information leadership for earnings forecasts (H2) and stock recommendations (H3). When an analyst experiences high *MPC* on a stock he or she covers, opportunities exist for the analyst to develop a mutual forbearance relationship with rivals covering a stock. Whether the analyst is likely to take a superordinate or subordinate role in covering the stock vis-à-vis his or her rivals depends on whether the stock is more likely to fall within the analyst's own sphere of influence (when the analyst's *PORTF* is large or *STKEXP* is high) or within a rival's sphere (when *PORTF* is small or *STKEXP* is low).

To test our hypotheses, for each dependent variable (*ACC*, *FLFR*, and *RLFR*), we partition the sample into three equal-size subsamples based on yearly values of analyst *PORTF* (small, medium, large) or *STKEXP* (low, medium, high), the sphere of influence proxies. Our hypotheses predict that multipoint contact (*MPC*) will be associated with greater forecast accuracy or information leadership most strongly for analysts in the large *PORTF* or high *STKEXP* subsamples for whom the stock is more likely to fall within their sphere of influence. Hence, we expect a significantly greater correlation between *MPC* and our dependent variables for the high sphere of influence subsample as compared to the low sphere of influence subsample. Table 4 presents the findings.

Panel 4A presents results for *ACC*. In the three regressions for large, medium, and small analyst *PORTF* subsamples, the coefficients for *MPC* (β_3) are negative and significant and, while significant, the difference between coefficients for the large and small portfolio subsamples is negative, contrary to H1. The next three regressions use *STKEXP* to gauge the likelihood that a stock falls within an analyst's sphere of influence. In these models, coefficients for *MPC* are also significant and negative, but the difference between coefficients for the high and low *STKEXP* subsamples is insignificant, again contrary to H1. These findings indicate that analysts' earnings forecasts were *less* accurate for stocks where they experienced high levels of multipoint contact and, opposite to H1, *even less* accurate for stocks likely to fall within their spheres of influence (i.e., large *PORTF* or high *STKEXP* subsamples). In sum, panel 4A offers no evidence to support H1, which predicted that multipoint contact would raise forecast accuracy on stocks by fostering mutual forbearance among analysts within their respective spheres of influence.

Panel 4B presents the results for information leadership in earnings forecasts (*FLFR*). In all three regressions, coefficients for *MPC* (β_3) are significant and positive, and coefficient increase across the subsamples, from 0.490 for analysts covering small portfolios, to 0.768 for those covering medium-sized portfolios, and to 0.918 for analysts covering large stock portfolios. Moreover, consistent with H2, the *MPC* coefficient for the large portfolio subsample is of significantly greater magnitude than for the small portfolio subsample (0.428, $t = 2.06$). The next three regressions repeat the analysis for the analyst stock-specific experience (*STKEXP*) subsamples. Here too, coefficients for *MPC* increase across the subsamples from 0.430 for analysts with low stock-specific experience, to 0.716 for those with moderate experience, and to 0.899 for analysts with high levels of experience. Again, consistent with H2, the coefficient for *MPC* is significantly larger for the high- than for the low-experience analyst subgroups (0.469, $t = 2.30$). Collectively, the results in panel 4B support the prediction of mutual forbearance theory that high levels of multipoint contact are associated with a significantly greater increase in forecast information leadership for stocks that fall within an analyst's sphere of influence (i.e., when the analyst's *STKEXP* is high and/or *PORTF* is large).

In panel 4C, which replicates the analysis in panel 4B, the results for information leadership in stock recommendations (*RLFR*) are similar to the results for *FLFR*. In the regressions for the *PORTF* subsamples, coefficients for *MPC* (β_3) increase, though not monotonically, from 0.040 for analysts covering small portfolios, to 0.002 for medium-sized portfolios, and to 0.213 for those covering large portfolios. In support of H3, in panel 4B, the coefficient for *MPC* is significantly larger for analysts covering large portfolios than for those covering small portfolios (0.173, $t = 2.51$). The next three regressions in panel 4C repeat the analysis for the analyst stock-specific experience (*STKEXP*) subsamples. Here, the coefficients for *MPC* increase monotonically across the subsamples from 0.006 for low stock-specific experience, to 0.033 for those of moderate experience, and to 0.178 for analysts possessing high stock-specific experience. Again, consistent with H3, the coefficient for *MPC* is significantly larger for high-experience than low-experience analysts (0.172, t-statistic is 3.36). Taken together, the findings in panel 4C add support for the mutual forbearance theory prediction that high levels of multipoint contact are associated with a significantly greater increase in recommendation information leadership for stocks that fall within an analyst's sphere of influence.

4.2. Reg FD Hypothesis Tests (H4, H5, and H6)

We next examine the impact of Reg FD on the propensity of analysts to forbear in the presence of multipoint contact. To test H4, H5, and H6, we create an indicator variable, *POSTFD* that equals one for the years 2001 and later and zero for the years 2000 and prior, and interact *POSTFD* with *MPC* in our regressions. In these regressions, the main effect of *MPC* estimates the effect of multipoint contact prior to Reg FD, the interaction term *MPC* × *POSTFD* estimates the *incremental* effect of multipoint contact under Reg FD period, and the sum of the *MPC* and *MPC* × *POSTFD* coefficients gives the effect of multipoint contact under Reg FD. We present the findings in Table 5. The final column computes the sum of coefficients for *MPC* and *MPC* × *POSTFD*.

