THREE ESSAYS IN CORPORATE FINANCE

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SINGAPORE MANAGEMENT UNIVERSITY

2015

Three Essays in Corporate Finance

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Submitted to Lee Kong Chian School of Business in partial fulfilment of the requirements for the Degree of Ph.D. in Business (Finance)

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2015

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ACKNOWLEDGEMENTS

I would like to express my utmost gratitude to my dissertation committee, Dr. Jeremy C. Goh, Dr. Roger K. Loh, Dr. Jerry Cao and Dr. Paul H. Malatesta, for their dedicated guidance and continuous encouragement. I am especially grateful to my dissertation chair, Dr. Goh, for his unwavering support and patience to my seemingly never-ending experimentations with new datasets and cross-disciplinary techniques. I have developed my own individuality and a strong sense of independence because of his rigorous challenges to my often ambitious but unpolished ideas.

I would like to thank my co-authors, Dr. Chiraphol N. Chiyachantana and Dr. Roger K. Loh, for their detailed guidance, for I would not have been able to progress and learn as much without them. They have shown great patience and have expended precious time and efforts, amidst their tight schedules, to induct a novice into their areas of specialty. I reserve nothing in my admiration and respect for them.

I would like to thank the faculty members and Ph.D. students of the Finance Group at the Lee Kong Chian School of Business for their input, valuable discussions and camaraderie. I am also indebted to the staff members at the Singapore Management University, especially Shelly Li, for assisting me with administrative issues and making my stay a very comfortable and memorable one.

Finally, and most importantly, I would like to thank the people that matters most to me: my father Chan Koon, my mother Sun Teck, my wife Diana, and my younger sister Melissa. It is impossible for me to complete this journey without their faith, support and loving kindness. I dedicate this dissertation to them.

SUMMARY

There are two foci in my research efforts to produce this dissertation. First, I explore and create novel datasets and methods that can expand our existing arsenal of empirical tools.[1] Following that, I deploy these tools to analyze three aspects of information science in social networks and earnings-related voluntary disclosures: Social network connectedness, natural language, and management credibility.

This dissertation has three essays on corporate finance. The first essay is motivated by the friendly board framework of Adams and Ferreira (2007). In this study, we measure the value of board advisory activities using Centrality Slice (CS) - the ratio of the network connectedness of executive directors to non-executive directors. We find that this measure positively relates to firm value, performance-turnover sensitivity, management forecast accuracy, and market reaction to forecast surprises. The results from our instrumented regression suggest that CS is an optimal selection outcome that varies across firms. As such, firms will likely enjoy better advisory benefits if their policies can support high CS in an optimal manner.

The second essay is co-authored with Roger K. Loh. In this study, we add two novel approaches to a large literature on analysts' conflicts of interests. Using analysts' tones during peer conference calls, and returns co-movement between their brokerages and hosts to proxy for the level of information advantage, we find that analysts from high returns co-moving brokerages exhibit language patterns that neither signal competition nor collusion. Our results show that the market values tones, with increasing reactions to the level of returns co-movement, consistent with the notion of pricing for competence. We also find that the market

[1] Datasets: BoardEx; Fair disclosure conference call transcripts; ANcerno with client identification.
Methodologies: Natural language programming; network centrality

is not naïve as it discounts sentiment tones from brokerages sanctioned during the Global Analyst Research Settlements.

The third essay is co-authored with Chiraphol N. Chiyachantana. Using a proprietary set of institutional trading data, we investigate how sophisticated investors utilize the information contained in management earnings forecasts characteristics to formulate their trading strategy. We find that these investors’ responses to a firm’s forecasts are not only increasing in the magnitude of earnings surprise, but also magnified by the firm’s prior forecast accuracy. We reveal transient institutions as the principal traders on these forecast characteristics and show that trading strategies using both forecast surprise and prior forecast accuracy are not only profitable to implement, but also outperform those that rely solely on forecast surprise.

CHAPTER ONE

The Centrality Slice

Abstract

Motivated by the friendly board framework of Adams and Ferreira (2007), we measure the value of board advisory activities using Centrality Slice (CS) - the ratio of the network connectedness of executive directors to non-executive directors. We find that this measure positively relates to firm value, performance-turnover sensitivity, management forecast accuracy, and market reaction to forecast surprises. The results from our instrumented regression suggest that CS is an optimal selection outcome that varies across firms. As such, firms will likely enjoy better advisory benefits if their policies can support high CS in an optimal manner.

Keywords: Centrality; firm value; earnings surprise; management earnings forecasts; social network

JEL Classification Codes: G14, G30

The Centrality Slice

1. Introduction

1.1. The advisory role of the board

The board is the highest decision making body in the firm for a wide range of strategic issues across the firm. A large number of studies examine the monitoring role of boards, while paying little attention to their advisory roles (see Bebchuk and Weisbach 2010 for a survey on the state of corporate governance research). Independent directors represent the voice of the shareholders and act as a counter-weight to the management on firm decisions that are suboptimal in improving firm value. However, this monitoring role is not the only board activity that adds value to the firm. A board is sometimes made up of experienced non-executives from the business, government and political circles, who can contribute valuable advice to the management. Our study is one of the few in the large literature on corporate governance that examines the advisory value of the board of directors. We adopt a different approach from the few existing studies that measure the economic value of advising (e.g., Coles, Daniel and Naveen 2008; Coles, Daniel and Naveen 2012; Dass, Kini, Nanda, Onal and Wang 2014; Faleye, Hoitash and Hoitash 2013; Hsu and Hu 2015). Under the friendly board framework of Adams and Ferreira (2007), we use social network centrality as a proxy for information quality and precision to show that firm value increases when the management is able and more willing to share information with the board.

1.2. Information sharing and board advising

In an influential paper, Adams and Ferreira (2007) theorize that management face a dilemma when it comes to deciding how much relevant firm-specific information they should share with the board. Specifically, the management deliberates a trade-off between receiving advisory benefits and subjecting themselves to more intense monitoring and interference by the board. This is especially so for a CEO who is unsure of his ability and believe that his board members have more precise information about the firm's strategic options than he does. Thus, with monitoring at too intensive a level (e.g., too many independent directors or better informed boards), the management may stop sharing information and the firm loses the value of board advisory as a result. The recommendations are clear: Make the boards friendlier (e.g., reducing the number of independent directors) or institute a separate board/committee to perform due diligence in monitoring. We extend this line of thought by hypothesizing that if the management is publicly known to have superior information quality and precision relative to their board of directors, then two things may happen: First, the management is confident of their abilities and not afraid to share their information in a constructive manner. Second, the non-executives will have lesser incentives to monitor and thus engage in more activities that are advisory in nature. Both conditions should then lead to better firm performance and market value, and we show that this is indeed the case. Firms with board executives that are professionally better connected relative to their non-executive directors are associated with higher firm values.

Our results may be surprising to the interesting strand of research that looks at the web of social network and ask whether such nexus have economic impacts on a wide range of topics including governance, incentive designs on contracting entities (managers and analysts for example) and firm performance. Most studies in this large literature document a negative relation between CEO connectedness and firm value and a positive one between board connectedness and firm value. For example, Brown, Gao, Lee and Stathopoulos (2012) and Hwang and Kim (2009) find that CEOs with large networks earn more than those with small networks and have lower pay-performance sensitivity. Fracassi and Tate (2012) show that CEOs have incentives to appoint friends into directorship positions and such connections destroy firm value amidst weak board monitoring. Cohen, Frazzini and Malloy (2012) find that

CEOs appoint overly optimistic analysts as independent directors, regardless of the latter's abilities. On the other hand, studies that show positive effects of CEO connections are few and specific. For example, Faleye, Kovacs and Venkateswaran (2012) show that CEO connections facilitate corporate innovations through their access to relevant network information, and such connections also act as insurance should their risky endeavors lead to career concerns. Other studies in this literature focus on board connectedness as a whole and find positive effects on average. For example, Renneboog and Zhao (2014) find that firms that are directly or indirectly connected via their board of directors go through efficient mergers and acquisitions (i.e., improved probability and shorter negotiation duration). Field, Lowry and Mkrtchyan (2013) find that busy directors, albeit being poor monitors, are excellent advisors and contribute positive value to IPO firms. Chuluun, Prevost and Puthenpurackal (2014) find that better board connections have larger media and analyst coverage. In the same study, they also show that these firms enjoy lower bond yield spreads.

1.3. Network centrality and superior information

Our measure of connectedness is network centrality, adopted from the field of social network theory, which differs from most of the current studies that use the number of outside directors as a proxy for monitoring, and the number of unique board members on other boards that each outside director holds as a proxy for connectedness. In a related paper that examines the value of advisory activities, Coles, Daniel and Naveen (2012) labels the former and latter as the quantity and quality of advising, respectively. We are however, not satisfied with this popular approach because not all connections are equal in reality. A connection to a Nobel Laureate in physics is not equivalent to one with an undergraduate degree in physics. Connections that exists outside the inner circle (e.g., Politics) do not enjoy the same information access to other clusters in the network. We also observe information brokers who have few connections but are indispensable in connecting clusters of different networks (e.g., financial institutions such as banks). As such, the influence of an individual is not only dependent on the quantity of their first-degree connections, but also more crucially, their positions in the wider social and professional network. We measure the value of such positions using the eigenvector (who one connects to), closeness (how fast one can reach the entire network) and betweenness (connecting network clusters) algorithms in social network theory, and combine them into one single measure of information quality and precision via principal component analysis (i.e., the first principal component).[2] We then compute the ratio of the centrality scores of executive to non-executive directors and use that as our main variable of interest. We call this variable the Centrality Slice (*CS*), which measures the relative information superiority between management and non-executives on the board.

The application of social network theory in the finance and accounting literature is a new endeavor. Larcker, So and Wang (2013) show that firms with high board centrality earn superior risk-adjusted stock returns and predict future returns-on-assets and earnings growth that are not fully understood by analysts at this point in time. Omer, Shelley and Tice (2013) find that centrality does not necessarily convey positive benefits beyond firms with high investment opportunities. Their study show that firms with higher aggregate connectedness are associated with lower firm performance on average. In a study that examines the centrality of CEOs, El-Khatib, Fogel and Jandik (2015) find that highly central CEOs bid for value and synergy destroying M&A deals, and these CEOs cannot be effectively disciplined by the managerial labor market. The message from most of these studies reinforces the consensus that power in the hands of the CEO is likely to be bad, while powerful boards bring net positive benefits to firm value. In a marked departure from consensus, we find empirical support for higher firm values when their management is more central relative to non-executive directors

[2] We are not the first to adopt principal component analysis in the finance literature. Larcker, David F, Eric C So, and Charles CY Wang, 2013. Boardroom centrality and firm performance, *Journal of Accounting and Economics* 55, 225-250. also use the first principal component extracted from (degree, eigenvector, closeness and betweenness) as their centrality measure.

in the network (i.e., high centrality slice). Our results also explains Omer, Shelley and Tice (2013)'s finding that firm performance drops when independent directors, but not inside directors, can access large quantities of information (eigenvector centrality).

1.4. Centrality slice, management earnings forecast accuracy and market reactions

Lastly, to validate that high centrality is indeed associated with information quality and precision, we examine the management forecast accuracy and market reactions to forecast surprises of the firms in our sample. In a related paper, Ajinkya, Bhojraj and Sengupta (2005) find that the number of independent directors are positively associated with frequent and more accurate management forecasts. We posit that in the absence of earnings management, a better informed management should be able to issue more accurate management forecasts. However, does powerful non-executives on the board improve or impede management's ability to do so? Our results do support Ajinkya, Bhojraj and Sengupta (2005)'s finding that the number of independent directors, a proxy for monitoring, improve management forecast accuracy. Interestingly, we also find that the absolute centrality score of management is not associated with better forecast accuracy, but *CS* is. Further, we examine the three-day cumulative abnormal returns, centered on management forecast announcement day, and find that they are positively associated with *CS* but negatively associated with absolute centrality score. Our results suggest that the market is not naïve as it does penalize firms with well-connected (powerful) management possibly out of agency problem concerns, but it also values firms with high *CS* that are likely to be benefiting from board advisory activities. Our study is thus the first to document the incremental value of board advisory activities, under the framework of Adams and Ferreira (2007), in the management earnings forecast literature.

The rest of the paper is organized as follows. Section 2 reviews additional literature and develops our hypotheses. Section 3 describes the data and methodology. Section 4 examines the relation between centrality slice and firm performance while Section 5 analyzes the relation between centrality slice and CEO turnover. Section 6 examines management earnings forecasts events and Section 7 concludes.

2. Additional literature review and hypothesis development

Social network centrality is an innovative methodology that allows us to measure the amount of information power held by an individual, through the analysis of a network map. For example, a director that directly connects to a large number of industries will receive information faster than one who is not. This value can be computed using the closeness centrality measure $(x) = \frac{1}{\sum_y d(y,x)}$, where *x* and *y* are two unique directors and *d* represents the distance between them (*d* is 1 if *x* and *y* sits in the same board). Closeness centrality thus measures the *potential speed of information* that a director enjoys. There are two other centrality measures that are commonly used: eigenvector and betweenness. Eigenvector centrality is motivated by the idea that 'not all connections are equal'. A director that has one connection to a dense network receives more information from it compared to another connection to a sparse one. The eigenvector centrality measure assigns higher relative scores to a director if he has more well-connected friends in the network, and this measure represents the *potential amount of information* that a director possesses. Lastly, directors in a network will have higher betweenness centrality scores if they connect two or more clusters (e.g. industries), and this measure represents the *value of brokering information* that a director possesses. Specifically, the betweenness measure assigns higher scores to a director if he lies on the shortest path between two or more clusters.

To measure the relative information superiority between management and non-executives on the board, we create the Centrality Slice (CS) variable, which is the first principal component of $(\frac{eigenvector_{executive}}{eigenvector_{non-executives}}, \frac{closeness_{executive}}{closeness_{non-executives}}, \frac{betweenness_{executive}}{betweenness_{non-executives}})$. Although raw centrality are absolute measures of information superiority, our economic interpretation of the *CS* is that of the level of advisory benefits that a firm enjoys. To recap, our argument follows the framework of Adams and Ferreira (2007), that a management with superior information relative to their non-executive board members are more confident and thus willing to share more information amidst lower monitoring incentives. This then translates into more benefits that are advisory in nature.

Our CS measure is closely related to the CEO pay slice (*CPS*) measure in Bebchuk, Cremers and Peyer (2011). *CPS* is measured as the proportion of CEO total compensation over that of the top five highest paid executives in the firm. In Bebchuk, Cremers and Peyer (2011), *CPS* is a proxy for CEO power and the authors find negative associations between *CPS* and firm, market performances and performance sensitivity of CEO turnover. We argue that *CS* measures external information dynamics and is a good complement to, rather than a replacement for, the *CPS* which proxies for the CEO's internal power dynamics. However, unlike the *CPS*, we hypothesize that higher *CS* creates value from more board advisory activities.

Hypothesis 1: Using CS as the proxy for the level of advisory benefits, we expect to observe a positive relation between CS and firm performance.

Next, we examine the performance sensitivity of CEO turnover. If *CS* positively relates to firm performance and value, then we expect to see a negative association between *CS* and the probability of turnover, including forced turnover. However, a lower turnover probability could signal an entrenchment problem which makes it harder for firms to replace high *CS* CEOs (see Bebchuk, Cremers and Peyer 2011). On the other hand, we expect to see a higher performance sensitivity of CEO turnover if high *CS* lowers the switching costs for such CEOs in the managerial labor market (see Faleye, Kovacs and Venkateswaran 2012).

Hypothesis 2a: CEOs with high centrality slice (CS) are less likely to be replaced.

Hypothesis 2b: Lower performance sensitivity of turnover for CEOs with high centrality slice (CS) indicates entrenchment issues, while higher performance sensitivity of turnover signals lower switching costs in the managerial labor market.

Accordingly, since high *CS* indicates beneficial advisory activities from superior information quality and precision, it then follows that firms with high *CS* have high management forecast accuracy. Further, if high *CS* is publicly observed, then we expect the market to react more strongly to the management earnings forecast surprises of high *CS* firms as well.

However, management earnings forecasting is inherently an uncertain process and highly accurate firm forecast is a suspect of earnings management. Prior work in the accounting literature on independent directors find that the likelihood of fraud, earnings manipulation and management earnings forecast accuracy are negatively associated with the presence of independent directors (see Ajinkya, Bhojraj and Sengupta 2005; Beasley 1996; Dechow, Sloan and Sweeney 1996; Klein 2002). If high CS is a condition for managerial entrenchment, then it is likely that a powerful CEO can manage firm earnings, while withstanding interferences from the board. To examine these issues, we look at the market reactions to management earnings forecast events in a multivariate regression setup. Specifically, we use the absolute management centrality as a proxy for managerial entrenchment, the number of independent directors as a proxy for monitoring intensity, and *CS* as the benefit of firm advisory activities. We also examine the same variables on the probability of earnings management (i.e., beat or meet consensus earnings forecasts by 1 cent).

Hypothesis 3a: Firms with high centrality slice (CS) issue forecasts that are more accurate.