Panel 5A reports the findings for forecast accuracy (*ACC*). The coefficient for the *MPC* main effect

Table 4 Mutual Forbearance, Forecast Accuracy, and Information Leadership

Group	α_1	ACC_{t-1}	$FLFR_{t-1}$	MPC (β_3)	$NIND$	$PORTF$	$STKEXP$	$NANL$	$HORIZON$	$SIZE$	$STDRET$	RD	Adj. R^2 (%)
					Panel 4A: Two-way clustered pooled regression for forecast accuracy (ACC_t)								
Small *PORTF*	0.660	0.273	0.001	**−0.189**	0.002	−0.036	0.080	0.121	−0.172	−0.027	−0.122	−0.0002	44.0
	(5.38)	(2.49)	(2.17)	(**−6.48**)	(0.30)	(−2.59)	(4.51)	(12.05)	(−13.53)	(−3.61)	(−5.82)	(−0.33)	
Medium *PORTF*	1.529	0.265	0.002	**−0.302**	−0.003	−0.353	0.047	0.110	−0.154	−0.022	−0.139	0.0001	44.1
	(6.70)	(38.29)	(3.95)	(**−9.72**)	(−0.27)	(−5.18)	(3.49)	(11.42)	(−11.31)	(−3.77)	(−9.08)	(0.21)	
Large *PORTF*	0.794	0.270	0.002	**−0.430**	−0.010	−0.098	0.068	0.092	−0.128	−0.021	−0.136	−0.0005	43.3
	(6.02)	(34.62)	(3.3)	(**−12.35**)	(−1.09)	(−4.57)	(4.53)	(7.96)	(−12.02)	(−3.2)	(−6.53)	(−0.64)	
(Large − Small)	0.134	−0.003	0.000	**−0.241**	−0.013	−0.062	−0.012	−0.029	0.044	0.006	−0.014	−0.0003	
	(0.74)	(−0.28)	(0.51)	(**−5.30**)	(−1.01)	(−2.43)	(−0.52)	(−1.88)	(2.65)	(0.56)	(−0.48)	(−0.27)	
Low *STKEXP*	0.660	0.273	0.000	**−0.243**	−0.007	−0.034	0.091	0.107	−0.165	−0.023	−0.121	−0.0010	41.8
	(5.66)	(43.05)	(0.54)	(**−7.82**)	(−0.9)	(−4.01)	(3.17)	(10.41)	(−13.04)	(−2.99)	(−6.07)	(−1.78)	
Medium *STKEXP*	0.597	0.267	0.002	**−0.286**	−0.003	−0.059	0.116	0.117	−0.156	−0.022	−0.127	−0.0002	44.5
	(4.54)	(26.30)	(3.48)	(**−11.52**)	(−0.31)	(−8.45)	(2.84)	(9.9)	(−12.71)	(−3.15)	(−6.71)	(−0.29)	
High *STKEXP*	0.808	0.268	0.003	**−0.299**	0.003	−0.055	0.011	0.099	−0.146	−0.021	−0.150	0.0020	44.8
	(5.64)	(35.98)	(3.8)	(**−9.19**)	(0.4)	(−6.17)	(0.35)	(8.05)	(−11.83)	(−3.69)	(−7.59)	(1.86)	
(High − Low)	0.148	−0.005	0.002	**−0.056**	0.010	−0.021	−0.081	−0.008	0.019	0.002	−0.029	0.0031	
	(0.80)	(−0.47)	(2.55)	(**−1.25**)	(0.90)	(−1.72)	(−1.91)	(−0.50)	(1.06)	(0.26)	(−1.03)	(2.49)	
					Panel 4B: Two-way clustered pooled regression for information leadership in forecasting ($FLFR_t$)								
Small *PORTF*	0.075	0.017	0.073	**0.490**	0.005	0.271	0.253	−0.050	0.166	−0.005	0.059	−0.0006	2.7
	(0.40)	(4.65)	(5.79)	(**4.57**)	(0.14)	(4.49)	(7.79)	(−1.23)	(5.69)	(−0.56)	(2.91)	(−0.87)	
Medium *PORTF*	1.830	0.028	0.107	**0.768**	0.042	−0.643	0.333	−0.081	0.229	0.002	0.056	−0.0001	5.0
	(3.11)	(6.00)	(5.88)	(**4.92**)	(1.04)	(−3.23)	(6.18)	(−1.95)	(7.90)	(0.21)	(2.13)	(−0.08)	
Large *PORTF*	1.676	0.020	0.107	**0.918**	0.022	−0.482	0.312	−0.056	0.223	−0.011	0.063	0.0001	5.9
	(6.18)	(2.99)	(5.94)	(**5.17**)	(0.98)	(−10.29)	(7.05)	(−1.62)	(9.77)	(−0.95)	(2.17)	(0.11)	
(Large − Small)	1.601	0.003	0.034	**0.428**	0.018	−0.753	0.059	−0.006	0.057	−0.006	0.004	0.0008	
	(4.83)	(0.38)	(1.54)	(**2.06**)	(0.43)	(−9.85)	(1.08)	(−0.12)	(1.54)	(−0.37)	(0.12)	(0.59)	
Low *STKEXP*	0.153	0.016	0.070	**0.430**	−0.048	0.157	0.446	0.020	0.133	−0.007	0.071	−0.0025	3.5
	(0.84)	(4.16)	(6.02)	(**3.89**)	(−2.08)	(3.68)	(9.02)	(0.63)	(3.68)	(−0.86)	(4.95)	(−5.25)	
Medium *STKEXP*	−0.952	0.013	0.103	**0.716**	−0.004	0.176	0.736	−0.031	0.195	−0.003	0.077	−0.0011	5.3
	(−5.92)	(2.90)	(5.22)	(**6.07**)	(−0.16)	(4.16)	(10.60)	(−0.80)	(7.75)	(−0.30)	(4.07)	(−0.85)	
High *STKEXP*	0.235	0.030	0.119	**0.899**	0.044	0.053	0.165	−0.128	0.241	0.006	0.039	0.0031	4.8
	(0.77)	(3.82)	(6.15)	(**5.25**)	(0.94)	(1.42)	(1.68)	(−3.23)	(12.78)	(0.61)	(1.00)	(2.61)	
(High − Low)	0.082	0.014	0.049	**0.469**	0.092	−0.104	−0.281	−0.148	0.108	0.013	−0.032	0.0056	
	(0.23)	(1.57)	(2.18)	(**2.30**)	(1.76)	(−1.84)	(−2.55)	(−2.90)	(2.65)	(1.00)	(−0.78)	(4.37)	

Table 4 (Continued)

Group	α_1	ACC_{t-1}	$FLFR_{t-1}$	*MPC* (β_3)	*NIND*	*PORTF*	*STKEXP*	*NANL*	*HORIZON*	*SIZE*	*STDRET*	*RD*	Adj. R^2 (%)
Panel 4C: Two-way clustered pooled regression for information leadership in recommendations ($RLFR_t$)													
Small *PORTF*	1.052	−0.003	−0.002	**0.040**	0.014	0.020	0.000	0.008	0.010	−0.006	−0.001	0.0005	0.47
	(8.10)	(−1.70)	(−1.08)	**(1.48)**	(0.81)	(1.36)	(−0.02)	(0.69)	(0.50)	(−1.22)	(−0.20)	(1.12)	
Medium *PORTF*	1.550	−0.002	−0.004	**0.002**	−0.017	−0.050	−0.004	−0.011	−0.037	−0.003	0.002	−0.0009	0.69
	(10.90)	(−0.42)	(−1.61)	**(0.04)**	(−1.12)	(−1.01)	(−0.34)	(−0.73)	(−1.73)	(−0.63)	(0.30)	(−1.21)	
Large *PORTF*	0.945	0.003	0.001	**0.213**	−0.001	−0.035	0.018	−0.009	0.042	0.001	0.010	0.0004	0.18
	(6.68)	(1.01)	(0.61)	**(3.35)**	(−0.08)	(−1.25)	(1.35)	(−0.70)	(1.78)	(0.29)	(2.16)	(0.47)	
(Large − Small)	−0.107	0.006	0.004	**0.173**	−0.015	−0.055	0.018	−0.017	0.033	0.007	0.011	−0.0001	
	(−0.56)	(1.77)	(1.21)	**(2.51)**	(−0.66)	(−1.75)	(1.10)	(−0.98)	(1.07)	(1.10)	(1.57)	(−0.14)	
Low *STKEXP*	1.082	−0.001	−0.004	**0.006**	0.009	0.014	0.009	−0.001	0.005	−0.003	−0.001	0.0005	0.46
	(9.99)	(−0.37)	(−1.93)	**(0.20)**	(0.68)	(1.05)	(0.86)	(−0.06)	(0.25)	(−0.66)	(−0.23)	(0.72)	
Medium *STKEXP*	1.028	0.000	−0.002	**0.033**	−0.020	0.022	0.014	−0.009	0.015	−0.001	0.010	−0.0001	0.59
	(7.25)	(−0.17)	(−0.99)	**(0.58)**	(−1.18)	(1.60)	(0.60)	(−0.90)	(0.59)	(−0.31)	(2.53)	(−0.19)	
High *STKEXP*	1.065	0.000	0.001	**0.178**	−0.007	0.019	0.033	0.003	−0.006	−0.004	0.003	−0.0014	0.46
	(8.25)	(0.11)	(0.49)	**(4.42)**	(−0.49)	(1.06)	(0.79)	(0.24)	(−0.36)	(−1.26)	(0.49)	(−1.20)	
(High − Low)	−0.018	0.002	0.006	**0.172**	−0.016	0.006	0.024	0.003	−0.010	−0.001	0.004	−0.0019	
	(−0.11)	(0.36)	(1.71)	**(3.36)**	(−0.81)	(0.25)	(0.55)	(0.20)	(−0.43)	(−0.18)	(0.54)	(−1.40)	

Notes. Sample consists of 307,355 analyst-stock-year observations (100,672 for *RLFR*). The sample for each year is partitioned into three equal-size groups based on either analyst *PORTF* (small, medium, large) or *STKEXP* (low, medium, high). Robust regressions are run using pooled data from 1991 to 2013 for *ACC* and *FLFR* and from 1994 to 2013 for *RLFR*. t-Statistics (in parentheses) are two-way clustered by firm and time. See the appendix for variable definitions.

Panel A: Model: $ACC_t = \alpha_1 + \beta_1\, ACC_{t-1} + \beta_2\, FLFR_{t-1} + \beta_3\, MPC + \beta_4\, NIND + \beta_5\, PORTF + \beta_6\, STKEXP + \beta_7\, NANL + \beta_8\, HORIZON + \beta_9\, SIZE + \beta_{10}\, STDRET + \beta_{11}\, RD + \varepsilon$.

Panel B: Model: $FLFR_t = \alpha_1 + \beta_1\, ACC_{t-1} + \beta_2\, FLFR_{t-1} + \beta_3\, MPC + \beta_4\, NIND + \beta_5\, PORTF + \beta_6\, STKEXP + \beta_7\, NANL + \beta_8\, HORIZON + \beta_9\, SIZE + \beta_{10}\, STDRET + \beta_{11}\, RD + \varepsilon$.

Panel C: Model: $RLFR_t = \alpha_1 + \beta_1\, ACC_{t-1} + \beta_2\, RLFR_{t-1} + \beta_3\, MPC + \beta_4\, NIND + \beta_5\, PORTF + \beta_6\, STKEXP + \beta_7\, NANL + \beta_8\, HORIZON + \beta_9\, SIZE + \beta_{10}\, STDRET + \beta_{11}\, RD + \varepsilon$.