Hypothesis 3b: Market returns react positively to firms with high CS and number of non-executive directors; while negatively to high management centrality

3. Data and summary statistics

3.1. The Centrality Slice (CS)

We extract directorship data from 2002 through 2013 from the BoardEx North America Director database. We first map the BoardEx directorship data into director pairs by company and year. For example, (director A, director B) is considered as a valid pair if they serve in the same board for the same year. Following which, I use these pairs to construct the network graphs for each year from 2003 through 2013. To compute the centrality measures (eigenvector, closeness and betweenness), we use the graph-tools python module, which is a program compiled in the C language that supports parallel processing.[3] We then average the centrality scores by executives and non-executives as tagged by BoardEx. Finally, we compute our measure Centrality Slice (*CS*) as the first principal component of $\left(\frac{eigenvector_{executive}}{eigenvector_{non-executives}}, \frac{closeness_{executive}}{closeness_{non-executives}}, \frac{betweenness_{executive}}{betweenness_{non-executives}}\right)$, which captures about 50% of the total variation.

3.2. The CEO Pay Slice (CPS) and other variables for firm performance

We follow Bebchuk, Cremers and Peyer (2011) and compute *CPS* as the ratio of the total compensation of the CEO to the top five executives, using data from Compustat's ExecuComp database from 2002 through 2013. *Tobin's Q* is defined as the market value of equity plus the book value of assets minus the sum of the book value of common equity and deferred taxes, before dividing by book value of assets. Return on Asset (*ROA*) is defined as the operating income divided by the book value of assets. For purposes of comparison, all other variables for our examination of firm performance are calculated as per Bebchuk, Cremers and Peyer (2011).

[3] We note that El-Khatib, Rwan, Kathy Fogel, and Tomas Jandik, 2015. CEO network centrality and merger performance, *Journal of Financial Economics*. took seven days to compute the closeness centrality for the graph of 2010 on a supercomputer ('Star of Arkansas') using MATLAB. In comparison, we completed the computation for all centrality measures on a normal workstation in four days.

First, we have the entrenchment index *Eindex* from Bebchuk, Cohen, and Ferrell (2009), which is the sum of six provisions that the Investor Responsibility Research Center (IRRC) monitors: incidence of staggered boards, golden parachutes, poison pills, supermajority voting requirements, limits on charter and bylaw amendments.

Next, we have a set of firm characteristics. *Log Book Value* is the log of the book value of assets. *Insider Ownership* is the fraction of shares held by insiders as reported by ExecuComp. *Capex/Assets* is the ratio of capital expenditures to assets. *Leverage* is the long-term debt to assets ratio. *R&D* is the ratio of R&D to sales. *Company Age* is the number of years since listed on CRSP. *Diversified* is a dummy of one if the firm reports more than one segment on Compustat's segment database.

We capture CEO and firm compensation characteristics with the following variables. *Founder* is a dummy of one if CEO is the same when the firm was first listed on CRSP. *CEO Outsider* is a dummy of one if the CEO was working at the firm for less than one year prior to appointment. *Abnormal Total Compensation* is the residual of a regression of total compensation of the top 5 executives on log book value with industry and year fixed effects. *Relative Equity Compensation* is the ratio of the fraction of equity compensation of the CEO to the average fraction of equity compensation of the next top 4 executives (EBC/TDC1, where EBC is the equity-based compensation calculated as the sum of the value of the restricted shares granted plus the Black-Scholes value of options granted). *CEO Ownership ≥ 20%* is a dummy of one if the CEO holds at least 20% of the total shares outstanding. *CEO Tenure* is the number of years since becoming CEO.

Lastly, we have the following variables for board characteristics. *CEO Is Chair* is a dummy of one if the CEO is also the Chair of the board. *CEO Is Only Director* is a dummy variable of one if the CEO is the only executive officer on the board. *Number of VPs* is the number of vice presidents among the top five executives.

Our final sample has 9,631 observations and we present the distribution of these variables in Table 1 Panel A. Panel B presents the cross-sectional correlation between selected variables of interests. The individual centrality slice measures are highly correlated with each other and the number of non-executive directors, while moderately correlated with *CPS*. Centrality Slice (*CS*) on the other hand, is not correlated with *CPS* and moderately correlated with the number of non-executive directors. We do not find other multi-collinearity concerns and do not display the rest of the matrix for brevity.

We present the results of the cross-sectional multivariate regression of Centrality Slice (*CS*) and CEO Pay Slice (*CPS*) on these variables, in Table 2. We find that *CS* is positively related to *CEO is Only Director*, *Industry Median CPS*, *Number of VPs*, *Eindex*, *Log Book Value*, *Company Age*, *Abnormal Total Compensation*, *Relative Equity Compensation*, *CEO Outsider*, *CEO is Chair,* and negatively associated with contemporaneous *Tobin's Q*, *insider ownership* (non-linear relationship), *Capex/Assets*, *R&D* and long *CEO Tenure*. Taken together, the results suggest that *CS* is more closely related to poor, rather than good governance. For *CPS,* we find that it is positively associated with *Abnormal Total Compensation*, but negatively related to *Relative Equity Compensation*, *CEO is Only Director*, *Number of VPs*, *Eindex*, *Log Book Value*, *R&D* and long *CEO Tenure*.

To address endogeneity concerns for both *CS* and *CPS* in later examinations on firm performance, we use the models in Table 2 as the first-stage regressions in a 2SLS specification. We apply the same set of instruments to both endogenous variables: *CEO is Only Director*, *Industry Median CPS*, *Number of VPs* and *Proportion of Female on Board*. The first three variables are the original instruments in Bebchuk, Cremers and Peyer (2011), which we find to be important instruments for CS as well. We add the fourth instrument *Proportion of Female on Board* because we find that female directors have significantly higher centrality scores than male directors (not reported), but we do not have good reasons to assume that the proportion of female directors correlates with the residuals of the second-stage regressions on firm performance. In other words, we argue that our instrument *Proportion of Female on Board*, in addition to *CEO is Only Director*, *Industry Median CPS* and *Number of VPs*, only affects firm performance via CS and CPS.[4]

3.3. CEO turnover

In addition to the usual CEO turnover variable (i.e., a change in CEO from year t to year t-1 is classified as a turnover event), we include a measure of forced CEO turnover as per Eisfeldt and Kuhnen (2013). We identify a turnover event as forced if (1) a CEO departure is announced less than six months before the event; or (2) no specified health reason; or (3) press release specifically report a firing, forcing out, or retire due to policy differences.

3.4. Management earnings forecast (MEF)

Our sample of management earnings forecast (2002 through 2013) comes from I/B/E/S Guidance database. We merge this sample with the unadjusted actual EPS from I/B/E/S details files and remove observations with missing analyst estimates within 90 days prior to management earnings forecast announcement date. We also remove forecasts that are issued more than 180 days from the corresponding earnings announcement date.

We measure *MEF Accuracy* as the earnings guidance issued by the firm minus the actual earnings, scaled by the stock price 2 days prior to earnings announcement date. We multiply the absolute value of this figure by -1, so that positive regressor coefficients indicate higher levels of forecast accuracy. *MEF Surprise* is the earnings guidance issued by the firm minus the median of the last I/B/E/S forecasts for each unique analysts 90 days through 2 days before the guidance announcement date, scaled by the stock price 2 days prior. *Analyst forecast dispersion* is the standard deviation of all analyst forecasts from 90 through 2 days prior to

[4] CS and CPS are not correlated (t = 0.4), which is important because we assume both variables to be endogenous to firm performance but not with each other (i.e., we apply the same set of instruments to both variables in the 2SLS specification).

announcement day. *Number of Analysts* is the number of unique forecasts from 90 through 2 days prior to announcement day. *Earnings Surprise is Positive* is a dummy of one if the earnings surprise is ≥ 0. *Forecast Duration* is the number of days between forecast and earnings announcements. *Firm Size* is the natural logarithm of market value. *Book-to-Market* is the book to market ratio. Our final sample for management earnings forecast analysis has 24,891 observations and we present the distribution of these variables in Table 1 Panel B.

4. Centrality slice (*CS*) and firm performance

Table 3 presents the results of the OLS and second-stage (instrumented) regressions with Tobin's Q as the dependent variable. We lag our main variables of interests, *CS* and *CPS*, and apply the same set of controls as Bebchuk, Cremers and Peyer (2011), which includes entrenchment index, firm size, insider ownership, profitability, capital expenditures to assets, leverage, R&D, and company age. We also include lagged Tobin's Q to effectively consider changes in firm value. There is however, one major difference in our specification. Rather than using industry-adjusted dependent variables (i.e., demeaning the dependent variable with the industry mean), we apply industry fixed effects instead. Gormley and Matsa (2014) show that models with industry-adjustments produce inconsistent estimates and can distort inferences and recommend researchers to use fixed effects estimators instead. Our regressions include year and industry (four digit SIC) fixed effects, with standard errors clustered at the firm level.

4.1.1. CS and Tobin's Q

We find a negative relation between *CS* and Tobin's Q in the OLS regression. However, such a relation may be endogenously determined because firms may optimally select the level of *CS* due to other governance constraints. Using the models in Table 2 as the first-stage in a 2SLS regression specification, we find that the coefficient for *CS* turns positive and significant when instrumented. We are confident that these instruments are valid given that the Hansen test of over-identifying restrictions fails to reject the null hypothesis. The economic impact of *CS* is significant. One standard deviation change in the value of *CS* is associated with an increase of 4.4% (0.205 x 0.215) in Tobin's Q for the subsequent year. *CPS* is however, positive but not significant. We separately run the 2SLS with only *CPS* and find that it is negative and significant, which is consistent with Bebchuk, Cremers and Peyer (2011). In addition, we also find consistent economic interpretations from the negative relations between Tobin's Q and *Log Book Value, Leverage, R&D Missing, Long CEO Tenure* and *Diversified*, while *lagged Tobin's Q*, *ROA* and *R&D* are positively associated with Tobin's Q. Our results remain consistent after including firm fixed effects to account for endogeneity issues attributable to firm-specific unobservables. The economic effect ends up larger for *CS* (15.5% change in Tobin's Q per standard deviation, t = 4.34), and some governance characteristics turns significant as well. In the instrumented regression with firm fixed effects, Tobin's Q is negatively related to *Insider Ownership* (t = -1.91), *Abnormal Total Compensation* (t = -3.19), and *CEO is Chair* (t = -2.66), while positively associated with *Founder* (t = 3.47).

4.1.2. CS and ROA

Next, we test the same regression specifications on another measure of firm performance – profitability as measured by ROA, and present the results in Table 4. *CS* is positively related to ROA in both the OLS (t = 1.93) and 2SLS (t = 2.28) regressions, consistent with our earlier finding on Tobin's Q. The economic magnitude of *CS* is significant at 0.7% change in ROA per standard deviation. Although *CPS* is not significant as a standalone endogenous variable, it is however, positive and significant when instrumented (t = 1.95). The coefficient for *CPS* implies an even larger economic magnitude (1.4% change in ROA per standard deviation) than *CS*. Under the optimal selection hypothesis put forth in Bebchuk, Cremers and Peyer (2011), in the absence of agency problems, an optimal CPS can be positively correlated with firm performance either because of powerful tournament incentives or simply because high value firms are likely to attract star CEOs. To the extent that our Centrality Slice (*CS*) measure captures the relative value of superior information (and thus likely to proxy for star CEOs), our results seem to support the tournament hypothesis rather than the latter. Although we account for endogeneity in our study, we remain cautious in our interpretation because of the large literature in this field of study that show that the benefits from tournament incentive designs are invariant and vary across a variety of firm characteristics (see Bainbridge 2002; Milgrom and Roberts 1994).

In sum, the positive correlation between *CPS* and firm performance (Tobin's Q and ROA) supports our hypothesis that firms with higher *CS* enjoys better firm performance. This in turn validates the economics behind the value of advisory activities in Adams and Ferreira (2007)'s model. Although our results are the opposite of many studies that find CEO power to be value destroying, it could in fact be consistent, considering that our instrumented regressions control for a multitude of variables including governance, firm and CEO characteristics. Our interpretation of the *CS* results is relatively straightforward: The positive relation of *CS* with firm value, in our specification, is reflective of an optimal selection outcome that varies across firms. The implication is that firms may not achieve first order improvements by implementing a policy of high *CS*, but they can enjoy better advisory benefits if they institute a system that optimally supports high *CS*.

5. Centrality slice (*CS*) and CEO turnover

In this section, we examine the consistency of CEO turnover events with the results in the previous section. If high *CS* generates additional positive firm value as shown in Table 3 and 4, then we should expect to see lower CEO replacements. However, such an outcome is also consistent with agency problems associated with powerful CEOs (Hermalin and Weisbach 1998). We interact *CS* with stock performance to separate these effects.

5.1.1. Lower likelihood of turnover

Table 5 shows the results from a logit regression with the dependent variables CEO turnover (1, 0) and CEO forced turnover (1, 0), with firm fixed effects. Models 1 and 3 use stock returns as the measure for stock performance, while models 2 and 4 use market returns and firm-specific returns (market returns – stock returns) as per Jenter and Kanaan (2015). We find a reduced probability of CEO turnover and forced turnover when *CS* is high. The economic significance is non-trivial. An increase in the standard deviation of *CS* by one reduces the probability of turnover by 8.3% (exp(0.205 x -0.389) -1) and forced turnover by 17.3%.

5.1.2. Performance sensitivity and forced turnover

We do not find support for agency problems in our results. The interaction terms for stock performance and *CS* are negative, implying that performance sensitivity increases with *CS*. Given that the probability of turnover increases by 3.8% per -50% in stock returns (exp(-0.5 x -0.078), one standard deviation increase in *CS* is associated with an increase in performance sensitivity of 22% ((exp(0.205 * -0.082) - 1)/3.8%) and 27% in models 1 and 2, respectively.

The probability of forced turnovers increases when the firm performs badly (i.e., stock and firm specific returns), but performance sensitivity appears to be muted. As expected of a competitive managerial labor market, the probability of forced turnovers increases when the market is performing well, though high *CS* reduces this probability, possibly due to its positive firm value effect that correlates with the firms' behavior in retaining good CEOs.

In sum, firms with high *CS* are more likely to retain their CEOs and we do not find evidence to suggest that this is driven by agency problems. On the contrary, we find that *CS* is more performance sensitive to normal turnover though muted in forced turnover. Taken together, our results add to those in Faleye, Kovacs and Venkateswaran (2012) where the authors find that high centrality lowers the switching costs for CEOs in the managerial labor market.

6. Centrality slice (*CS*) and management earnings forecast

In this last section, we examine the management earnings characteristics of high *CS* firms. First, we hypothesize that firms with high *CS* should have high management forecast accuracy due to superior information sharing. Second, if high *CS* signals high quality and precise information, then market reactions to forecast surprise should be stronger for high CS firms.

Table 6 presents the results from a multivariate regression, with management earnings forecast accuracy (percentile rank) as the dependent variable and standardized regressors. We add the following standard controls in the regression: *Analyst forecast dispersion*, *number of analysts*, dummy to indicate if *Earnings Surprise is Positive*, length in days between forecast and actual earnings announcement (*duration*), *Book-to-Market* and *Firm Size*.

6.1.1. CS and management earnings forecast accuracy

As expected, *CS* is indeed positively related to forecast accuracy (0.607, t = 3.35). Larger analyst coverage and more independent directors are associated with more accurate forecasts, consistent with the finding in Ajinkya, Bhojraj and Sengupta (2005). However, the economic significance of these variables are weaker than analyst forecast dispersion (-4.297, t = 2.17) which proxies for market uncertainty.

6.1.2. Market reactions to forecast surprise conditional on CS

To understand whether the *CS* effect comes from better information sharing or earnings management, we examine the market reactions to management earnings forecast events in a multivariate setup. If *CS* is an indication of agency problems, then market reactions to forecast surprises should be muted. On the other hand, a positive and significant market reaction to forecast surprise would be consistent with better information sharing. In addition to *CS*, we include the raw management centrality (*Management Centrality*) score to capture adverse market expectations on powerful management that could be hard to monitor.

Our dependent variable is the 3-day cumulative abnormal returns (CAR) centered on announcement day, obtained by subtracting the corresponding size and book-to-market (2 x 3) benchmark return from the cumulative stock returns over the three days.[5] We multiply the coefficients by 100 and present the multivariate regression results with standardized regressors in Table 7 Panel B.

We find support for the superior information hypothesis. Controlling for forecast surprise and other control variables, we find that *CS* and *Management Centrality* positively and negatively relate to event CAR, respectively. The interaction term for *Surprise* and *CS* is positive and significant (t = 2.29). One standard deviation increase in *CS* corresponds to a 0.3% increase in market reaction (CAR) to forecast surprise, while the interaction term for surprise and management centrality is negative though not significant.

If the superior information hypothesis is robust, then we predict that the overall informative-ness of a firm with high monitoring intensity will fall because such activities reduce management incentives to share information. As such, we should expect to see opposite results to the interaction term for surprise, and number of independent directors which proxies for monitoring intensity. We find that this is indeed the case. The interaction term is negative and significant (-0.3%, t = -4.34).

6.1.3. CS and small earnings surprise

Our last test for this section is a logistic regression with small earnings surprise dummy as the dependent variable. We define an earnings announcement as a small surprise event if the difference between the actual earnings and median analyst consensus forecast is within 1 cent. We associate firms that miss or beat earnings by less than 1 cent with a higher likelihood of

[5] Our benchmark returns are from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

earnings management. Therefore, if high *CS* is associated with powerful CEOs that are hard to monitor, then we should observe a positive relation between *CS* and small earnings surprises. In Table 8, we show that *CS* is either not associated with or negatively related to small earnings surprise. *Number of independent directors*, a proxy for monitoring intensity, predicts less likelihood of small earnings surprise as well.

In sum, we do not find evidence suggesting that high *CS* is associated with agency problems. On the contrary, market reactions to *CS* are consistent with our expectations that firms with high CS enjoy better advisory benefits from superior information sharing.