Table 5 Mutual Forbearance, Forecast Accuracy, and Information Leadership: Impact of Regulation FD

Group	α_1	*POSTFD*	ACC_{t-1}	$FLFR_{t-1}$	*MPC* (β_3)	*MPC* × *POSTFD* (β_{31})	*NIND*	*PORTF*	*STKEXP*	*NANL*	*HORIZON*	*SIZE*	*STDRET*	*RD*	Adj. R^2 (%)	$\beta_3+\beta_{31}$
						Panel 5A: Two-way clustered pooled regression for forecast accuracy (ACC_t)										
Small *PORTF*	0.633	−0.186	0.261	0.003	**−0.241**	**0.143**	−0.013	−0.011	0.080	0.114	−0.161	−0.020	−0.124	0.0001	43.7	**−0.098**
	(5.70)	(−5.04)	(32.24)	(4.48)	**(−8.29)**	**(3.32)**	(−1.82)	(−0.90)	(6.32)	(10.63)	(−12.80)	(−3.16)	(−7.24)	(0.19)		**(−1.89)**
Medium *PORTF*	1.314	−0.154	0.257	0.004	**−0.388**	**0.173**	−0.013	−0.268	0.052	0.106	−0.144	−0.018	−0.139	0.0004	43.8	**−0.215**
	(6.11)	(−5.02)	(37.67)	(6.47)	**(−9.68)**	**(3.37)**	(−1.14)	(−4.36)	(5.32)	(10.41)	(−10.51)	(−3.39)	(−10.29)	(0.52)		**(−3.30)**
Large *PORTF*	0.849	−0.159	0.260	0.003	**−0.495**	**0.164**	−0.020	−0.118	0.068	0.091	−0.114	−0.017	−0.138	−0.0004	43.0	**−0.331**
	(6.50)	(−5.21)	(35.35)	(6.26)	**(−14.77)**	**(3.48)**	(−2.12)	(−6.38)	(5.99)	(7.23)	(−10.56)	(−3.05)	(−7.68)	(−0.48)		**(−5.72)**
(Large − Small)	0.216	0.027	−0.001	0.001	**−0.254**	**0.021**	−0.007	−0.107	−0.012	−0.023	0.047	0.003	−0.014	−0.0005		**−0.233**
	(1.26)	(0.57)	(−0.12)	(0.62)	**(−5.72)**	**(0.34)**	(−0.60)	(−4.83)	(−0.71)	(−1.36)	(2.83)	(0.37)	(−0.54)	(−0.49)		**(−3.06)**
Low *STKEXP*	0.615	−0.190	0.262	0.002	**−0.274**	**0.112**	−0.021	−0.024	0.095	0.110	−0.151	−0.017	−0.124	−0.0007	41.8	**−0.162**
	(6.24)	(−6.22)	(50.23)	(3.39)	**(−10.60)**	**(2.74)**	(−2.49)	(−3.57)	(5.18)	(10.76)	(−11.82)	(−2.72)	(−7.94)	(−1.23)		**(−3.35)**
Medium *STKEXP*	0.587	−0.151	0.255	0.004	**−0.330**	**0.115**	−0.015	−0.050	0.112	0.115	−0.144	−0.018	−0.129	0.0000	43.9	**−0.215**
	(4.85)	(−4.69)	(25.81)	(5.59)	**(−10.99)**	**(2.88)**	(−1.75)	(−8.54)	(3.32)	(9.20)	(−11.45)	(−2.88)	(−7.88)	(0.05)		**(−4.30)**
High *STKEXP*	0.768	−0.142	0.260	0.004	**−0.373**	**0.163**	−0.007	−0.049	0.035	0.092	−0.138	−0.017	−0.150	0.0022	44.4	**−0.21**
	(5.40)	(−4.00)	(35.48)	(5.45)	**(−9.59)**	**(3.60)**	(−0.74)	(−5.87)	(1.29)	(7.28)	(−10.90)	(−3.33)	(−8.69)	(2.02)		**(−3.52)**
(High − Low)	0.153	0.049	−0.002	0.002	**−0.099**	**0.051**	0.013	−0.026	−0.061	−0.018	0.013	0.000	−0.026	0.0029		**−0.048**
	(0.89)	(1.04)	(−0.25)	(2.42)	**(−2.12)**	**(0.83)**	(1.06)	(−2.41)	(−1.85)	(−1.13)	(0.73)	(0.00)	(−1.13)	(2.37)		**(−0.62)**
						Panel 5B: Two-way clustered pooled regression for information leadership in forecasting ($FLFR_t$)										
Small *PORTF*	0.116	−0.050	0.018	0.073	**0.350**	**0.106**	0.003	0.271	0.254	−0.045	0.166	−0.007	0.057	−0.0006	2.7	**0.456**
	(0.64)	(−1.01)	(4.42)	(5.85)	**(3.81)**	**(1.48)**	(0.08)	(4.69)	(7.88)	(−1.17)	(5.50)	(−0.89)	(2.83)	(−0.86)		**(3.91)**
Medium *PORTF*	2.480	0.066	0.028	0.104	**0.459**	**0.493**	0.052	−0.840	0.326	−0.067	0.211	−0.010	0.049	−0.0004	5.2	**0.952**
	(4.29)	(1.42)	(5.12)	(5.93)	**(3.09)**	**(2.42)**	(1.11)	(−4.22)	(7.01)	(−1.76)	(6.74)	(−0.95)	(1.68)	(−0.58)		**(3.78)**
Large *PORTF*	1.772	0.054	0.021	0.104	**0.490**	**0.720**	0.024	−0.460	0.319	−0.053	0.203	−0.021	0.058	−0.0002	6.1	**1.21**
	(6.82)	(1.07)	(2.94)	(5.98)	**(3.44)**	**(2.33)**	(1.01)	(−9.29)	(8.37)	(−1.65)	(8.18)	(−2.20)	(1.76)	(−0.18)		**(3.56)**
(Large − Small)	1.656	0.104	0.004	0.031	**0.141**	**0.614**	0.021	−0.730	0.065	−0.008	0.037	−0.014	0.000	0.0004		**0.755**
	(5.22)	(1.47)	(0.45)	(1.45)	**(0.83)**	**(1.94)**	(0.47)	(−9.61)	(1.31)	(−0.16)	(0.95)	(−1.10)	(0.01)	(0.35)		**(2.10)**
Low *STKEXP*	0.239	0.129	0.017	0.068	**0.410**	**0.003**	−0.036	0.149	0.449	0.021	0.119	−0.016	0.069	−0.0029	3.6	**0.413**
	(1.27)	(2.47)	(4.32)	(5.94)	**(3.74)**	**(0.03)**	(−1.76)	(3.55)	(10.30)	(0.68)	(3.35)	(−1.91)	(4.33)	(−6.73)		**(2.78)**
Medium *STKEXP*	−0.933	0.159	0.014	0.101	**0.730**	**−0.073**	0.008	0.164	0.749	−0.025	0.183	−0.010	0.074	−0.0015	5.4	**0.657**
	(−5.04)	(2.56)	(3.05)	(5.16)	**(5.93)**	**(−0.64)**	(0.28)	(3.78)	(11.27)	(−0.64)	(7.06)	(−1.11)	(3.53)	(−1.19)		**(3.91)**
High *STKEXP*	0.422	0.104	0.030	0.117	**0.531**	**0.399**	0.056	0.045	0.113	−0.108	0.228	−0.004	0.031	0.0028	4.9	**0.93**
	(1.54)	(1.29)	(3.42)	(6.37)	**(3.78)**	**(2.42)**	(1.00)	(1.17)	(1.20)	(−3.32)	(11.13)	(−0.43)	(0.74)	(2.27)		**(4.29)**
(High − Low)	0.184	−0.025	0.013	0.048	**0.121**	**0.396**	0.092	−0.103	−0.336	−0.129	0.109	0.012	−0.038	0.0057		**0.517**
	(0.55)	(−0.26)	(1.33)	(2.23)	**(0.60)**	**(1.96)**	(1.55)	(−1.81)	(−3.24)	(−2.89)	(2.65)	(0.98)	(−0.84)	(4.35)		**(1.81)**

Table 5 (Continued)

Group	α_1	*POSTFD*	ACC_{t-1}	$FLFR_{t-1}$	*MPC* (β_3)	*MPC* × *POSTFD* (β_{31})	*NIND*	*PORTF*	*STKEXP*	*NANL*	*HORIZON*	*SIZE*	*STDRET*	*RD*	Adj. R^2 (%)	$\beta_3+\beta_{31}$
					Panel 5C: Two-way clustered pooled regression for information leadership in recommendations ($RLFR_t$)											
Small *PORTF*	1.044	0.022	−0.003	−0.002	**0.074**	**−0.046**	0.015	0.019	0.001	0.008	0.009	−0.006	−0.001	0.0005	0.49	**0.028**
	(8.09)	(0.75)	(−1.67)	(−1.08)	**(1.40)**	**(−0.84)**	(0.85)	(1.28)	(0.06)	(0.66)	(0.47)	(−1.31)	(−0.17)	(1.07)		**(0.37)**
Medium *PORTF*	1.598	0.022	−0.002	−0.004	**0.007**	**−0.013**	−0.017	−0.071	−0.003	−0.010	−0.038	−0.003	0.002	−0.0009	0.75	**−0.006**
	(10.4)	(0.49)	(−0.39)	(−1.63)	**(0.05)**	**(−0.09)**	(−1.12)	(−1.44)	(−0.24)	(−0.69)	(−1.81)	(−0.72)	(0.30)	(−1.29)		**(−0.03)**
Large *PORTF*	0.993	−0.069	0.003	0.001	**0.046**	**0.242**	−0.003	−0.034	0.016	−0.009	0.044	0.001	0.010	0.0004	0.71	**0.288**
	(7.37)	(−2.08)	(0.94)	(0.60)	**(0.36)**	**(1.71)**	(−0.20)	(−1.23)	(1.25)	(−0.72)	(1.83)	(0.27)	(2.11)	(0.54)		**(1.51)**
(Large − Small)	−0.051	−0.091	0.006	0.004	**−0.027**	**0.288**	−0.018	−0.053	0.016	−0.017	0.035	0.007	0.010	0.0000		**0.261**
	(−0.28)	(−2.06)	(1.69)	(1.20)	**(−0.20)**	**(1.90)**	(−0.76)	(−1.68)	(0.93)	(−0.98)	(1.13)	(1.13)	(1.54)	(−0.04)		**(1.29)**
Low *STKEXP*	1.099	−0.023	−0.001	−0.004	**0.025**	**−0.051**	0.008	0.015	0.008	−0.001	0.004	−0.003	−0.001	0.0006	0.49	**−0.026**
	(9.84)	(−0.75)	(−0.38)	(−1.94)	**(0.40)**	**(−0.73)**	(0.63)	(1.13)	(0.69)	(−0.06)	(0.23)	(−0.62)	(−0.27)	(0.77)		**(−0.28)**
Medium *STKEXP*	1.055	−0.047	−0.001	−0.002	**−0.050**	**0.115**	−0.021	0.025	0.010	−0.009	0.016	−0.001	0.010	−0.0001	0.70	**0.065**
	(7.17)	(−1.43)	(−0.21)	(−0.96)	**(−0.56)**	**(1.14)**	(−1.26)	(1.78)	(0.39)	(−0.88)	(0.63)	(−0.28)	(2.48)	(−0.09)		**(0.48)**
High *STKEXP*	1.037	0.061	0.001	0.001	**0.154**	**0.114**	−0.005	0.016	0.037	0.004	−0.008	−0.005	0.003	−0.0014	0.71	**0.268**
	(8.23)	(3.05)	(0.26)	(0.46)	**(2.43)**	**(1.85)**	(−0.31)	(0.85)	(0.88)	(0.34)	(−0.51)	(−1.46)	(0.52)	(−1.23)		**(3.03)**
(High − Low)	−0.063	0.084	0.002	0.006	**0.128**	**0.165**	−0.013	0.001	0.028	0.004	−0.012	−0.002	0.004	−0.0020		**0.293**
	(−0.37)	(2.27)	(0.46)	(1.69)	**(1.43)**	**(1.77)**	(−0.64)	(0.04)	(0.65)	(0.26)	(−0.51)	(−0.29)	(0.58)	(−1.45)		**(2.27)**