7. Conclusion

Using social network centrality as a proxy for information quality and precision, we provide empirical support for the theoretical model in Adams and Ferreira (2007), in which the authors show that the advisory value of the board can be unlocked by improving the willingness of management to share their information with the independent directors on the board.

We hypothesize that a more networked management, relative to their non-executives on the board is both a proxy for superior information (quality and precision) and lesser incentives for independent directors to monitor and interfere with business decisions. As a result, management with higher centrality slice (*CS*) are more willing to share their information in a constructive manner, and independent directors can engage in more activities that are advisory in nature. Firm value improves as a result.

We begin our study by examining the relation between *CS* and firm value, through instrumented regressions with a barrage of variables including the CEO Pay Slice from Bebchuk, Cremers and Peyer (2011) which proxies for CEO power as well. We find a positive relation between *CS* and firm value. Next, we examine the likelihood of CEO turnover and do not find evidence of agency problems. Instead, we find that high *CS* is associated with lower turnover likelihood and higher performance sensitivity, which is consistent with lower switching costs for CEOs with higher *CS*. In our final section, we examine the relation between *CS* and management forecast accuracy, as well as market reactions to such events conditional on *CS*. We find that firms with high *CS* issue forecasts that are more accurate and markets react more strongly to the forecast surprises of high *CS* firms. Taken together, we find support for our superior information hypothesis but not for agency problems. This in turn validates the economics behind the theoretical model of Adams and Ferreira (2007).

Although our results are surprising with respect to the large literature on corporate governance that examines similar issues, they can be consistent if we consider that our instrumented regressions also control for many other governance, firm and CEO characteristics. To that extent, our *CS* results could be reflective of an optimal selection outcome that varies across firms. Thus, we do not expect firms to achieve immediate improvements by simply adopting a policy of high *CS*. However, they are likely to enjoy better advisory benefits if they can shape their firm policies to support high *CS* in an optimal manner.

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Table 1: Descriptive statistics

Descriptive statistics from 2002 – 2013 are reported. Panel A reports the annual variables. *Eigenvector Slice*, *Closeness Slice* and *Betweenness Slice* are the ratios of eigenvector centrality, closeness centrality and betweenness centrality between Executive Directors and Non-executive directors, respectively. *Centrality Slice (CS)* is the first principal component of eigenvector slice, closeness slice and betweenness slice. *Number of independent directors* is the total number of independent directors as reported by BoardEx. *CEO Pay Slice (CPS)* is the fraction of CEO total compensation to the total compensation of the top 5 executives (ExecuComp item TDC1). *Industry median CPS* is the median CPS in the four-digit standard industrial classification (SIC) group. *Tobin's q* is the market value of equity plus the book value of assets minus the book value of equity, divided by the book value of assets. *ROA* is the operating income divided by book value of assets. *Eindex* is the entrenchment index of Bebchuk, Cohen, and Ferrell (2009). *Log Book Value* is the log of the book value of assets. *Insider Ownership* is the fraction of shares held by insiders as reported by ExecuComp. *Capex/Assets* is the ratio of capital expenditures to assets. *Leverage* is the long-term debt to assets ratio. *R&D* is the ratio of R&D to sales. *Company Age* is the number of years since listed on CRSP. *Founder* is a dummy of one if CEO is the same when the firm was first listed on CRSP. *CEO Outsider* is a dummy of one if the CEO was working at the firm for less than one year prior to appointment. *Abnormal Total Compensation* is the residual of a regression of total compensation of the top 5 executives on log book value with industry and year fixed effects. *Relative Equity Compensation* is the ratio of the fraction of equity compensation of the CEO to the average fraction of equity compensation of the next top 4 executives (EBC/TDC1, where EBC is the equity-based compensation calculated as the sum of the value of the restricted shares granted plus the Black-Scholes value of options granted). *CEO Ownership ≥ 20%* is a dummy of one if the CEO holds at least 20% of the total shares outstanding. *CEO Tenure* is the number of years since becoming CEO. *Diversified* is a dummy of one if the firm reports more than one segment on Compustat's segment database. *CEO Is Chair* is a dummy of one if the CEO is also the Chair of the board. *CEO Is Only Director* is a dummy variable of one if the CEO is the only executive officer on the board. *Number of VPs* is the number of vice presidents among the top five executives. Panel B reports the correlation matrix for selected variables of interests. Panel C reports the quarterly variables for management earnings forecast and earnings events. *Management forecast accuracy (MEF)* is the announced forecast minus actual earnings per share (EPS), and deflated by stock price two days prior to announcement day. *Analyst forecast dispersion* is the standard deviation of all analyst forecasts from 90 through 2 days prior to announcement day. *Number of Analysts* is the number of unique forecasts from 90 through 2 days prior to announcement day. *Earnings Surprise is Positive* is a dummy of one if the earnings surprise is ≥ 0. *Forecast Duration* is the number of days between forecast and earnings announcements. *Firm Size* is the natural logarithm of market value. *Book-to-Market* is the book to market ratio.

Panel A: Descriptive statistics of annual variables

Variable	Number of observations	Mean	Standard deviation	Minimum	Maximum
Eigenvector Slice	9,631	0.097	0.197	0	1
Closeness Slice	9,631	0.158	0.088	0	0.735
Betweenness Slice	9,631	0.083	0.150	0	1
Centrality Slice	9,631	0.233	0.205	0	1.588
Number of Non-executive Directors	9,631	8.741	2.649	2	25
CEO Pay Slice (CPS)	9,631	0.403	0.113	0	0.955
Industry Median CPS	9,631	0.393	0.036	0.151	0.603
Tobin's Q	9,631	1.805	1.117	0.704	8.115
Eindex	9,631	2.765	1.219	0	6
Log Book Value	9,631	7.998	1.656	2.594	14.698
Inside Ownership	9,631	0.016	0.043	0	2.090
Insider Ownership Squared	9,631	0.002	0.047	0	4.368
ROA	9,631	0.121	0.102	-1.691	1.183
Capex/Assets	9,631	0.043	0.048	-0.001	0.496
Leverage	9,631	0.190	0.169	0	1.872
R&D	9,631	0.056	0.457	0	28.451
R&D Missing	9,631	0.425	0.494	0	1
Company Age	9,631	28.615	20.385	1	88
Founder	9,631	0.158	0.365	0	1
Abnormal Total Compensation	9,631	0.040	0.486	-2.693	4.029
Relative Equity Compensation	9,631	1.217	0.862	0	30.903
CEO Ownership ≥ 20%	9,631	0.007	0.081	0	1
CEO Tenure	9,631	6.659	6.506	0	50
Diversified	9,631	0.351	0.477	0	1
CEO Is Outsider	9,631	0.706	0.456	0	1
CEO Is Chair	9,631	0.584	0.493	0	1
CEO Is Only Director	9,631	0.579	0.494	0	1
Females on Board	9,631	0.117	0.097	0	1
Number of VPs	9,631	3.275	0.967	1	4

Panel B: Cross-sectional correlation between selected variables

Variable	Eigen Slice	Close Slice	Bet Slice	Cent Slice	Non-exec	CPS	Q	Eindex
Eigenvector Slice	1							
Closeness Slice	0.20826	1						
Betweenness Slice	0.65154	0.24726	1					
Centrality Slice	0.83649	0.5709	0.85607	1				
Number of Non-executives	-0.01909	-0.47522	-0.04009	-0.19211	1			
CEO Pay Slice (CPS)	0.03277	-0.17573	0.03106	-0.0356	0.08546	1		
Tobin's Q	-0.00035	0.17012	-0.03365	0.03964	-0.22748	-0.04223	1	
Eindex	0.00203	-0.11991	0.00356	-0.04023	0.08499	0.09509	-0.09362	1

Panel C: Descriptive statistics of quarterly variables for forecast and earnings events

Variable	Number of observations	Mean	Standard deviation	Minimum	Maximum
MEF Accuracy	24,891	-0.007	0.059	-5.403	0
MEF Surprise	23,877	-0.002	0.042	-1.528	5.483
Forecast Dispersion (MEF)	24,891	0.033	0.057	0	2.548
Number of Analyst (MEF)	24,891	7.054	5.893	1	50
Forecast Dispersion (Earnings)	24,891	0.027	0.067	0	4.534
Number of Analyst (Earnings)	24,891	7.977	6.439	1	50
Duration	24,891	75.537	28.126	1	180
Book-to-market	24,891	0.522	1.164	0.000	146.665
Log Book Value	24,891	14.105	1.630	8.596	20.121

Table 2: Centrality Slice (CS), CEO Pay Slice (CPS) and firm characteristics

The dependent variable is centrality slice (CS) and CEO pay slice (CPS). CS is the first principal component of $(\frac{Executive\ Directors_{eigen}}{Non\text{–}Executives_{eigen}}, \frac{Executive\ Directors_{between}}{Non\text{–}Executives_{between}}, \frac{Executive\ Directors_{close}}{Non\text{–}Executives_{close}})$, where subscripts indicate the centrality measures. CPS is the fraction of CEO total compensation to the total compensation of the top 5 executives (ExecuComp item TDC1). Coefficients and t-statistics (in parentheses) are reported. *CEO Is Only Director* is a dummy variable of one if the CEO is the only executive officer on the board. *Female on Board* is the ratio of female directors to all board directors. *Industry median CPS* is the median CPS in the four-digit standard industrial classification (SIC) group. *Number of VPs* is the number of vice presidents among the top five executives. *Tobin's Q* is the market value of equity plus the book value of assets minus the book value of equity, divided by the book value of assets. *Eindex* is the entrenchment index of Bebchuk, Cohen, and Ferrell (2009). *Log Book Value* is the log of the book value of assets. *Insider Ownership* is the fraction of shares held by insiders as reported by ExecuComp. *ROA* is the operating income divided by book value of assets. *Capex/Assets* is the ratio of capital expenditures to assets. *Leverage* is the long-term debt to assets ratio. *R&D* is the ratio of R&D to sales. *R&D Missing* is a dummy of one if the R&D figure is missing in that year. *Company Age* is the number of years since listed on CRSP. *Founder* is a dummy of one if CEO is the same when the firm was first listed on CRSP. *Abnormal Total Compensation* is the residual of a regression of total compensation of the top 5 executives on log book value with industry and year fixed effects. *Relative Equity Compensation* is the ratio of the fraction of equity compensation of the CEO to the average fraction of equity compensation of the next top 4 executives (EBC/TDC1, where EBC is the equity-based compensation calculated as the sum of the value of the restricted shares granted plus the Black-Scholes value of options granted). *CEO Ownership ≥ 20%* is a dummy of one if the CEO holds at least 20% of the total shares outstanding. *CEO Tenure* is the number of years since becoming CEO. *Diversified* is a dummy of one if the firm reports more than one segment on Compustat's segment database. *CEO Outsider* is a dummy of one if the CEO was working at the firm for less than one year prior to appointment. *CEO Is Chair* is a dummy of one if the CEO is also the Chair of the board. Year and SIC fixed effects apply. Standard errors are clustered at the firm level, *, **, and *** indicate two-tailed statistical significance at the 10, 5 and 1 percent levels, respectively.

Table 2 (Cont'd)

Variable	Centrality Slice (CS)	CEO Pay Slice (CPS)
	(1)	(2)
Intercept	0.022	0.527 ***
	(0.54)	(10.35)
CEO is Only Director	0.014 ***	-0.165 ***
	(4.17)	(19.9)
Female on Board	0.028	-0.019
	(1.47)	(-0.42)
Industry Median CPS	0.528 ***	-0.074
	(11.27)	(-0.94)
Number of VPs	0.009 ***	-0.005
	(5.63)	(-1.49)
Tobin's Q	-0.009 ***	-0.004
	(-4.36)	(-0.88)
Eindex	0.005 ***	-0.006 *
	(3.18)	(-1.84)
Log Book Value	0.005 ***	-0.009 ***
	(2.84)	(-2.9)
Insider Ownership	-0.293 ***	0.121
	(-4.3)	(0.8)
Insider Ownership Squared	0.133 ***	-0.022
	(4.35)	(-0.31)
ROA	0.028	-0.017
	(1.27)	(-0.31)
Capex/Assets	-0.139 ***	-0.06
	(-3.35)	(-0.59)
Leverage	0.006	0.013
	(0.45)	(0.51)
R&D	-0.006 ***	-0.012 ***
	(-2.82)	(-2.81)
R&D Missing	0.003	0.001
	(0.47)	(0.08)
Company Age	0 **	0
	(2.36)	(1.46)
Founder	-0.001	0.004
	(-0.08)	(0.23)
Abnormal Total Compensation	0.07 ***	0.013 *
	(16.96)	(1.76)
Relative Equity Compensation	0.035 ***	-0.004 *
	(8.32)	(-1.74)
CEO Ownership > 20%	0.013	-0.04
	(0.6)	(-1.09)
CEO Tenure (1 year)	-0.003	-0.031 ***
	(-0.68)	(-3.48)
CEO Tenure (2 years)	-0.013 ***	-0.052 ***
	(-3.26)	(-7.41)
CEO Tenure (3 - 4 years)	-0.007 **	-0.039 ***
	(-2.06)	(-5.84)
CEO Tenure (5-6 years)	0.001	-0.018 ***
	(0.36)	(-2.7)
CEO Tenure Missing	-0.006	0.017
	(-0.28)	(0.39)
Diversified	0.001	0.002
	(0.3)	(0.16)
CEO Outsider	0.006 *	0.01
	(1.72)	(1.22)
CEO Is Chair	0.007 *	0.002
	(1.88)	(0.31)
Number of observations	9,168	9,168
Adjusted R-squared	0.30	0.26
Fixed Effects	Year, SIC	Year, SIC

Table 3: Tobin's Q and Centrality Slice (CS)

The dependent variable is Tobin's Q, measured as the market value of equity plus the book value of assets minus the book value of equity, divided by the book value of assets. Coefficients and t-statistics (in parentheses) are reported. *Centrality slice (CS)* is the first principal component of $(\frac{Executive\ Directors_{eigen}}{Non{-}Executives_{eigen}}, \frac{Executive\ Directors_{between}}{Non{-}Executives_{between}}, \frac{Executive\ Directors_{close}}{Non{-}Executives_{close}})$, where subscripts indicate the centrality measures. *CEO pay slice (CPS)* is the fraction of CEO total compensation to the total compensation of the top 5 executives (ExecuComp item TDC1). *Eindex* is the entrenchment index of Bebchuk, Cohen, and Ferrell (2009). *Log Book Value* is the log of the book value of assets. *Insider Ownership* is the fraction of shares held by insiders as reported by ExecuComp. *ROA* is the operating income divided by book value of assets. *Capex/Assets* is the ratio of capital expenditures to assets. *Leverage* is the long-term debt to assets ratio. *R&D* is the ratio of R&D to sales. *R&D Missing* is a dummy of one if the R&D figure is missing in that year. Company Age is the number of years since listed on CRSP. *Founder* is a dummy of one if CEO is the same when the firm was first listed on CRSP. *Abnormal Total Compensation* is the residual of a regression of total compensation of the top 5 executives on log book value with industry and year fixed effects. *Relative Equity Compensation* is the ratio of the fraction of equity compensation of the CEO to the average fraction of equity compensation of the next top 4 executives (EBC/TDC1, where EBC is the equity-based compensation calculated as the sum of the value of the restricted shares granted plus the Black-Scholes value of options granted). *CEO Ownership ≥ 20%* is a dummy of one if the CEO holds at least 20% of the total shares outstanding. *CEO Tenure* is the number of years since becoming CEO. *Diversified* is a dummy of one if the firm reports more than one segment on Compustat's segment database. *CEO Outsider* is a dummy of one if the CEO was working at the firm for less than one year prior to appointment. *CEO Is Chair* is a dummy of one if the CEO is also the Chair of the board. Year and SIC fixed effects apply. Standard errors are clustered at the firm level, *, **, and *** indicate two-tailed statistical significance at the 10, 5 and 1 percent levels, respectively.