Notes. Sample consists of 307,355 analyst-stock-year observations (100,672 for *RLFR*). The sample for each year is partitioned into three equal-size groups based on either analyst *PORTF* (small, medium, large) or *STKEXP* (low, medium, high). Robust regressions are run using pooled data from 1991 to 2013 for *ACC* and *FLFR* and from 1994 to 2013 for *RLFR*. t-statistics (in parentheses) are two-way clustered by firm and time. See the appendix for variable definitions.

Panel A: Model: $ACC_t = \alpha_1 + \alpha_2\, POSTFD + \beta_1\, ACC_{t-1} + \beta_2\, FLFR_{t-1} + \beta_3\, MPC + \beta_{31}\, MPC\ POSTFD + \beta_4\, NIND + \beta_5\, PORTF + \beta_6\, STKEXP + \beta_7\, NANL + \beta_8\, HORIZON + \beta_9\, SIZE + \beta_{10}\, STDRET + \beta_{11}\, RD + \varepsilon$.

Panel B: Model: $FLFR_t = \alpha_1 + \alpha_2\, POSTFD + \beta_1\, ACC_{t-1} + \beta_2\, FLFR_{t-1} + \beta_3\, MPC + \beta_{31}\, MPC\ POSTFD + \beta_4\, NIND + \beta_5\, PORTF + \beta_6\, STKEXP + \beta_7\, NANL + \beta_8\, HORIZON + \beta_9\, SIZE + \beta_{10}\, STDRET + \beta_{11}\, RD + \varepsilon$.

Panel C: Model: $RLFR_t = \alpha_1 + \alpha_2\, POSTFD + \beta_1\, ACC_{t-1} + \beta_2\, RLFR_{t-1} + \beta_3\, MPC + \beta_{31}\, MPC\ POSTFD + \beta_4\, NIND + \beta_5\, PORTF + \beta_6\, STKEXP + \beta_7\, NANL + \beta_8\, HORIZON + \beta_9\, SIZE + \beta_{10}\, STDRET + \beta_{11}\, RD + \varepsilon$.

is negative for all three *PORTF* subsamples, becoming increasingly negative as analyst portfolio size increases. Furthermore, while the interaction term $MPC \times POSTFD$ (β_{31}) is positive, we observe an increasingly negative overall effect of multipoint contact under Reg FD since the sum of *MPC* and $MPC \times POSTFD$ ($\beta_3 + \beta_{31}$) declines from −0.098 to −0.331 as *PORTF* increases. Hence, we find no support for H4, which predicted that Reg FD would enhance the beneficial effect of multipoint contact on forecast accuracy for stocks within an analyst's sphere of influence. The results using *STKEXP* to evaluate analysts' spheres of influence are similar, again failing to support H4.

Panel 5B presents results for information leadership in earnings forecasts (*FLFR*). Recall from panel 4B that *MPC* has an increasingly positive association with *FLFR* as *PORTF* or *STKEXP* increases. The results in panel 5B suggest that this increasing relationship is concentrated within the post-FD period. Examining coefficients for the main effect of *MPC* (β_3) suggests a stronger association for stocks within an analyst's sphere of influence (i.e., large *PORTF*). For instance, the increase in β_3 is insignificant when comparing the smallest to largest *PORTF* group (0.141, $t = 0.83$). In contrast, the coefficient for the interaction term β_{31} is significantly larger (0.614, $t = 1.94$) for the largest versus smallest *PORTF* subsample. Moreover, the joint effect ($\beta_3 + \beta_{31}$) is significantly larger (0.755, $t = 2.10$) for the largest relative to smallest *PORTF* subsample. Regressions for the *STKEXP* subsamples yield analogous findings. Together, these findings give strong support to H5, which predicted that Reg FD would magnify the positive effect of multipoint contact on information leadership in earnings forecasts for stocks within an analyst's sphere of influence. Indeed, the insignificant main effect coefficients suggest that mutual forbearance was concentrated in the period following the enactment of Reg FD.