Table 3 (Cont'd)

Variable	Tobin's Q			
	OLS	Second Stage (Instrumented)		
Intercept	0.783 *** (9.17)	1.405 *** (4.57)	0.65 *** (3.74)	0.023 (0.09)
CS, t-1	**-0.076 **** **(-1.95)**		**0.215 **** **(2.22)**	**0.77 ***** **(4.34)**
CPS, t-1	-0.105 (-1.23)	-0.795 * (-1.76)	0.166 (0.4)	0.717 (0.98)
Tobin's Q, t-1	0.604 *** (25.96)	0.592 *** (25.57)	0.611 *** (26.08)	0.301 *** (11.26)
Eindex	-0.001 (-0.12)	0.015 (1.44)	-0.001 (-0.14)	-0.016 * (-1.5)
Log Book Value	-0.028 *** (-4.15)	-0.045 *** (-4.56)	-0.033 *** (-3.54)	0.099 *** (2.52)
Insider Ownership	-0.263 (-0.91)	-0.637 * (-1.87)	-0.355 (-1.09)	-0.987 * (-1.91)
Insider Ownership Squared	0.104 (0.81)	0.272 * (1.83)	0.147 (1.03)	0.56 ** (2.29)
ROA	1.578 *** (4.23)	1.506 *** (4.48)	1.554 *** (4.4)	1.706 *** (7.56)
Capex/Assets	0.431 (1.25)	0.412 (1.2)	0.412 (1.23)	1.261 *** (2.76)
Leverage	-0.174 (-1.65)	-0.261 ** (-2.33)	-0.161 (-1.6)	-0.747 *** (-5.42)
R&D	0.151 *** (4.2)	0.086 ** (2.01)	0.154 *** (4.49)	0.092 (1.19)
R&D Missing	-0.043 (-1.65)	-0.047 (-1.37)	-0.075 * (-1.79)	-0.11 * (-1.87)
Company Age	0 (0.88)	0.001 ** (2.22)	0 (0.94)	0.003 (0.45)
Founder	0.004 (0.14)	-0.013 (-0.45)	-0.005 (-0.15)	0.38 *** (3.47)
Abnormal Total Compensation, t-1	0.029 (1.55)	0.09 ** (2.28)	-0.006 (-0.15)	-0.147 *** (-3.19)
Relative Equity Compensation, t-1	0.002 (0.4)	0.028 * (1.55)	-0.006 (-0.43)	-0.007 (-0.29)
CEO Ownership > 20%	0.115 (1.1)	0.127 (1.22)	0.107 (0.99)	-0.06 (-0.35)
CEO Tenure (1 year)	-0.005 (-0.23)	-0.03 (-1.29)	-0.015 (-0.7)	-0.019 (-0.84)
CEO Tenure (2 years)	0.005 (0.22)	-0.009 (-0.38)	0.02 (0.81)	0.054 ** (2.31)
CEO Tenure (3 - 4 years)	-0.028 (-1.7)	-0.032 * (-1.86)	-0.015 (-0.7)	0.016 (0.7)
CEO Tenure (5-6 years)	-0.047 *** (-2.78)	-0.052 *** (-3.03)	-0.044 ** (-2.4)	-0.006 (-0.28)
CEO Tenure Missing	0.081 (0.89)	0.147 (1.39)	0.083 (0.85)	-0.019 (-0.1)
Diversified	-0.066 *** (-3.16)	-0.048 ** (-2.03)	-0.063 *** (-2.8)	-0.024 (-0.75)
CEO Outsider	-0.004 (-0.26)	-0.037 (-1.56)	-0.008 (-0.45)	0.014 (0.32)
CEO Is Chair	0.014 (0.87)	0.01 (0.57)	0.015 (0.73)	-0.082 *** (-2.66)
Number of observations	9,631	9,572	9,168	9,168
Adjusted R-squared	0.73	0.64	0.73	
Fixed Effects	Year, SIC	Year, SIC	Year, SIC	Year, SIC, Firm
Hansen J statistic		Fail to reject null	Fail to reject null	Fail to reject null

Table 4: ROA and Centrality Slice (CS)

The dependent variable is Return on Assets (ROA), measured as the operating income divided by the book value of asset ratio. Coefficients and t-statistics (in parentheses) are reported. *Centrality slice (CS)* is the first principal component of ($\frac{Executive\ Directors_{eigen}}{Non\text{-}Executives_{eigen}}, \frac{Executive\ Directors_{between}}{Non\text{-}Executives_{between}}, \frac{Executive\ Directors_{close}}{Non\text{-}Executives_{close}}$), where subscripts indicate the centrality measures. *CEO pay slice (CPS)* is the fraction of CEO total compensation to the total compensation of the top 5 executives (ExecuComp item TDC1). *Tobin's Q* is the market value of equity plus the book value of assets minus the book value of equity, divided by the book value of assets. *Eindex* is the entrenchment index of Bebchuk, Cohen, and Ferrell (2009). *Log Book Value* is the log of the book value of assets. *Insider Ownership* is the fraction of shares held by insiders as reported by ExecuComp. *Capex/Assets* is the ratio of capital expenditures to assets. *Leverage* is the long-term debt to assets ratio. *R&D* is the ratio of R&D to sales. *R&D Missing* is a dummy of one if the R&D figure is missing in that year. *Company Age* is the number of years since listed on CRSP. *Founder* is a dummy of one if CEO is the same when the firm was first listed on CRSP. *Abnormal Total Compensation* is the residual of a regression of total compensation of the top 5 executives on log book value with industry and year fixed effects. *Relative Equity Compensation* is the ratio of the fraction of equity compensation of the CEO to the average fraction of equity compensation of the next top 4 executives (EBC/TDC1, where EBC is the equity-based compensation calculated as the sum of the value of the restricted shares granted plus the Black-Scholes value of options granted). *CEO Ownership ≥ 20%* is a dummy of one if the CEO holds at least 20% of the total shares outstanding. *CEO Tenure* is the number of years since becoming CEO. *Diversified* is a dummy of one if the firm reports more than one segment on Compustat's segment database. *CEO Outsider* is a dummy of one if the CEO was working at the firm for less than one year prior to appointment. *CEO Is Chair* is a dummy of one if the CEO is also the Chair of the board. Year and SIC fixed effects apply. Standard errors are clustered at the firm level, *, **, and *** indicate two-tailed statistical significance at the 10, 5 and 1 percent levels, respectively.

Table 4 (Cont'd)

Variable	Return on Assets (ROA)		
	OLS	Second Stage (Instrumented)	
Intercept	-0.108 *** (-7.4)	-0.094 * (-1.9)	-0.158 *** (-5.75)
CS, t-1	**0.01 **** **(1.93)**		**0.035 **** **(2.28)**
CPS, t-1	0.031 *** (2.73)	-0.032 (-0.46)	0.127 ** (1.95)
Tobin's Q, t-1	0.031 *** (15.44)	0.031 *** (14.09)	0.032 *** (14.88)
Eindex	0.001 (0.7)	0 (0.28)	0 (0.11)
Log Book Value	0.009 *** (5.57)	0.01 *** (5.17)	0.009 *** (5.25)
Insider Ownership	-0.036 (-0.84)	-0.016 (-0.33)	-0.008 (-0.16)
Insider Ownership Squared	0.015 (0.8)	0.008 (0.34)	0.003 (0.16)
Capex/Assets	0.005 (0.14)	0.025 (0.67)	-0.018 (-0.41)
Leverage	-0.121 *** (-8.65)	-0.121 *** (-7.78)	-0.128 *** (-9.34)
R&D	-0.037 *** (-3.96)	-0.031 *** (-5.31)	-0.035 *** (-3.94)
R&D Missing	0.014 *** (3.2)	0.021 *** (3.78)	0.016 *** (2.47)
Company Age	0 (1.39)	0 (1.65)	0 (1.19)
Founder	-0.001 (-0.33)	0 (0.02)	0.002 (0.37)
Abnormal Total Compensation, t-1	-0.008 *** (-2.62)	-0.006 (-1.08)	-0.013 ** (-2.1)
Relative Equity Compensation, t-1	0 (-0.25)	-0.001 (-0.21)	-0.004 * (-1.73)
CEO Ownership > 20%	0.017 (1.34)	0.013 (0.99)	0.016 (1.31)
CEO Tenure (1 year)	-0.006 ** (-2.2)	-0.007 * (-1.88)	-0.004 (-1.22)
CEO Tenure (2 years)	0.001 (0.21)	-0.001 (-0.19)	0.004 (1.09)
CEO Tenure (3 - 4 years)	0.003 (1.05)	0.002 (0.77)	0.007 ** (1.94)
CEO Tenure (5-6 years)	0 (0.14)	0.002 (0.73)	0.003 (1.12)
CEO Tenure Missing	0.015 ** (2.18)	0.009 (1.35)	0.013 * (1.87)
Diversified	-0.005 (-1.48)	-0.007 * (-1.87)	-0.007 ** (-2.19)
CEO Outsider	-0.002 (-0.78)	-0.002 (-0.55)	-0.003 (-1.22)
CEO Is Chair	-0.001 (-0.39)	-0.003 (-0.87)	-0.004 (-1.13)
Number of observations	9,631	9,572	9,168
Adjusted R-squared	0.33	0.22	0.24
Fixed Effects	Year, SIC	Year, SIC	Year, SIC
Hansen J statistic		Fail to reject null	Fail to reject null

Table 5: CEO turnover and Centrality Slice (CS)

This table presents the logit regressions with the dependant variable as turnover dummy equal to one if the CEO for firm i in year t is not the same as in year t + 1. Coefficients and t-statistics (in parentheses) are reported. *Centrality slice (CS)* is the first principal component of $\left(\frac{Executive\ Directors_{eigen}}{Non\text{-}Executives_{eigen}}, \frac{Executive\ Directors_{between}}{Non\text{-}Executives_{between}}, \frac{Executive\ Directors_{close}}{Non\text{-}Executives_{close}}\right)$, where subscripts indicate the centrality measures. *CEO pay slice (CPS)* is the fraction of CEO total compensation to the total compensation of the top 5 executives (ExecuComp item TDC1). *ROA* is the operating income divided by the book value of asset ratio. *Stock return* is the return over the last calendar year before the change in CEO. *Market return* is the value-weighted CRSP return. *Firm-specific return* is the difference between the firm return and market return. *CEO Tenure* is the number of years since becoming CEO. *CEO Age > 60* is a dummy of one if the CEO's age is above 60. *CEO Is Chair* is a dummy of one if the CEO is also the Chair of the board. Standard errors are clustered at the firm level, *, **, and *** indicate two-tailed statistical significance at the 10, 5 and 1 percent levels, respectively.

Variable	CEO Turnover Dummy		CEO Forced Turnover Dummy	
	(1)	(2)	(3)	(4)
Intercept	-2.68 ***	-2.66 ***	-4.141 ***	-4.292 ***
	(-19.22)	(-18.57)	(-15.44)	(-15.16)
Centrality Slice	-0.371 **	-0.389 **	-0.917 ***	-0.777 **
	(-2.24)	(-2.32)	(-2.47)	(-2.19)
CPS	-0.098	-0.165	-0.388	-0.19
	(-0.35)	(-0.57)	(-0.66)	(-0.32)
ROA	-0.495 ***	-0.488 ***	-0.537 ***	-0.531 ***
	(-3.75)	(-3.73)	(-3.07)	(-2.86)
Stock Returns	-0.078 ***		-0.085 *	
	(-3.01)		(-1.85)	
Stock Returns x CPS	0.04		-0.05	
	(0.66)		(-0.47)	
Stock Returns x Slice	-0.082 **		0.014	
	(-2.36)		(0.15)	
Firm-Specific Returns		-0.069 **		-0.145 ***
		(-2.27)		(-2.65)
Firm-Specific Returns x CPS		0.006		0.017
		(0.09)		(0.13)
Firm-Specific Returns x Slice		-0.091 **		0.087
		(-2.3)		(0.87)
Market Returns		-0.412		2.475 **
		(-0.7)		(2.05)
Market Returns x CPS		1.248		-3.295
		(0.92)		(-1.11)
Market Returns x Slice		0.281		-2.621 **
		(0.42)		(-2.18)
CEO Tenure (1 year)	0.157	0.159	-0.243	-0.253
	(1.43)	(1.44)	(-0.84)	(-0.87)
CEO Tenure (2 years)	0.107	0.109	0.446 **	0.451 **
	(0.94)	(0.96)	(1.95)	(1.97)
CEO Tenure (3 - 4 years)	0.402 ***	0.404 ***	0.287	0.292
	(4.53)	(4.55)	(1.38)	(1.4)
CEO Tenure (5-6 years)	0.395 ***	0.394 ***	0.526 ***	0.53 ***
	(4.16)	(4.15)	(2.57)	(2.6)
CEO Age > 60	1.538 ***	1.533 ***	1.288 ***	1.28 ***
	(21.54)	(21.45)	(8.3)	(8.25)
CEO Is Chair	-0.251 ***	-0.25 ***	-0.544 ***	-0.545 ***
	(-3.88)	(-3.88)	(-3.62)	(-3.62)
Number of observations	14,606	14,606	14,606	14,606
Pseudo R-squared	0.08	0.08	0.07	0.07
Wald's Test	607.47 ***	610.2 ***	177.58 ***	179.5 ***

Table 6: Management forecast (MEF) accuracy and Centrality Slice (CS)

The dependant variable is management forecast accuracy (percentile rank), calculated as the forecast minus actual earnings per share (EPS), and deflated by stock price two days prior to announcement day. Coefficients of standardized independent variables and t-statistics (in parentheses) are reported. *Centrality slice (CS)* is the first principal component of ($\frac{Executive\ Directors_{eigen}}{Non\text{-}Executives_{eigen}}$, $\frac{Executive\ Directors_{between}}{Non\text{-}Executives_{between}}$, $\frac{Executive\ Directors_{close}}{Non\text{-}Executives_{close}}$), where subscripts indicate the centrality measures. *Management Centrality* is the first principal component of the three centrality measures. *Number of Non-executives* is the total number of non-executive directors as reported by BoardEx. *Analyst forecast dispersion* is the standard deviation of all analyst forecasts from 90 through 2 days prior to announcement day. *Number of Analysts* is the number of unique forecasts from 90 through 2 days prior to announcement day. *Earnings Surprise is Positive* is a dummy of one if the earnings surprise is ≥ 0. *Forecast Duration* is the number of days between forecast and earnings announcements. *Firm Size* is the natural logarithm of market value. *Book-to-Market* is the book to market ratio. Quarter and forecast type fixed effects apply. Standard errors are clustered by announcement day, *, **, and *** indicate two-tailed statistical significance at the 10, 5 and 1 percent levels, respectively.

Variable	Management Forecast (MEF) Accuracy (percentile rank)
Intercept	49.259 *** (9.41)
Centrality slice	0.607 *** (3.35)
Management Centrality	-0.123 (-0.69)
Number of Non-executives	0.996 *** (13.56)
Analyst Forecast Dispersion	-4.297 *** (-15.37)
Number of Analysts	0.405 ** (2.17)
Earnings Surprise is Positive	-2.9 *** (-5.3)
Forecast Duration	-0.168 *** (-22.11)
Book-to-Market	-4.931 *** (-15.27)
Firm Size	2.166 *** (13.85)
Number of observations	23,786
Adjusted R-squared	0.12
Fixed Effects	Quarter, Forecast type

Table 7: Management forecast (MEF) surprise and Centrality Slice (CS)

Panel A shows the univariate relation between the ten ranks of management earnings forecast surprise and the 3-day cumulative abnormal returns (CAR) centered on announcement day. Panel B shows the multivariate regression model with CAR as the dependent variable. Coefficients (x100) of standardized independent variables and t-statistics (in parentheses) are reported. *Forecast surprise* is the management forecast value minus the median consensus analyst forecast from 90 through 2 days prior to announcement day. *Centrality slice (CS)* is the first principal component of ($\frac{Executive\ Directors_{eigen}}{Non{-}Executives_{eigen}}, \frac{Executive\ Directors_{between}}{Non{-}Executives_{between}}, \frac{Executive\ Directors_{close}}{Non{-}Executives_{close}}$), where subscripts indicate the centrality measures. *Management Centrality* is the first principal component of the three centrality measures. *Number of Non-executives* is the total number of non-executive directors as reported by BoardEx. *Analyst forecast dispersion* is the standard deviation of all analyst forecasts from 90 through 2 days prior to announcement day. *Number of Analysts* is the number of unique forecasts from 90 through 2 days prior to announcement day. *Earnings Surprise is Positive* is a dummy of one if the earnings surprise is ≥ 0. *Forecast Duration* is the number of days between forecast and earnings announcements. *Firm Size* is the natural logarithm of market value. *Book-to-Market* is the book to market ratio. Quarter and forecast type fixed effects apply. Standard errors are clustered by announcement day, *, **, and *** indicate two-tailed statistical significance at the 10, 5 and 1 percent levels, respectively.

Panel A: Univariate CARs of each rank of management forecast surprise

Rank	N	CAR (-1,1)
Top	3,478	8.719 *** (28.32)
2	3,516	6.725 *** (26.97)
3	3,470	3.838 *** (16.03)
4	3,753	1.626 *** (7.52)
5	3,450	-0.22 (-0.91)
6	3,512	-2.147 *** (-8.87)
7	3,581	-3.852 *** (-15.12)
8	3,570	-6.017 *** (-20.71)
9	3,586	-8.764 *** (-30.63)
Bottom	3,493	-11.691 *** (-34.55)

Panel B: Multivariate regression

Variable	CAR (-1, 1)	
	(1)	(2)
Intercept	-10.677 *** (-3.42)	-4.698 (-0.43)
Forecast Surprise	4.732 *** (13.47)	7.869 *** (6.81)
Centrality Slice		0.111 ** (2.17)
Slice * Surprise		0.269 ** (2.29)
Management Centrality		-0.146 *** (-2.69)
Management Centrality * Surprise		-0.197 (-0.9)
Number of Non-executives		0.018 (-0.87)
Independent * Surprise		-0.345 *** (-4.34)
Analyst Forecast Dispersion	0.24 ** (2.42)	0.129 (0.31)
Dispersion * Surprise	-0.525 *** (-6.64)	-0.47 *** (-5.48)
Number of Analysts	-0.232 ** (-2.18)	-0.318 *** (-2.87)
Analysts * Surprise	-0.333 (-0.81)	-0.239 (-1.02)
Book-to-Market	0.505 *** (4.91)	0.256 ** (2.22)
Firm Size	0.255 *** (3.41)	0.058 (0.78)
Number of observations	30,197	24,859
R-Squared	0.09	0.07
Fixed Effects	Quarter, Forecast type	*Quarter, Forecast type*

Table 8: Small earnings surprise and Centrality Slice (CS)

This table presents the logit regressions with the dependant variable as small earnings surprise dummy equal to one if the difference between consensus median analyst forecast and actual earnings per share is within 1 cent. Coefficients and t-statistics (in parentheses) are reported. *Centrality slice (CS)* is the first principal component of $\left(\frac{Executive\ Directors_{eigen}}{Non\text{-}Executives_{eigen}}, \frac{Executive\ Directors_{between}}{Non\text{-}Executives_{between}}, \frac{Executive\ Directors_{close}}{Non\text{-}Executives_{close}}\right)$, where subscripts indicate the centrality measures. *Number of Non-executives* is the total number of non-executive directors as reported by BoardEx. *Analyst forecast dispersion* is the standard deviation of all analyst forecasts from 90 through 2 days prior to announcement day. *Number of Analysts* is the number of unique forecasts from 90 through 2 days prior to announcement day. *Earnings Surprise is Positive* is a dummy of one if the earnings surprise is ≥ 0. *Forecast Duration* is the number of days between forecast and earnings announcements. *Firm Size* is the natural logarithm of market value. *Book-to-Market* is the book to market ratio. Quarter and forecast type fixed effects apply. Standard errors are clustered by announcement day, *, **, and *** indicate two-tailed statistical significance at the 10, 5 and 1 percent levels, respectively.

Variable	Small Earnings Surprise	
	meet or beat by 1 cent	within 1 cent
Intercept	-0.592 ** (-4.16)	-0.476 * (-2.87)
Centrality slice	-0.01 (-1.07)	-0.014 * (-2.07)
Management Centrality	-0.006 (0.34)	-0.005 (0.26)
Number of Non-executives	-0.019 *** (-23.44)	-0.024 *** (-39.72)
Analyst Forecast Dispersion	-0.253 *** (-189.59)	-0.257 *** (-207.32)
Number of Analysts	0.036 *** (12.87)	0.009 (0.75)
Earnings Surprise is Positive		0.189 *** (52.03)
Forecast Duration to Earnings Announcement	-0.004 *** (-97.35)	-0.004 *** (-87.37)
Book-to-Market	-0.024 ** (-4.37)	-0.017 * (-2.2)
Firm Size	0.028 *** (10.59)	0.03 *** (11.85)
Number of observations	23,879	23,879
Walds Test	966.3 ***	1062.7 ***
LR	1128.7 ***	1245.2 ***
Fixed Effects	Quarter, Forecast type	Quarter, Forecast type

CHAPTER TWO

Questioning your peers – Evidence from conference calls

Abstract

We add two novel approaches to a large literature on analysts' conflicts of interests. Using analysts' tones during peer conference calls, and returns co-movement between their brokerages and hosts to proxy for the level of information advantage, we find that analysts from high returns co-moving brokerages exhibit language patterns that neither signal competition nor collusion. Our results show that the market values tones, with increasing reactions to the level of returns co-movement, consistent with the notion of pricing for competence. We also find that the market is not naïve as it discounts sentiment tones from brokerages sanctioned during the Global Analyst Research Settlements.

Keywords: Conference calls; earnings surprises; equity analysts; financial institutions; natural language

JEL Classification Codes: G14, G24

Questioning your peers – Evidence from conference calls

1. Introduction

Equity analysts are information vectors in capital markets that play an important role in validating the credibility of firm disclosures (Healy and Palepu 2001). Investors perceive them to be well-informed information brokers, and the markets move according to their opinions as a result (Cole 2001; Nocera 1997). A large number of studies examine the value and characteristics of analyst activities (e.g., Bailey, Li, Mao and Zhong 2003; Brown, Hagerman, Griffin and Zmijewski 1987; Brown and Rozeff 1979; Francis and Soffer 1997; Fried and Givoly 1982; Givoly and Lakonishok 1980; Lys and Sohn 1990; Womack 1996), and more importantly, question the integrity of information brokers in the face of conflicting interests (e.g., Beyer and Guttman 2011; Hong and Kubik 2003; Jackson 2005; Michaely and Womack 1999). In this paper, we provide new evidence on these conflicts through examining the analysts' choice of language during conference calls hosted by their counterparts.[6]

Many papers show evidence of analyst optimism due to career concerns, be it for generating trading volume for their employers or increasing their attractiveness for better outside opportunities. However, the predictions from our current understanding about analyst incentives remain perplexing when we consider cases where analysts may adopt competitive behaviors on behalf of their employers when they question the competition. Since some of the brokerages share a more connected information environment with the competition than to others, we posit that analysts from such firms should also possess superior information. However, do they use it to compete, collude or signal competence? Our results are largely

[6] We define counterparts as firms belonging to the double-digit SIC classification for financial institutions, 60 through 69.

consistent with the competence hypothesis, and we do not find support for competitive behaviors.

Our research design is simple. First, we compute the returns co-movements between brokerages and financial institutions to measure the closeness in information environment shared by the brokerage-institution pairs. We interpret this variable as the level of information advantage that analysts from the brokerage have when they cover the financial institution. We find that returns co-movements are not stronger within the 2-digit SIC sub-types, which validates the measure as a complementary expectations-based clustering mechanism for firms. Second, we examine the language patterns of the analysts during earnings conference calls and observe the corresponding market returns over three trading days centered on the conference call date.

We choose conference call tones for two reasons. First, conference calls are an increasingly common form of voluntary disclosure (Bushee, Matsumoto and Miller 2003), especially after the ratification of Regulation Fair Disclosure (REG FD) in October 2000. Unlike press releases, regulatory filings and reports, the questions and answers (Q&A) section of a transcribed conference captures spontaneous and unscripted participant responses. Second, using natural language programming (NLP) techniques, we are able to extract rich information from such responses to complement existing quantitative measures such as analyst forecast revisions. Truly, we do find significant market reactions to language patterns that supports the findings of many papers that show that the market prices language patterns. In this study, we find that abnormal returns are positively associated with sentiment, and negatively associated with litigious, superfluous and complex tones. We show that the market values the tones of brokerages that have high co-moving returns with the conference call host (financial institutions).

There is a possibility that the market reacts naively to the language patterns of analysts, especially if the latter represent large financial institutions. We find that this is not the case. Using the list of investment banks sanctioned during the Global Analyst Research Settlements in April 2003 as a dummy group, our results show that the market reacts negatively to the positive tones of the analysts from this group.[7] However, we find that this negativity is relatively mute during the Global Financial Crisis (GFC) period, possibly due to market expectations of heightened scrutiny.

Lastly, we like to point out to the reader that our focus on interactions between purely financial institutions is neither myopic nor trivial. The economically devastating 2007-08 GFC with its lingering aftermath speaks for the need of a deeper examination of the interactions between financial institutions, in our case, via their analysts. Financial analysts are among the few important market intermediaries that have the power to influence investors' decisions, and our study improves the understanding as to how the latter reacts to the analysts' interactions with financial institutions.[8]

Our paper adds two novel approaches to a large literature examining market reactions to analyst behaviors under the assumption that conflict of interest exists. Using language patterns as an outcome of analyst behavior and returns co-movement as a measure of the level of shared information environment between brokerages and the financial institutions, we find support for neither competitive nor collusive behaviors. Our results also suggest that the market does not react naively to analyst tones and perceive competency in analysts from brokerages with high returns co-movement to the financial firms these analysts cover.

[7] The Global Analyst Research Settlements was an enforcement agreement, regarding research analyst conflicts of interests, between the US Securities and Exchange Commission (SEC), NASD Inc., the New York Stock Exchange (NYSE), the New York Attorney General (NYAG), other state regulators and the following ten firms: Bear Stearns, Credit Suisse First Boston, Goldman Sachs, Lehman Brothers, J.P. Morgan, Merrill Lynch, Morgan Stanley, Citigroup, UBS Warburg and Piper Jaffray.
[8] Other important intermediaries that produces new information or validates disclosures are regulators and auditors.

The rest of the paper is organized as follows. Section 2 provides a brief background and literature review. Section 3 describes the data and methodology we use. Section 4 explores the characteristics of analyst tones during earnings conference calls hosted by financial institutions, while Section 5 examines the effect of analyst tones on market reactions during such events. Section 6 presents additional tests and Section 7 concludes.

2. Background and literature review

2.1. Analysts and their conflicting interests

Michaely and Womack (1999) find that underwriter analysts have strong incentives to market stocks underwritten by their investment banks. Consistent with the conflict of interest hypothesis, the authors did not find any evidence of superior information from the underwriter analysts. On career prospects in terms of promotions and outside opportunities, Hong and Kubik (2003) find that analysts are rewarded for being optimistic. In another take on this angle, Cohen, Frazzini and Malloy (2012) find that poorly performing sell-side analysts who are overly optimistic do get appointed as independent directors of the firms that they previously covered. Although most studies show that analysts enjoy better incentives by being optimistically biased, Jackson (2005) argued that analysts are also conflicted between generating trading volume for their employers and upholding their professional reputation.

2.2. Returns co-movement and superior information

We use returns co-movement to identify brokerages that may be more sensitive to the abovementioned incentive concerns. Many studies primarily model returns co-movement as the result of segmentations in the information environment. Co-movement has been shown to exist based on multiple segmentation characteristics from price (e.g., Green and Hwang 2009) to portfolio preferences and styles (e.g., Barberis and Shleifer 2003; Wahal and Yavuz 2013) to market frictions (e.g., Barberis, Shleifer and Wurgler 2005) to shared investment banking networks (e.g., Grullon, Underwood and Weston 2014) and analyst coverage (e.g., Muslu, Rebello and Xu 2014). As such, investors may believe that brokerages reveal better information when evaluating a firm within a highly connected information environment. We find that this is indeed the case. In additional sub-sample tests, we show that analysts from brokerages with high returns co-movements do not necessarily share the same sub-industry categories (e.g., 60 through 62 for investment banks), are more accurate and not optimistically biased relative to others.

2.3. Analyst tones during earnings conference calls

We study analyst tones during earnings conference calls for a number of reasons. Following the ratification of REG FD by the Securities and Exchange Commission (SEC) in October 2000, companies cannot selectively disclose material information to the private entities. The prevailing practice of reporting and disclosing such information since then is via the issuance of press releases, which are sometimes accompanied by SEC Form 8-K, or conference calls. In addition to being an increasingly common form of voluntary disclosure (Bushee, Matsumoto and Miller 2003), many studies have found significant reactions to conference call events from the market and informed participants such as analysts (e.g., Frankel, Johnson and Skinner 1999; Bowen, Davis and Matsumoto 2002; Kimbrough 2005). Recently, Matsumoto, Pronk and Roelofsen (2011) find that earnings conference calls are more informative than its accompanying press release, while Cicon (2014) find that earnings conference calls, and not any other calls, are valued by the market.

There are two sections to an earnings conference call. The management of the host firm will begin with a presentation, followed by a Q&A session. The Q&A segment of the conference call provides a unique opportunity to examine raw and spontaneous responses which are less likely to be scripted (Li 2010). Many studies examine the content of both sections and conclude that the Q&A segment is more informative than its preceding segment (e.g., Matsumoto, Pronk and Roelofsen 2011).

The transcribed Q&A section of earnings conference calls is also valuable for one other reason. Multiple parties may carefully scrutinize and contribute amendments to analyst reports or news prior to release, and this may mask the language signals of the originators' intentions. Such language patterns are however, preserved in the transcript. Further, the wealth of data afforded by language patterns complements existing outcome measures such as forecast revisions, which are not spontaneous and may suffer from issues regarding persistency and staleness.

Long seen as a qualitative measure too noisy for quantitative analysis, the usage of language in large-scale empirics was recently made possible due to advances in methodologies in NLP and made popular by cheaper computing resources. Language patterns in document sources ranging from media news, analyst reports, SEC filings, internet postings to conference calls are shown to have predictive powers on stock prices, returns, abnormal returns and trading volumes (e.g., Li 2008; Tetlock, Saar-Tsechansky and Macskassy 2008; Feldman, Govindaraj, Livnat and Segal 2008; Li 2010; Davis and Tama-Sweet 2012; Demers and Vega 2011; Loughran and McDonald 2011; Ferris 2012; Garcia 2013; Price, Doran, Peterson and Bliss 2012, Twedt and Rees 2012; Chen, De, Hu and Hwang 2013, Huang, Zang and Zheng 2014). Although most studies focus on sentiment (i.e., positivity or negativity), some researchers look at the complexity of language use in a variety of disclosure mediums (e.g., Brochet, Naranjo and Yu 2012; Li 2008; Smith and Smith 1971) and find that language complexity affects earnings persistency, trading volume and price movements in a negative way.

Generally, NLP extracts information from language patterns via statistical procedures based on classification schemes such as bag-of-words, parts-of-speech or others such as the Naïve Bayesian Classification Scheme (e.g., Huang, Zang and Zheng 2014; Li 2010). Most studies on the financial impacts of language focus on semantics at the word level. In the dictionary approach (e.g., Loughran and McDonald 2011; Tetlock 2007; Jegadeesh and Wu 2013), researchers classify words into various categories (e.g., positive, negative, litigious, superfluous) and predict market outcomes based on the frequency of tagged words for each observation in the sample. We choose this approach in our study for two reasons. First, using a pre-defined word list to classify our sample is simple, transparent and consistent over any large sample size. Second, tonality measures based on word frequency counts are quick and easy to compute.

3. Data and summary statistics

3.1. Conference call transcripts

We obtain conference call transcripts from the Fair Disclosure Wires of Factiva and ProQuest, from 2002 through 2014 and for firms with double-digit SIC codes 60 through 69.[9] Conference calls start with a presentation by a senior manager from the host firm, followed by questions and answers (Q&A) from analysts and investors. For each transcript, we split the Q&A section for each response *j* of participant *i* and remove stop words from the transcripts.[10] We consider a passage of uninterrupted speech by participant *i* as a valid response, and this can be in the form of a short sentence or paragraph of sentences made up of questions and comments.

We extract analyst-institution pairs from our conference call sample and match them with the ANALYST-ESTIMID pair in the RECDDET dataset of I/B/E/S. The ANALYST variable in RECDDET records the first letter of the analyst's last name (e.g., ARFSTROM J; CALIO E), and the ESTIMID variable records a truncated version of the institution name (e.g.,

[9] Includes coverage by CQ Roll Call, CCBN, and Thomson Reuters, amongst others.
[10] Stop words are frequently occurring words that do not convey any relevant linguistic information in our study.

JPMORGA; KEEFE; RBCDOMIN; MERRILL). To minimize type I errors, we require analyst-institution-dates to overlap with ANALYST-ESTIMID-ANNDATS. For those pairs that do not have overlapping institutions or coverage dates in IBES, we match them by perusing the analysts' curriculum vitae (CV) from open sources such as LinkedIn, ZoomInfo and their brokerages' websites.

3.2. Tone variables relating to word semantics

Prior to the development of word classification schemes for words that are specific to the field of finance, researchers rely very much on the Harvard Dictionary.[11] In Loughran and McDonald (2011), they show that such approaches misclassifies many common words in financial texts. The authors then constructed five word categories trained from SEC 10-K samples: positive, negative, uncertainty, litigious, strong modal and weak modal, and show that their product relates more strongly to excess returns, trading volume, and litigation woes than the Harvard-IV word list.

In this study, we distill tonality information from the earnings conference call transcripts using the dictionary approach in Loughran and McDonald (2011). First, we classify the words in our transcript sample according to the five word categories (positive, negative, uncertainty, litigious and superfluous) using William McDonald's word list.[12] With the exception of positive and negative tones, we represent each of the other tone variables as a proportion of classified words over total number of words in each response:

$$tone_{type} = \frac{no.of\ words_{type}}{no.of\ words_{response}}$$

[11] The Harvard Inquirer is a common word list with 182 tag categories. Examples include positive, negative, strong, weak, active, pleasure and pain. Finance researchers typically use the Harvard-IV negative and positive word list.

[12] http://www3.nd.edu/~mcdonald/Word_Lists.html

Most papers calculate sentiment as a proportion of positive or negative words over the total number of sentiment words. We calculate sentiment in a slightly different manner, as follows:

$$tone_{sentiment} = \frac{(no.of\ words_{pos} - no.of\ words_{neg})}{(no.of\ words_{pos\ and\ neg})}$$

Our method scales $\text{tone}_{\text{sentiment}}$ from -1 (absolute negative) to 1 (absolute positive), which corresponds with the range of our outcome variables (e.g., cumulative abnormal returns and earnings surprises range from negative to positive territory). This makes for more intuitive interpretations in our models.

3.3. Tone variables relating to word complexity

We also investigate tones relating to complexity, in additional tests. We calculate the complexity of each analyst response using two measures: Gunning-Fog index and Flesch-Kincaid (inverse).

$$Gunning\_Fog = 0.4 \times \frac{words}{sentences} + 100 \times \frac{words\ with\ 3\ or\ more\ syllabus}{words}$$

$$Flesch\_Kincaid = (206.835 - 1.015 \times \frac{words}{sentences} - 84.6 \times \frac{syllabus}{words})^{-1}$$

3.4. Returns co-movement between brokerage and financial institutions

We estimate the returns co-movement β between listed broker b and financial institution (host) *h* using the following market model starting from 90 through 2 days prior to the conference call date:

$$Ret_{b,t} = \alpha + \beta_{b,h,t}Ret_{h,t} + \varepsilon$$

Table 1 panel A presents the breakdown of listed and non-listed brokers in our dataset. We start with 14,964 conference calls hosted by financial firms that has participation from listed brokerages, from 2002 through 2014. On average, we observe 4.1 listed and 2.5 non-listed brokerages per conference call. We group brokerages with β above and below median as top-rank and bottom-rank, respectively. We perform this grouping on all brokerage-host pairs by quarter. We show in Table 1 panel B that the differences between the means of the two ranks range from 0.15 to 0.29 and are statistically significant from 0 in all years. We reduce the final dataset to 11,907 conference calls by requiring all events to have brokerage participation from both ranks.