Panel 5C presents the findings for information leadership in recommendations, *RLFR*. As *PORTF* increases, the coefficient for *MPC* (β_3) is unchanged (−0.027, $t = -0.20$). However, the coefficient for the $MPC \times POSTFD$ (β_{31}) interaction again increases by a significant amount (0.288 $t = 1.90$), moving from the smallest to largest *PORTF* subsample. Furthermore, the joint effect of $MPC + MPC \times POSTFD$ ($\beta_3 + \beta_{31}$) also increases from the smallest to the largest *PORTF* subsample, but insignificantly so (0.261, $t = 1.29$). When analyst spheres of influence are assessed by *STKEXP*, we again find no change in the coefficient for the main effect of *MPC* but significant increases in both $MPC \times POSTFD$ and $MPC + MPC \times POSTFD$ from the low- to high-experience subgroups. These results for information leadership in stock recommendations show support for H6, which predicted that Reg FD would magnify the positive effect of multipoint contact on information leadership for stocks within an analyst's sphere of influence. Moreover, as with the findings for information leadership in earnings forecasts (*FLFR*), the insignificant main effect coefficients for *MPC* in the *RLFR* regressions suggest that mutual forbearance was concentrated in the period following the enactment of Reg FD.

4.3. Sensitivity Analyses

In addition to the empirical analysis presented in the tables, we have run several additional specifications as sensitivity analyses, which, for brevity, are not tabulated. In one, rather than estimating the robust regressions reported above, we winsorize observations at the 1st and 99th percentiles and estimate OLS regressions. The results are generally unaffected. In some cases, however, the results are marginally stronger, and all regressions have higher adjusted R^2. Because this is potentially driven by outliers inflating explanatory power, we prefer the robust regressions.

We also re-estimate the models using the earliest available forecast for a given analyst following a given stock in a given year rather than averaging across all forecasts in a given year. As expected, this reduces mean analyst accuracy. However, none of the theoretical results are affected; we again find no results for *ACC*, strong results for *FLFR*, and somewhat weaker but supportive results for *RLFR*. Similarly, we re-estimate the models using the last available forecast prior to the fiscal year. Again, other than in this case mean accuracy improving, there are no substantive differences in the findings.[9]

5. Discussion and Conclusion

Although securities analyst behavior and performance has been extensively documented, their patterns of competition remain less articulated despite the frequency with which they cover the same stocks. To address this gap in our understanding, we examine how sell-side security analysts' forecast accuracy and information leadership are influenced by

[9] We also examine the impact of other regulatory changes that occurred after Reg FD and affected the functioning of financial analysts, such as the Global Settlement, which required changes in the disclosures analysts were required to make as well as in communication patterns among firms, and Sarbanes-Oxley (SOX), which intensified reporting requirements for publicly traded firms. To examine the influence of these changes on mutual forbearance, we examine time-trends in the coefficient for $MPC \times STKEXP$. No trend appears in the coefficient for $MPC \times STKEXP$ in the regressions for *ACC* or *RLFR*, in later years corresponding to the other regulatory changes. For the *FLFR* regression, the coefficient for $MPC \times STKEXP$ continues to rise until 2006. This is consistent with mutual forbearance fostering information leadership under Reg FD, with the effect reinforced by the Global Settlement and SOX.

the multipoint contact among them. We theorize that multipoint contact results in mutual forbearance leading to more accurate forecasts and greater information leadership within their own spheres of influence rather than in their rivals' spheres. We also predict that mutual forbearance became stronger following the enactment of Reg FD. Although Bowers et al. (2014) have documented a link between multipoint contact among securities analysts and their forbearance from bold forecasts, particularly under Reg FD, their study does not attend to the role of spheres of influence, which critically determines the direction of mutual forbearance—who forbears to whom—on a given stock.

The findings support our predictions for information leadership in both earnings forecasts and, although less conclusively, stock recommendations. The multipoint contact analysts experience has the predicted association with their coordination of information leadership across stocks within their respective spheres of influence (indexed by analysts' stock-specific experience and portfolio size). Additionally, our findings support our contention that, enabled by the multipoint contact arising naturally among them, analysts responded to the competitive challenges posed by Reg FD by focusing their efforts on achieving information leadership for stocks within their own spheres of influence and following in the coverage of stocks within their rivals' spheres, and thus stabilizing and increasing the predictability of their rivalry for information leadership in earnings forecasts and to a lesser extent stock recommendations. Regulations anticipated to encourage competition may thus result in weakened competition when applied to markets characterized by multipoint contact among participants.

The predicted effects are not evident for forecast accuracy, however. Contrary to expectations we observe a negative association between multipoint contact and forecast accuracy, an association that is insensitive to either spheres of influence or Reg FD. One interpretation of these findings is that mutual forbearance results *not* in analysts coordinating their joint effort more effectively across their spheres of influence but rather—and consistent with the oft-invoked collusive view of mutual forbearance—in analysts investing less effort to minimize forecast error on stocks where they experience high multipoint contact with their rivals than on stocks where they experience low multipoint contact with their rivals and so more intense competition. Indeed, the reduction in competition resulting from analysts' increased coordination of information leadership across their spheres of influence may have supported this lower effort.

Why might analysts emphasize coordination of investments in information leadership rather than forecast accuracy across spheres of influence? We see three possibilities. One is the greater importance to analysts of information leadership relative to forecast accuracy. Prior research shows that analysts have incentives to favor informativeness (i.e., information leadership) over accuracy. This interpretation is consistent with findings that trading volume, but not forecast accuracy, is related to analysts' compensation (Groysberg et al. 2011) and movement up the brokerage hierarchy (Zhang 2005). The competitive disadvantage an analyst faces in attracting investor attention by being less influential may thus dominate the competitive disadvantage of being less accurate.[10] These asymmetric incentives may lead analysts to direct their efforts toward achieving (and coordinating) information leadership (i.e., *FLFR* and *RLFR*) rather than toward reducing forecast error within their spheres of influence. A second account is related to differences in the observability of forecast accuracy and information leadership. Forecast accuracy is readily visible to other analysts and investors. Information leadership is more difficult to discern and dependent on the responses of other analysts, which may vary in degree and speed across stocks as well as forecasts and recommendations. As a result, the influence of particular earnings forecasts or stock recommendations is not obvious ex ante. Because outright collusion among securities analysts would be illegal, mutual forbearance may be less likely to emerge in more visible competitive behaviors. The third is that, despite information leadership being more difficult to discern, it is easier to coordinate deference on timing than accuracy, which is based on ex post realizations of earnings. As a result, information leadership rather than accuracy advantages emerges within spheres of influence.