4. Characteristics of analyst tones during conference calls hosted by financial institutions

4.1. Cross-sectional analysis on tone characteristics

We begin our examination with a univariate comparison of the tone characteristics between listed and non-listed brokerages at the response level. In Table 2, our measure of *Sentiment*, which scales from -1 (most negative) to 1 (most positive), shows that analysts on the whole tend to be more positive towards financial institutions. Further, analysts from listed brokerages are statistically more positive (t = 9.14) than their non-listed counterparts. We observe that this difference in *Sentiment* is driven by positive (t = 13.24) rather than negative (t = -1.14) tones. On average, analysts from listed brokerages are less litigious (t = -5.09) and adopt more uncertain (t = 7.34) and complex tones (t = 8.12 (*Gunning_Fog*); t = 2.97 (*Flesch_Kincaid*)) compared to their non-listed counterparts.

4.1.1. Multivariate regression setup

We then proceed with our examination on tones using a set of explanatory variables in a multivariate regression setting. Given that our sample of conference calls occur right after earnings announcements, we expect earnings surprise to have a large influence on *sentiment*. We measure earnings surprise (*Surp*) as the actual earnings minus the median of the last forecasts for all unique analysts 90 days prior to the earnings announcement date. Our sample period includes the Global Financial Crisis and we mark all conference call dates within 1 July 2007 through 31 December 2009 with a dummy variable (*Crisis*) of 1, and 0 otherwise. *Listed* is a dummy variable of 1 if the analyst represent a listed brokerage, and 0 otherwise. *Comove* represents the magnitude of returns co-movement between listed brokerages and hosts. Other control variables include: *Sanction* is a dummy of variable of 1 if the analysts represent one of ten financial institutions sanctioned under the 2003 Global Analyst Research Settlement. *Dispest*, the analysts forecast dispersion up to 90 days prior to announcement day; *Nanalyst*, the number of unique forecasts up to 90 days prior to announcement day; *Size*, the natural logarithm of market value; and *Bm*, the book to market. We present the results in Table 3 and discuss them below.

4.1.2. Brokerages and co-movement

We examine the differences between listed and non-listed brokerages in the first model for each tone (i.e., model 1 – *Sentiment*; model 4 - *Litigious*; model 7 - *Uncertainty*; model 10 - *Superfluous*; model 13 – *Gunning_Fog*; and model 16 – *Flesch_Kincaid*). We replace *Listed* with *Comove* in the second model, and add *Sanction* to the third model for each tone. The intercepts in Model 1 to 3 seem to suggest that analysts adopt neutral to positive sentiment tones during their interactions with financial institutions. Overall, analysts tend to be more litigious (t = 2.35), uncertain (t = 4.36), superfluous (t = 2.83) and complex (t = 16.42 (Gunning-Fog); t = 53.23 (Flesch-Kincaid)).

Under the multivariate setting, the differences in tones between listed and non-listed brokerages are no longer significant. Instead, high returns co-movement takes over as a significant predictor of high sentiment (t = 4.24) and low litigious (t = -4.33), uncertainty (t = -1.92) and superfluous (t = -1.94) tones. Taken together, we do not find support for competitive behaviors among analysts from brokerages that share a tighter information environment with their hosts.

Lastly, we find that analysts from sanctioned brokerages adopt tones that are high in sentiment (t = 3.95), uncertainty (t = 2.58) and complexity (t = 1.77 (Gunning-Fog)).

4.1.3. Earnings surprise, crisis and other variables of interests

Our results in Table 3 are generally consistent with the intuitions about how analyst tones vary across various dimensions. Earnings surprise does not seem to affect tones other than sentiment (t = 2.93). Analyst tones are more litigious (t = 3.42) but not negative during the financial crisis period. Higher analyst dispersion prior to the conference call predicts negative sentiments (t = -2.1) and complexity (t = 1.94 (Gunning_Fog)). Larger analyst coverage are positively associated with complex tones (t = 1.99). Larger firms predict more uncertain tones (t = 3.87) and high book-to-market firms tend to experience more litigious (t = 2.87), uncertain (t = 2.08) and complex tones (t = 1.74 (Flesch-Kincaid)).

4.2. Are the tones of high returns co-movement brokerages optimistically biased?

We aggregate the responses in our sample at the event level before splitting them into good news (earnings surprise >= 0) and bad news (earnings surprise < 0). Specifically, we replace the brokerage dummy variables with the average score of their tones, for every conference call in our sample. *Sanction* is the average tone of analysts from the 10 brokerages sanctioned during the 2003 Global Analyst Research Settlement. *ToneAvg* is the average analysts' tone measured at the conference call level. We then regress the tones of high *Comove* brokerages on these variables to obtain their cross-sectional relations. We present the results in Table 4.

We expect to see positively significant intercept values for the various tones if analysts are optimistically predisposed to financial institutions, and negatively significant values if they behave in a competitive manner. We do not find this to be the case for sentiment, litigious, uncertainty, and superfluous tones. With Flesch_Kincaid (but not Gunning_Fog), we find that high *Comove* brokerages use more complex tones (t = 5.19) during good news. We find further support for the hypothesis that high *Comove* brokerages are tone-neutral from the lack of significant associations between the tones of high *Comove* and average brokerages (*ToneAvg*) for sentiment, superfluous and Gunning_Fog. High *Comove* brokerages are also less litigious (t = -3.58) and complex (t = -5.21 (Flesch_Kincaid)) than the average brokerage during good news and less uncertain (t = -1.91) during bad news. Taken together, we find that high *Comove* brokerages are generally tone-neutral when they question financial institutions, and thus do not find support for collusive behaviors.

5. Effect of analyst tones on market reactions during earnings conference calls hosted by financial firms

In the previous section, we test whether high *Comove* analysts are optimistic or pessimistic in their tones, and found no support for either case. In this section, we use market returns to validate the information content of the tones of high *Comove* analysts. We expect CAR to be significantly associated with these analysts' tones if the latter carry additional information over and beyond earnings surprise and the average tone of all analysts at the conference call.

We regress the 3-day event CAR, centered on conference call date, on the list of variables in Table 4 with additional independent variables as follows: *ToneHigh* is the average analysts' tone from brokerages with above median co-moving beta, measured at the conference call level; *ToneLow* is the average analysts' tone from brokerages with below median co-moving beta; and *ToneListed* is the average analysts' tone from listed brokerages. Independent variables are standardized in the regressions, and we present our results in Table 5. The first model for each tone (i.e., Model 1, 4, 7, 10, 13, and 16) examines the relation between the tones of listed brokerages with market reactions. We replace the tones of listed brokerages (*ToneListed*) with those of high and low *Comove* brokerages (*ToneHigh* and *ToneLow*) in the second and third models. Due to concerns about possible multi-collinearity between the independent variables, we also report the highest condition index for each model. In addition, we check the variance inflation factors (VIF) of all our models and do not find any alarming concerns about multi-collinearity issues (i.e., all VIFs < 2).

5.1. The relation between CAR and average analyst tones

CARs are positively associated with sentiment (t = 8.74) and negatively associated with litigious (t = - 2.84), superfluous (t = -3.26) and complex (t = -2.08) tones, which is consistent with the empirical predictions from current studies (e.g., Li 2008; Loughran and McDonald 2011; Price, Doran, Peterson and Bliss 2012). The sentiment tone of the average analyst (*ToneAvg*) has the most impact on CAR (0.75% to 0.76% per standard deviation), followed by litigious (-0.32% to -0.35%), superfluous (-0.12% to -0.34%) and Gunning_Fog (-0.16% to -0.23%). We note that the economic significance of the sentiment tone of the average analyst (*ToneAvg*) is between 0.6 to 1 times that of earnings surprise (0.81% to 1.3%).

5.2. The relation between CAR and listed brokerages

The sentiment, uncertainty and complex tones of listed brokerages do not seem to affect CARs. On the other hand, litigious and superfluous tones of listed brokerages are negatively associated with CARs, which is consistent with our expectations should we observe any significant market reactions to tones. Splitting *ToneListed* into *ToneHigh* and *ToneLow*, we find that with the exception of uncertainty tones, CARs are now significantly associated with the tones of *ToneHigh* but not *ToneLow*. Specifically, CAR is positively associated with sentiment (t = 3.35) and negatively associated with litigious (t = -2.12), superfluous (t = -2.48) and complex tones (t = -1.87 (Gunning_Fog); t = -1.66 (Flesch_Kincaid)). This implies that the tones of high *Comove* brokerages indeed carry incremental information over those of the average analyst, as well as earnings surprise, and the market prices it in a manner consistent with our competency hypothesis. In terms of economic significance, with the exception of Gunning_Fog, *ToneHigh* carries less weight compared to the average analyst: sentiment (0.29% vs 0.76%); litigious (-0.24% vs -0.32%); superfluous (-0.28% vs -0.34%); Gunning_Fog (-0.20% vs -0.16%).

5.3. CARs and sanctioned brokerages

Similar to Table 4, we include the tones of analysts from sanctioned banks (*Sanction*) to show that the market does not follow analyst tones in a naïve manner, even when the analysts come from large financial institutions and are likely to be more competent than the competition. Indeed, given that the sentiment tone of *Sanction* tends to be positive as shown in Table 4, we interpret the negative relation between CAR and *Sanction* as the market discounting the sentiment tone (t = -3.39) of the sanctioned brokerages. We further show that this result only appears during good news, in the following section. Interestingly, we find that the discount is attenuated during the financial crisis period (*sanction* * *crisis*, t = 1.82), possibly due to expectations about higher levels of scrutiny. We do not find any significant market reactions to other *Sanction* tones including complexity.

5.4. *Tones that market cares about during good news, bad news and no news*

Table 6 shows the relation between CARs and tones during good and bad news. We do not observe a uniform market reaction to the tones. On sentiment, we observe the following: *ToneAvg* increases from 0.49 (t = 5.11) to 0.86 (t = 4.94) from good news to the bad news; *ToneHigh* increases from 0.17 (t = 1.69) to 0.51 (t = 3.16); and *ToneLow* turns significant (0.29, t = 1.98) during bad news. We thus conclude that the market cares about sentiment more during bad news. We find this to be the case for litigious and uncertainty as well, with *ToneAvg* turning significant only on bad news (litigious: -0.97, t = -5.2; uncertainty: -0.30; t = -2). *ToneHigh* does not seem to have any explanatory powers for this subsample analysis on litigious and uncertainty, which could arise from the issue of small sample sizes given that tones are very noisy measures. The average analyst tone appears to be important for superfluous during both bad and good news, but the market incrementally cares about *ToneHigh* (-0.30, t = -2.53) only during good news. Lastly, we find that CARs are negatively associated with the complex tones of *ToneHigh* during bad news (*Gunning_Fog*: -0.32, t = -1.88; *Flesch_Kincaid*: -0.46, t = -1.78).

For *Sanction*, we find that CAR is negatively and significantly associated with the sentiment tones of sanctioned brokerages only during good news. Again, this effect is attenuated during the crisis period (0.183, t = 1.75). Other than sentiment, *Sanction* is only significant on superfluous tones during bad news (-0.36, t = -3.02).

In Table 7, we perform the same regressions on events where the absolute earnings surprise is less than 1 cent. This is the subset of firms that either meet consensus analyst estimates or miss/beat the estimates by 1 cent, events in which we assume earnings surprise to convey little to no information. To capture the asymmetric market reactions to events that miss estimates by 1 cent, we define *SurpNeg* as a dummy variable of 1 if the earnings surprise is negative, and 0 otherwise. We find *ToneAvg* to be significant for all tones (sentiment: 0.5, t = 2.24; litigious: -0.54, t = -2.33; uncertainty: -0.57, t = 2.18; superfluous: -1.06, t = -2.69; Gunning_Fog: -0.36, t = -1.64; and Flesch_Kincaid: -0.54, t = -1.52), while *ToneHigh*, *ToneLow* and *Sanction* do not garner any incremental CARs over *ToneAvg* in all cases. We note that the interaction term *Sanction* * *Crisis* is significant for some tones, but do not discuss them because of the small number of non-zero observations for these variables.

In sum, we find that the market weighs tones more heavily during bad news events, which complements existing evidences of bad news being more credible than good news (e.g., Hutton, Miller and Skinner 2003; Skinner 1994) or good news more likely to leak out earlier than bad news thereby leading to market having already reacted prior to announcement

(Kothari, Shu and Wysocki 2009). We also find that market discounts the sentiment tone of sanctioned brokerages only during good news.

6. Additional tests

In untabulated results, we regress CAR against all tones in a 'kitchen-sink' approach. Our results are largely comparable with those in Table 5. We then add a dummy variable for events where analysts from sanctioned brokerages cover their sanctioned counterparts, but do not find any significant results for this variable.

We examine two measures of analyst bias used in past studies to further examine our finding that the market believes that high *Comove* brokerages are more competent. First, we compute the analyst forecast accuracy for each and every analyst-financial institution pair. Second, we compute an optimism score similar to the Relative Forecast Optimism score in Hong and Kubik (2003) for each and every analyst-financial institution pair, averaged over the past 4 quarters. We compare the difference in means between the high and low *Comove* samples and find that analysts from high *Comove* brokerages are more accurate, but not more optimistic than their low *Comove* counterparts.

Gilson, Healy, Noe and Palepu (2001) demonstrate that analysts who specialize by industry issue more precise forecasts than non-specialist analysts. That raises the question whether should we simply replace our *Comove* variable with SIC sub-groups. We tackle this question by examining the magnitude of *Comove* between industry sub-samples. Using 2-digit SIC, we split our sample into three groups: investment bank pairs (60 through 62), financial institution pairs (60 through 69) and other pairs. We compare the difference in means between investment bank and institution plus other pairs, as well as just institution pairs and other pairs. We do not find any evidence that *Comove* is higher within the investment bank or financial institution groups.

7. Conclusion

We examine analysts' tones during conference calls hosted by financial institutions. The spontaneous and unscripted responses captured in the Q&A section of conference calls is a rich source of soft information that complements existing quantitative measures in the large literature examining analysts' conflicts of interests. In this study, we examine the characteristics and market reactions to a large variety of tones, specifically sentiments, litigious, uncertainty, superfluous and complexity. We also compute the returns co-movement as a proxy for the level of shared information environment between brokerages and hosts, and find that analysts from high co-moving brokerages tend to be more positive and less litigious, uncertain, superfluous and complex. However, we do not find any supporting evidence for tone biasness (relative) when we split the event sample into good/bad news and compare the correlation between the average analyst tones and high co-moving ones in a multivariate setting. Additional tests using forecast accuracy and relative forecast optimism show that analysts from high co-moving brokerages are more accurate but not optimistically biased.

Our results from regressing CAR on tones show that the market values analyst tones during conference calls and its reaction increases with the level of co-movement. The market appears to weigh tones more heavily during events with negative earnings surprises, but is not naïve as it discounts the tones of analysts from brokerages sanctioned during the Global Analyst Research Settlements in 2003.

In sum, we do not find support for analysts adopting competitive or collusive behaviors when questioning their peers, and show that the market incrementally prices analysts' tones from high co-moving brokerages in a manner consistent with the competence hypothesis.

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Table 1: Sample descriptive statistics

Sample statistics from 2002 – 2014 are reported. Panel A shows the sample of our conference call transcripts with the breakdown of listed and non-listed brokerages, by year. Panel B shows the co-movement beta for the two groups split at the median. Co-movement beta is measured as the beta coefficient obtained by regressing daily host returns on brokerage returns from 90 through 2 days prior to announcement day. Panel C shows the cross-sectional correlations between the independent and control variables. *Surp* is the median consensus forecast up to 90 days prior to announcement day. *Crisis* is a dummy variable indicating the period from 1 Jul 2007 through 31 Dec 2009. *Sanction* is the average tone of analysts from the 10 brokerages sanctioned during the 2003 Global Settlement. *ToneHigh* is the average analysts' tone from brokerages with above median co-moving beta, measured at the conference call level. *ToneLow* is the average analysts' tone from brokerages with below median co-moving beta. *ToneListed* is the average analysts' tone from listed brokerages. *ToneAvg* is the average of all analysts' tone. Tones are measured as follows: *Sentiment* is the proportion of (positive – negative) to (positive + negative) words for each analyst-conference call pair. *Litigious* is the proportion of litigious words to total number of words. *Superfluous* is the proportion of superfluous words to total number of words. *Uncertainty* is the proportion of uncertainty words to total number of words. *Gunning_Fog* is calculated as $(0.4 \times \frac{no.\ of\ words}{no.\ of\ sentences} + 100 \times \frac{no.of\ complex\ words}{no.of\ words})$, where words are complex if they have 3 or more syllabus. *Flesch_Kincaid* is calculated as $\left(206.835 - 1.015 \times \frac{no.\ of\ words}{no.\ of\ sentences} - 84.6 \times \frac{no.\ of\ syllabus}{no.\ of\ words}\right)^{-1}$. *Dispest* is the analysts forecast dispersion up to 90 days prior to announcement day. *Nanalyst* is the number of unique forecasts up to 90 days prior to announcement day. *Size* is the natural logarithm of market value. *Bm* is the book to market.

Panel A: Sample size and breakdown of listed and non-listed brokerages

Year	# concalls	# concalls available to compute beta	Mean # Non-listed Brokerages per call	Mean # Listed Brokerages per call
2002	158	143	2.2	3.3
2003	411	372	2.5	3.6
2004	984	898	2.5	4.0
2005	916	835	2.5	3.9
2006	972	906	2.5	4.0
2007	1028	934	2.4	4.2
2008	1053	943	2.4	3.6
2009	1160	1038	2.6	3.7
2010	1710	1557	2.7	4.5
2011	2042	1874	2.6	4.6
2012	2003	1850	2.6	4.7
2013	1785	1700	2.6	4.9
2014	2009	1914	2.6	4.6
Full Sample	16231	14964	2.5	4.1

Panel B: Co-movement beta comparison between top and bottom ranks

Year	Bottom-Rank		Top-Rank		Beta Difference (t-score)	# concalls having both categories
	# brokerages per call	beta	# brokerages per call	beta		
2002	1.27	0.50	1.41	0.72	0.22 *** (7.33)	100
2003	1.18	0.37	1.42	0.56	0.19 *** (10.96)	233
2004	1.41	0.25	1.63	0.40	0.15 *** (19.46)	626
2005	1.30	0.23	1.54	0.39	0.16 *** (20.34)	572
2006	1.44	0.27	1.67	0.48	0.21 *** (19.99)	625
2007	1.73	0.37	1.92	0.61	0.24 *** (24.22)	752
2008	1.49	0.57	1.73	0.86	0.29 *** (22.79)	758
2009	1.52	0.48	1.76	0.69	0.21 *** (19.62)	833
2010	1.94	0.45	2.13	0.67	0.22 *** (31.94)	1312
2011	2.01	0.50	2.21	0.72	0.22 *** (31.65)	1592
2012	2.04	0.57	2.25	0.85	0.28 *** (37.69)	1599
2013	2.03	0.39	2.22	0.61	0.22 *** (37.01)	1439
2014	1.75	0.29	1.99	0.50	0.21 *** (36.51)	1466
Full Sample	1.96	0.40	1.75	0.62		11907

Panel C: Cross-sectional correlations between tones and control variables

I. Sentiment

Variable	Surp	ToneAvg	ToneListed	ToneHigh	ToneLow	Sanction	Dispest	Nanalyst	Bm	Size
Surp	1									
ToneAvg	-0.01	1								
ToneListed	0.00	0.03	1							
ToneHigh	-0.01	0.02	-0.35	1						
ToneLow	-0.01	0.01	0.65	0.48	1					
Sanction	0.00	0.03	0.35	0.17	0.49	1				
Dispest	0.07	-0.09	-0.01	-0.02	-0.02	-0.01	1			
Nanalyst	0.00	-0.04	-0.02	-0.01	-0.03	0.00	0.05	1		
Bm	0.05	-0.05	-0.01	-0.01	-0.01	-0.01	0.05	-0.05	1	
Size	0.00	-0.08	-0.01	0.00	0.00	0.02	0.05	0.44	-0.01	1

II. Litigious

Variable	Surp	ToneAvg	ToneListed	ToneHigh	ToneLow	Sanction	Dispest	Nanalyst	Bm	Size
Surp	1.00									
ToneAvg	0.04	1.00								
ToneListed	-0.02	-0.08	1.00							
ToneHigh	-0.01	-0.08	0.70	1.00						
ToneLow	-0.02	-0.17	0.49	-0.28	1.00					
Sanction	0.01	-0.11	0.52	0.39	0.17	1.00				
Dispest	0.08	0.04	0.00	0.00	-0.01	0.03	1.00			
Nanalyst	0.00	0.02	0.00	0.00	0.01	-0.01	0.03	1.00		
Bm	0.05	0.01	0.00	0.00	0.00	0.00	0.06	-0.05	1.00	
Size	-0.01	0.02	0.01	0.01	0.00	0.00	0.03	0.41	-0.01	1.00

III. Uncertainty

Variable	Surp	ToneAvg	ToneListed	ToneHigh	ToneLow	Sanction	Dispest	Nanalyst	Bm	Size
Surp	1.00									
ToneAvg	0.00	1.00								
ToneListed	0.00	-0.04	1.00							
ToneHigh	0.01	-0.07	0.65	1.00						
ToneLow	-0.01	-0.02	0.49	-0.36	1.00					
Sanction	-0.02	-0.02	0.48	0.33	0.15	1.00				
Dispest	0.08	0.01	-0.01	0.00	0.00	-0.02	1.00			
Nanalyst	0.00	0.03	0.00	0.00	0.00	0.05	0.03	1.00		
Bm	0.05	0.02	-0.01	-0.01	-0.01	-0.01	0.06	-0.05	1.00	
Size	-0.01	0.04	0.00	0.00	0.00	0.02	0.03	0.41	-0.01	1.00

IV. Superfluous

Variable	Surp	ToneAvg	ToneListed	ToneHigh	ToneLow	Sanction	Dispest	Nanalyst	Bm	Size
Surp	1.00									
ToneAvg	0.00	1.00								
ToneListed	0.00	-0.39	1.00							
ToneHigh	0.00	-0.39	0.73	1.00						
ToneLow	0.00	-0.24	0.55	-0.22	1.00					
Sanction	-0.01	-0.10	0.60	0.42	0.32	1.00				
Dispest	0.08	0.00	0.00	0.00	0.01	0.00	1.00			
Nanalyst	0.00	0.00	0.01	0.01	0.01	0.00	0.03	1.00		
Bm	0.05	0.00	0.00	0.00	0.00	0.00	0.06	-0.05	1.00	
Size	-0.01	0.02	-0.02	-0.02	-0.02	0.00	0.03	0.41	-0.01	1.00

V. Gunning Fog

Variable	Surp	ToneAvg	ToneListed	ToneHigh	ToneLow	Sanction	Dispest	Nanalyst	Bm	Size
Surp	1.00									
ToneAvg	0.00	1.00								
ToneListed	0.01	-0.01	1.00							
ToneHigh	0.01	0.01	0.64	1.00						
ToneLow	0.00	-0.01	0.47	-0.35	1.00					
Sanction	0.01	0.01	0.48	0.41	0.11	1.00				
Dispest	0.08	0.03	0.03	0.04	-0.01	0.04	1.00			
Nanalyst	0.00	0.08	0.03	0.02	0.01	-0.01	0.03	1.00		
Bm	0.05	-0.01	0.00	0.01	0.00	0.00	0.06	-0.05	1.00	
Size	-0.01	0.06	0.01	0.03	-0.01	0.01	0.03	0.41	-0.01	1.00

VI. Flesch Kincaid

Variable	Surp	ToneAvg	ToneListed	ToneHigh	ToneLow	Sanction	Dispest	Nanalyst	Bm	Size
Surp	1.00									
ToneAvg	0.01	1.00								
ToneListed	0.00	-0.11	1.00							
ToneHigh	0.01	-0.50	0.44	1.00						
ToneLow	0.00	0.51	0.50	-0.64	1.00					
Sanction	0.00	-0.46	0.56	0.58	-0.20	1.00				
Dispest	0.08	0.02	0.01	0.01	0.00	0.01	1.00			
Nanalyst	0.00	0.05	0.01	0.00	0.01	0.00	0.03	1.00		
Bm	0.05	0.00	0.00	0.00	0.00	0.00	0.06	-0.05	1.00	
Size	-0.01	0.03	0.00	0.01	-0.01	0.02	0.03	0.41	-0.01	1.00

Table 2: Language characteristics difference between listed and non-listed brokerages

With the exception of complexity scores (*Gunning_Fog* and *Flesch_Kincaid*), we use the language dictionary from Loughran and McDonald (2011) to classify the words spoken by analysts during conference calls.[13] Scores (x100) are calculated at the analyst-conference call level. *Sentiment* is the proportion of (positive – negative) to (positive + negative) words for each analyst-conference call pair. *Positive* is the proportion of positive words to (positive + negative) words. *Negative* is the proportion of negative words to (positive + negative words). *Litigious* is the proportion of litigious words to total number of words. *Superfluous* is the proportion of superfluous words to total number of words. *Uncertainty* is the proportion of uncertainty words to total number of words. *Gunning_Fog* is calculated as $(0.4 \times \frac{no.\ of\ words}{no.\ of\ sentences} + 100 \times \frac{no.of\ complex\ words}{no.of\ words})$, where words are complex if they have 3 or more syllabus. *Flesch_Kincaid* is calculated as $\left(206.835 - 1.015 \times \frac{no.\ of\ words}{no.\ of\ sentences} - 84.6 \times \frac{no.\ of\ syllabus}{no.\ of\ words}\right)^{-1}$. Difference in means and t-statistics (in parentheses) are reported. *, **, and *** indicate two-tailed statistical significance at the 10, 5 and 1 percent levels, respectively.

Tones	Non-listed Brokers	Listed Brokers	Difference (listed minus non-listed)
Sentiment	0.349	2.501	2.152 *** (9.14)
Positive	27.980	29.971	1.991 *** (13.24)
Negative	27.608	27.451	-0.157 (-1.14)
Litigious	0.258	0.231	-0.027 *** (-5.09)
Superfluous	0.003	0.003	0 (-0.09)
Uncertainty	2.347	2.457	0.11 *** (7.34)
Gunning_Fog	592.473	604.417	11.944 *** (8.12)
Flesch_Kincaid	0.847	0.852	0.004 *** (2.97)
N	37,773	66,885	

[13] Available at http://www3.nd.edu/~mcdonald/Word_Lists.html

Table 3: The relation between beta and tones

The dependant variables are tones, measured as follows: *Sentiment* is the proportion of (positive – negative) to (positive + negative) words for each analyst-conference call pair. *Litigious* is the proportion of litigious words to total number of words. *Superfluous* is the proportion of superfluous words to total number of words. *Uncertainty* is the proportion of uncertainty words to total number of words. *Gunning_Fog* is calculated as $(0.4 \times \frac{no.\ of\ words}{no.\ of\ sentences} + 100 \times \frac{no.of\ complex\ words}{no.of\ words})$, where words are complex if they have 3 or more syllabus. *Flesch_Kincaid* is calculated as $\left(206.835 - 1.015 \times \frac{no.\ of\ words}{no.\ of\ sentences} - 84.6 \times \frac{no.\ of\ syllabus}{no.\ of\ words}\right)^{-1}$. Coefficients (x100) and t-statistics (in parentheses) are reported. *Surp* is the median consensus forecast up to 90 days prior to announcement day. *Listed* is a dummy variable indicating listed brokerages. *Crisis* is a dummy variable indicating the period from 1 Jul 2007 through 31 Dec 2009. *Comove* measures the amount of co-movement between host and brokerages, measured as the beta coefficient obtained by regressing daily host returns on brokerage returns from 90 through 2 days prior to announcement day. *Sanction* is a dummy variable indicating one of the 10 brokerages sanctioned during the 2003 Global Settlement. *Dispest* is the analysts forecast dispersion up to 90 days prior to announcement day. *Nanalyst* is the number of unique forecasts up to 90 days prior to announcement day. *Size* is the natural logarithm of market value. *Bm* is the book to market. Analysts and quarter fixed effects apply. Standard errors are clustered by announcement day, *, **, and *** indicate two-tailed statistical significance at the 10, 5 and 1 percent levels, respectively.

Panel A: Sentiment and litigious tones

Variable	Sentiment			Litigious		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	7.343 **	1.135	-0.61	-0.002	0.096 **	0.093 **
	(2.38)	(0.36)	(-0.2)	(-0.05)	(2.52)	(2.35)
Surp	18.286 ***	17.632 ***	17.539 ***	-0.169	-0.159	-0.159
	(3.41)	(2.95)	(2.93)	(-1.09)	(-0.79)	(-0.79)
Crisis	-3.932	1.295	1.521	0.224 ***	0.194 ***	0.188 ***
	(-1.28)	(0.37)	(0.44)	(3.95)	(3.62)	(3.42)
Surp * Crisis	-13.934 **	-14.871 **	-14.719 **	0.189	0.376	0.376
	(-2.4)	(-2.27)	(-2.24)	(0.97)	(1.52)	(1.52)
Listed	0.023			-0.012		
	(0.04)			(-0.88)		
Comove		3.226 ***	3.232 ***		-0.077 ***	-0.077 ***
		(4.23)	(4.24)		(-4.39)	(-4.33)
Comove * Surp		7.044	7.117		-0.168	-0.167
		(0.77)	(0.77)		(-0.53)	(-0.52)
Comove * Crisis		1.054	0.487		-0.03	-0.036
		(0.83)	(0.37)		(-0.82)	(-0.99)
Sanction			3.655 ***			0.006
			(3.95)			(0.25)
Sanction * Crisis			0.787			0.021
			(0.76)			(0.98)
Dispest	-2.873 **	-2.84 **	-2.854 **	0.039 *	0.022	0.021
	(-2.56)	(-2.1)	(-2.1)	(1.8)	(1.09)	(1.09)
Nanalyst	-0.063	-0.079 *	-0.074	0.003 ***	0.002	0.002 *
	(-1.55)	(-1.7)	(-1.59)	(2.89)	(1.64)	(1.66)
Size	0.065	-0.004	-0.013	-0.01 **	0.004	0.003
	(0.4)	(-0.02)	(-0.06)	(-2.32)	(0.68)	(0.66)
Bm	-0.387 **	-0.283	-0.288 *	0.02 ***	0.013 ***	0.013 ***
	(-2.26)	(-1.63)	(-1.66)	(3.7)	(2.87)	(2.87)
N	83,864	51,314	51,314	83,864	51,314	51,314
Adj. R^2	*0.14*	*0.14*	*0.14*	*0.06*	*0.04*	*0.04*

Table 3 (Cont'd)

Panel B: Uncertainty and superfluous tones

Variable	Uncertainty			Superfluous		
	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Intercept	2.743 *** (5.04)	2.821 *** (4.42)	2.748 *** (4.36)	0.001 (0.85)	0.003 ** (2.48)	0.004 *** (2.83)
Surp	-0.14 (-0.49)	-0.191 (-0.55)	-0.194 (-0.56)	-0.006 (-0.86)	-0.003 (-0.63)	-0.003 (-0.63)
Crisis	-0.391 (-0.73)	-0.327 (-0.5)	-0.295 (-0.46)	0.003 ** (1.97)	0.003 (0.92)	0.002 (0.78)
Surp * Crisis	0.121 (0.39)	0.228 (0.58)	0.234 (0.6)	0.007 (0.89)	0 (-0.06)	0 (-0.06)
Listed	0.049 (1.34)			0 (0.29)		
Comove		-0.095 * (-1.88)	-0.097 * (-1.92)		-0.003 * (-1.92)	-0.003 * (-1.94)
Comove * Surp		-0.423 (-0.87)	-0.423 (-0.87)		0.009 (1)	0.009 (1.01)
Comove * Crisis		0.061 (0.62)	0.056 (0.56)		0.002 (0.63)	0.001 (0.41)
Sanction			0.149 *** (2.58)			-0.001 (-0.62)
Sanction * Crisis			-0.04 (-0.59)			0.002 (0.56)
Dispest	0.096 * (1.73)	0.085 (1.17)	0.085 (1.17)	0.001 (0.69)	0 (0.15)	0 (0.14)
Nanalyst	-0.004 * (-1.7)	-0.005 (-1.59)	-0.005 (-1.55)	0 (-0.91)	0 (-0.86)	0 (-0.87)
Size	0.042 *** (4.08)	0.052 *** (3.88)	0.052 *** (3.87)	0 (1.13)	0.001 (1.35)	0.001 (1.37)
Bm	0.029 *** (2.75)	0.022 ** (2.1)	0.022 ** (2.08)	-0.001 (-1.22)	-0.001 (-1.22)	-0.001 (-1.22)
N	83,864	51,314	51,314	83,864	51,314	51,314
Adj. R^2	*0.08*	*0.07*	*0.07*	*0.16*	*0.21*	*0.21*

Table 3 (Cont'd)

Panel C: Gunning Fog and Flesch Kincaid scores

	Gunning_Fog			Flesch_Kincaid		
Variable	Model 13	Model 14	Model 15	Model 16	Model 17	Model 18
Intercept	489.648 *** (14.07)	571.134 *** (16.41)	566.439 *** (16.42)	0.81 *** (45.55)	0.824 *** (53.52)	0.824 *** (53.23)
Surp	-69.246 (-1.47)	-94.122 (-1.49)	-94.362 (-1.5)	-0.011 (-0.43)	-0.025 (-0.91)	-0.025 (-0.91)
Crisis	97.575 *** (2.75)	25.235 (0.7)	26.683 (0.75)	0.037 ** (2.05)	0.024 (1.33)	0.025 (1.47)
Surp * Crisis	57.328 (1.17)	94.416 (1.34)	94.787 (1.35)	0.005 (0.16)	0.001 (0.04)	0.001 (0.04)
Listed	-1.657 (-0.48)			-0.005 (-1.43)		
Comove		-0.999 (-0.17)	-1.09 (-0.19)		-0.001 (-0.39)	-0.002 (-0.44)
Comove * Surp		-19.244 (-0.27)	-19.174 (-0.27)		0.027 (1.03)	0.027 (1.01)
Comove * Crisis		-7.429 (-0.68)	-8.278 (-0.74)		0.005 (0.45)	0.007 (0.52)
Sanction			0.098 * (1.77)			0 (0.06)
Sanction * Crisis			-0.006 (-0.09)			-0.006 (-0.79)
Dispest	10.602 ** (2.05)	12.784 * (1.94)	0.128 * (1.94)	-0.003 (-0.3)	-0.007 (-0.5)	-0.007 (-0.5)
Nanalyst	0.749 ** (2.25)	0.739 ** (1.96)	0.007 ** (1.99)	0 (1.16)	0 (0.66)	0 (0.63)
Size	-1.419 (-1.02)	-0.667 (-0.41)	-0.007 (-0.42)	0.001 (0.51)	0.001 (1.32)	0.001 (1.35)
Bm	0.552 (0.47)	0.271 (0.23)	0.003 (0.22)	0.002 ** (2.33)	0.001 * (1.74)	0.001 * (1.74)
N	83,868	234,408	51,316	83,868	51,316	51,316
Adj. R^2	*0.13*	*0.13*	*0.13*	*0.00*	*0.02*	*0.02*

Table 4: Cross-sectional characteristics of the tones of high beta brokerages

The dependant variables are tones, measured as follows: *Sentiment* is the proportion of (positive – negative) to (positive + negative) words for each analyst-conference call pair. *Litigious* is the proportion of litigious words to total number of words. *Superfluous* is the proportion of superfluous words to total number of words. *Uncertainty* is the proportion of uncertainty words to total number of words. *Gunning_Fog* is calculated as $(0.4 \times \frac{no.\ of\ words}{no.\ of\ sentences} + 100 \times \frac{no.of\ complex\ words}{no.of\ words})$, where words are complex if they have 3 or more syllabus. *Flesch_Kincaid* is calculated as $\left(206.835 - 1.015 \times \frac{no.\ of\ words}{no.\ of\ sentences} - 84.6 \times \frac{no.\ of\ syllabus}{no.\ of\ words}\right)^{-1}$. Coefficients (x100) of standardized independent variables and t-statistics (in parentheses) are reported. *Surp* is the median consensus forecast up to 90 days prior to announcement day. *Crisis* is a dummy variable indicating the period from 1 Jul 2007 through 31 Dec 2009. *Sanction* is the average tone of analysts from the 10 brokerages sanctioned during the 2003 Global Settlement. *ToneAvg* is the average analysts' tone measured at the conference call level. *Dispest* is the analysts forecast dispersion up to 90 days prior to announcement day. *Nanalyst* is the number of unique forecasts up to 90 days prior to announcement day. *Size* is the natural logarithm of market value. *Bm* is the book to market. Standard errors are clustered by announcement day, *, **, and *** indicate two-tailed statistical significance at the 10, 5 and 1 percent levels, respectively.