Our paper makes a key contribution to accounting research on equity analysts. As Schipper (1991) notes, accounting research has focused too narrowly on the statistical properties of forecasts, without considering the decision context and economic incentives affecting these forecasts. We follow her counsel by attempting to provide a broader depiction of analysts' economic incentives specifically related to competition in both forecasts and recommendations. Furthermore, we attempt to shift the focus from the outputs of analysts' decision processes to the inputs. Mutual forbearance is one possible mechanism through which analysts can achieve the degree of differentiation and specialization necessary to obtain the substantial rewards associated

[10] Normally, the trade-off between information leadership and accuracy is along the time dimension, with earlier forecasts having a greater impact but potentially being less accurate. However, a recent paper by Louis et al. (2013) suggests that analysts might willingly provide less accurate forecasts when they believe firms are managing their earnings and, notably, these *less* accurate forecasts are *more* informative.

with establishing a reputation for innovative reporting and attracting institutional investor attention (Groysberg 2010, Reingold and Reingold 2006).

Our analysis also contributes to the literature in industrial organization and strategy by being among the first to demonstrate that mutual forbearance arises not just among competing firms but among competing individuals as well (Bowers et al. 2014). We also show which actors will forbear from competition in which domains (i.e., actors experiencing multipoint contact in domains outside their spheres of influence), which, although a critical part of the theory, had not yet been demonstrated empirically, for either competing firms or individuals. There is however one salient difference between our findings for analysts and prior research that has examined inter-firm competition. In prior studies, mutual forbearance was always viewed as a mechanism to dampen competition, which would always be seen as less than optimal from a social welfare perspective. In our setting, it is unclear whether the information environment deteriorates because of mutual forbearance. On the one hand, by allowing analysts to become information leaders on certain stocks and followers on others, mutual forbearance may have increased the quality and timeliness of information available to capital markets. On the other hand, by stabilizing and increasing the predictability of competition for information leadership, mutual forbearance may indeed encourage some analysts to invest less effort in minimizing forecast error, even within their own spheres of influence.

In sum, our study demonstrates the value of examining patterns of analysts' competitive interactions. Focusing on this underexplored aspect of analyst functioning might help orient future work in this area. While we focus our attention on forecast accuracy and information leadership, future research might consider other dimensions of analyst competition, including forecast revision frequency, boldness, and optimism, as well as initiation and cessation of coverage, to assess the broader scope and impact of mutual forbearance among these important financial intermediaries. Moreover, although we focus on competition among analysts, future research might usefully attend to competition among the brokerage firms that employ them. Finally, as multipoint competition is but one model of competition and cooperation advanced in the industrial organization and strategic management literatures, it would be useful for future research to consider the relevance of these other models to analyst functioning.

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Appendix. Variable Definitions

Variable	Definition
ACC_t	Negative of absolute forecast error, scaled by price, multiplied by 100 ($-100\lvert EPS_{est} - EPS_{act}\rvert/PRICE$), averaged across all available forecasts for a given analyst-stock combination
$FLFR_t$	Leader-follower ratio for forecasts as defined by Cooper et al. (2001). *FLFR* is the ratio of the cumulative number of days by which the preceding two forecasts on that stock lead the forecast of interest to the cumulative number of days by which the subsequent two forecasts on that stock follow the focal forecast, excluding those forecasts made during periods of management guidance. See Figure 1 for a detailed example. *FLFR* is averaged across all available forecasts for a given analyst-stock-year.
$RLFR_t$	Leader-follower ratio for recommendations as defined by Cooper et al. (2001). *RLFR* is the ratio of the cumulative number of days by which the preceding two recommendations on that stock lead the recommendation of interest to the cumulative number of days by which the subsequent two recommendations on that stock follow the recommendation, excluding those recommendations made during periods of management guidance. See Figure 1 for a detailed example. *RLFR* is averaged across all available recommendations for a given analyst-stock-year.
MPC	Multipoint contact as defined by Baum and Korn (1996). For a given analyst-stock combination, computed as the average of the proportion of stocks, other than the focal stock, jointly covered with rival analysts on the focal stock. See Figure 2 for a detailed example.
NIND	Ln of one plus number of distinct industries (two-digit SIC codes) covered by a given analyst
PORTF	Ln of number of distinct firms followed by a given analyst
STKEXP	Ln of one plus coverage experience in years for a given analyst-stock pair
NANL	Ln of number of analysts covering a given stock
HORIZON	Ln of one plus time lag in days between the last forecast/recommendation and analyst issues for a stock before the end of its fiscal year and the stock's fiscal year-end. *HORIZON* is averaged across all available forecasts for a given analyst-stock combination.
SIZE	Ln of total assets for a given stock (AT)
STDRET	Standard deviation of daily returns, multiplied by 100, for a given stock
RD	R&D intensity, measured as the firm's R&D expense (XRD) scaled by its total revenues (SALE), multiplied by 100, for a given stock
POSTFD	Indicator variable set to 1 for the years 2001 and later, and 0 for the years 2000 and prior

Note. All variables are updated annually.

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