Panel A: Sentiment and litigious tones of high *comove* brokerages

Variable	Sentiment		Litigious	
	Bad (<0)	Good (>=0)	Bad (<0)	Good (>=0)
Intercept	3.267 (0.71)	-4.253 (-1.42)	-0.021 (-0.17)	0.064 (0.96)
Surp	11.557 (0.39)	-12.041 (-0.64)	-1.185 (-0.69)	1.475 ** (2.12)
Crisis	-1.493 * (-1.67)	0.356 (0.54)	0.04 (0.95)	0.032 (1.17)
Surp * Crisis	9.751 (0.26)	-1.034 (-1.41)	3.133 * (1.72)	0.037 (1.1)
Sanction	20.449 *** (9.96)	20.978 *** (15.89)	32.779 *** (4.65)	25.827 *** (8.61)
Sanction * Crisis	1.475 (0.36)	1.198 (0.41)	-8.988 (-1.01)	6.915 (0.95)
ToneAvg	4.682 (1.58)	1.865 (1)	1.491 (0.15)	-17.161 *** (-3.58)
ToneAvg * Crisis	-1.132 (-0.2)	-4.035 (-0.84)	-5.332 (-0.25)	-14.917 (-1.24)
Dispest	2.336 * (1.86)	1.06 (1.29)	-0.002 (-0.05)	-0.024 (-0.89)
Nanalyst	-0.045 (-0.62)	-0.129 *** (-2.98)	-0.003 (-1.21)	0.003 *** (2.84)
Bm	-0.191 (-0.79)	0.318 (1.14)	-0.008 (-1.56)	0 (0.07)
Size	-0.117 (-0.37)	0.38 * (1.84)	0.003 (0.34)	-0.004 (-0.91)
N	2,392	5,385	2,392	5,385
Adj. R^2	0.12	0.12	0.18	0.20

Table 4 (Cont'd)

Panel B: Uncertainty and superfluous tones of high *comove* brokerages

Variable	Uncertain		Superfluous	
	Bad (<0)	Good (>=0)	Bad (<0)	Good (>=0)
Intercept	0.037 (0.11)	0.244 (1.24)	0.004 (0.52)	0.004 (0.48)
Surp	3.232 (0.76)	1.763 (0.97)	-0.004 (-0.22)	0.041 (0.94)
Crisis	-0.023 (-0.11)	0.087 (0.51)	0 (0.42)	0.001 (1.08)
Surp * Crisis	0.067 (0.01)	0.092 (1.28)	-0.006 (-0.34)	0.002 (1)
Sanction	21.28 *** (8.41)	19.885 *** (7.97)	44.531 *** (3.45)	17.588 * (1.72)
Sanction * Crisis	-1.061 (-0.16)	1.829 (0.37)	-3.842 (-0.23)	-22.433 * (-1.84)
ToneAvg	-8.515 * (-1.91)	-6.341 (-1.53)	13.201 (0.54)	-36.123 (-1.11)
ToneAvg * Crisis	3.666 (0.38)	-2.312 (-0.29)	29.74 (0.83)	-51.728 (-1.52)
Dispest	0.095 (0.94)	-0.021 (-0.6)	-0.001 (-1.11)	-0.001 (-0.6)
Nanalyst	-0.005 (-1.17)	-0.002 (-0.54)	0 (0.15)	0 (0.96)
Bm	0.014 (0.95)	0.018 (0.77)	0 (0.58)	0 (-1.32)
Size	0.014 (0.62)	-0.007 (-0.5)	0 (-0.53)	0 (-0.47)
N	2,392	5,385	2,392	5,385
Adj. R^2	0.12	0.10	0.55	0.33

Table 4 (Cont'd)

Panel C: Gunning Fog and Flesch Kincaid scores of high *comove* brokerages

Variable	Gunning_Fog		Flesch_Kincaid	
	Bad (<0)	Good (>=0)	Bad (<0)	Good (>=0)
Intercept	-40.764 (-1.47)	-29.735 * (-1.64)	-0.005 (-0.04)	0.508 *** (5.19)
Surp	-3.648 (-0.02)	161.867 (1.06)	0.069 (0.59)	0.141 (1.55)
Crisis	32.809 (1.05)	-29.164 (-1.1)	0.079 (0.25)	-0.721 *** (-4.98)
Surp * Crisis	217.805 (0.77)	16.037 (1.44)	0.045 (0.26)	0.005 (0.94)
Sanction	25.747 *** (10.19)	23.972 *** (14.29)	27.584 *** (7.69)	23.732 *** (4.5)
Sanction * Crisis	2.325 (0.54)	10.443 (1.21)	-35.638 * (-1.81)	7.97 (0.85)
ToneAvg	1.731 (0.7)	0.013 (0.01)	-1.009 (-0.06)	-62.185 *** (-5.21)
ToneAvg * Crisis	-4.487 (-0.81)	5.377 (1.2)	-8.28 (-0.23)	85.079 *** (4.99)
Dispest	17.41 ** (2)	9.268 (1.41)	0.007 (0.59)	0.001 (0.57)
Nanalyst	-0.158 (-0.38)	0.325 (1.33)	-0.001 * (-1.82)	0.001 ** (2.54)
Bm	3.409 *** (3.23)	0.193 (0.13)	0.002 *** (3.06)	0.001 (0.67)
Size	1.823 (1)	1.545 (1.29)	0.001 (0.59)	0.001 (1.02)
N	2,392	5,385	2,392	5,385
Adj. R^2	0.18	0.17	0.42	0.68

Table 5: The relation between cumulative abnormal returns and brokerage tones

The dependant variable is cumulative abnormal returns, measured over the window (-1, 1) centered on conference call date. Coefficients (x100) of standardized independent variables and t-statistics (in parentheses) are reported. *Surp* is the median consensus forecast up to 90 days prior to announcement day. *Crisis* is a dummy variable indicating the period from 1 Jul 2007 through 31 Dec 2009. *Sanction* is the average tone of analysts from the 10 brokerages sanctioned during the 2003 Global Settlement. *ToneHigh* is the average analysts' tone from brokerages with above median co-moving beta, measured at the conference call level. *ToneLow* is the average analysts' tone from brokerages with below median co-moving beta. *ToneListed* is the average analysts' tone from listed brokerages. *ToneAvg* is the average of all analysts' tone. Tones are measured as follows: *Sentiment* is the proportion of (positive – negative) to (positive + negative) words for each analyst-conference call pair. *Litigious* is the proportion of litigious words to total number of words. *Superfluous* is the proportion of superfluous words to total number of words. *Uncertainty* is the proportion of uncertainty words to total number of words. *Gunning_Fog* is calculated as $(0.4 \times \frac{no.\ of\ words}{no.\ of\ sentences} + 100 \times \frac{no.of\ complex\ words}{no.of\ words})$, where words are complex if they have 3 or more syllabus. *Flesch_Kincaid* is calculated as $\left(206.835 - 1.015 \times \frac{no.\ of\ words}{no.\ of\ sentences} - 84.6 \times \frac{no.\ of\ syllabus}{no.\ of\ words}\right)^{-1}$. *Dispest* is the analysts forecast dispersion up to 90 days prior to announcement day. *Nanalyst* is the number of unique forecasts up to 90 days prior to announcement day. *Size* is the natural logarithm of market value. *Bm* is the book to market. Standard errors are clustered by announcement day, *, **, and *** indicate two-tailed statistical significance at the 10, 5 and 1 percent levels, respectively.

Panel A: Relative and litigious tones

Variable	Dependant Variable = CAR (-1,1)					
	Sentiment			Litigious		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	-0.206	-0.237	0.022	0.06	0.031	0.075
	(-0.84)	(-0.87)	(0.14)	(0.25)	(0.12)	(0.5)
Surp	0.806 ***	0.956 ***	1.353 ***	0.812 ***	0.961 ***	1.357 ***
	(6.35)	(6.56)	(5.14)	(6.37)	(6.52)	(5.05)
Crisis			0.708 **			0.423
			(2.3)			(1.37)
Surp * Crisis			-0.432			-0.438
			(-1.21)			(-1.21)
Sanction			-0.251 ***			0.1
			(-3.39)			(1.04)
Sanction * Crisis			0.181 *			-0.046
			(1.82)			(-0.38)
ToneHigh		0.149 **	0.294 ***		-0.127	-0.235 **
		(2.17)	(3.35)		(-1.57)	(-2.12)
ToneLow		0.024	0.146 *		-0.06	-0.161 *
		(0.39)	(1.85)		(-0.93)	(-1.84)
ToneListed	0.042			-0.114 *		
	(0.72)			(-1.89)		
ToneAvg	0.754 ***	0.899 ***	0.763 ***	-0.348 ***	-0.325 ***	-0.32 ***
	(11.31)	(11.47)	(8.74)	(-4.5)	(-3.42)	(-2.84)
Dispest	-0.047	-0.009	-0.055	-0.087	-0.062	-0.104
	(-0.69)	(-0.12)	(-0.57)	(-1.32)	(-0.87)	(-1.2)
Nanalyst	0.197 ***	0.169 **	0.146 **	0.215 ***	0.184 ***	0.162 **
	(2.99)	(2.54)	(2.17)	(3.27)	(2.74)	(2.4)
Bm	0.531	1.413	-0.71	0.126	0.357	-1.257
	(0.31)	(0.63)	(-0.23)	(0.07)	(0.16)	(-0.43)
Size	-0.226 ***	-0.241 ***	-0.251 ***	-0.283 ***	-0.297 ***	-0.318 ***
	(-2.9)	(-2.92)	(-2.62)	(-3.62)	(-3.59)	(-3.33)
N	10,962	9,346	7,227	10,962	9,346	7,227
Adj. R^2	0.04	0.04	0.04	0.03	0.03	0.03
Top cond. index	3.29	3.82	4.64	3.29	3.83	4.65
Fixed Effects	*Quarter*	*Quarter*	*None*	*Quarter*	*Quarter*	*None*

Table 5 (Cont'd)

Panel B: Uncertainty and superfluous tones

Variable	Dependant Variable = CAR (-1,1)					
	Uncertainty			Superfluous		
	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Intercept	0.052	0.034	0.055	0.046	0.029	0.048
	(0.22)	(0.13)	(0.36)	(0.19)	(0.11)	(0.31)
Surp	0.806 ***	0.955 ***	1.339 ***	0.806 ***	0.958 ***	1.365 ***
	(6.25)	(6.39)	(4.94)	(6.25)	(6.41)	(5.03)
Crisis			0.412			0.417
			(1.33)			(1.35)
Surp * Crisis			-0.428			-0.45
			(-1.17)			(-1.23)
Sanction			-0.074			-0.082
			(-0.98)			(-0.92)
Sanction * Crisis			-0.019			0.145
			(-0.19)			(1.42)
ToneHigh		0.097	0.075		-0.169	-0.282 **
		(1.3)	(0.71)		(-1.42)	(-2.48)
ToneLow		-0.017	-0.045		-0.017	-0.02
		(-0.27)	(-0.55)		(-0.37)	(-0.52)
ToneListed	0.067			-0.118 **		
	(1.13)			(-2.21)		
ToneAvg	-0.043	0.023	-0.017	-0.118 *	-0.17 *	-0.339 ***
	(-0.7)	(0.33)	(-0.22)	(-1.77)	(-1.71)	(-3.26)
Dispest	-0.095	-0.068	-0.112	-0.096	-0.069	-0.111
	(-1.43)	(-0.96)	(-1.32)	(-1.44)	(-0.97)	(-1.3)
Nanalyst	0.202 ***	0.168 **	0.15 **	0.201 ***	0.17 **	0.148 **
	(3.07)	(2.52)	(2.22)	(3.06)	(2.55)	(2.2)
Bm	-0.309	-0.294	-2.029	-0.348	-0.288	-2.095
	(-0.18)	(-0.13)	(-0.68)	(-0.2)	(-0.13)	(-0.7)
Size	-0.279 ***	-0.3 ***	-0.32 ***	-0.278 ***	-0.3 ***	-0.321 ***
	(-3.55)	(-3.61)	(-3.33)	(-3.55)	(-3.63)	(-3.37)
N	10,962	9,346	7,227	10,962	9,346	7,227
Adj. R^2	0.02	0.03	0.03	0.02	0.03	0.03
Top cond. index	3.29	3.82	4.64	3.29	3.82	4.64
Fixed Effects	*Quarter*	*Quarter*	*None*	*Quarter*	*Quarter*	*None*

Table 5 (Cont'd)

Panel C: Gunning Fog and flesch Kincaid scores

Variable	Dependant Variable = CAR (-1,1)					
	Gunning_Fog			Flesch_Kincaid		
	Model 13	Model 14	Model 15	Model 16	Model 17	Model 18
Intercept	0.027	0.006	0.067	0.315	0.018	0.057
	(0.11)	(0.02)	(0.43)	(0.21)	(0.07)	(0.37)
Surp	0.809 ***	0.958 ***	1.343 ***	0.806 ***	0.958 ***	1.345 ***
	(6.29)	(6.44)	(4.96)	(6.26)	(6.43)	(4.97)
Crisis			0.423			0.43
			(1.37)			(1.39)
Surp * Crisis			-0.413			-0.426
			(-1.14)			(-1.18)
Sanction			-0.053			0.023
			(-0.68)			(0.19)
Sanction * Crisis			0.028			0.026
			(0.22)			(0.16)
ToneHigh		-0.132	-0.201 *		-0.197 *	-0.243 *
		(-1.6)	(-1.87)		(-1.91)	(-1.66)
ToneLow		0.04	0.061		0.027	-0.03
		(0.59)	(0.67)		(0.49)	(-0.46)
ToneListed	0.02			-0.009		
	(0.32)			(-0.18)		
ToneAvg	-0.229 ***	-0.226 ***	-0.161 **	-0.038	-0.148	-0.111
	(-3.7)	(-3.3)	(-2.08)	(-0.72)	(-1.62)	(-1.06)
Dispest	-0.093	-0.062	-0.099	-0.095	-0.066	-0.105
	(-1.41)	(-0.88)	(-1.15)	(-1.43)	(-0.94)	(-1.23)
Nanalyst	0.208 ***	0.175 ***	0.147 **	0.204 ***	0.173 ***	0.148 **
	(3.17)	(2.63)	(2.19)	(3.1)	(2.59)	(2.2)
Bm	-0.553	-0.281	-1.964	-0.331	-0.17	-1.9
	(-0.32)	(-0.12)	(-0.65)	(-0.19)	(-0.07)	(-0.63)
Size	-0.26 ***	-0.272 ***	-0.302 ***	-0.281 ***	-0.29 ***	-0.313 ***
	(-3.28)	(-3.25)	(-3.12)	(-3.58)	(-3.48)	(-3.26)
N	10,962	9,346	7,227	10,962	9,346	7,227
Adj. R^2	0.02	0.03	0.03	0.02	0.03	0.03
Top cond. index	3.30	3.84	4.66	3.30	3.84	4.65
Fixed Effects	*Quarter*	*Quarter*	*None*	*Quarter*	*Quarter*	*None*

Table 6: The relation between cumulative abnormal returns and brokerage tones during good and bad news

The dependant variable is cumulative abnormal returns, measured over the window (-1, 1) centered on conference call date. Coefficients (x100) of standardized independent variables and t-statistics (in parentheses) are reported. *Surp* is the median consensus forecast up to 90 days prior to announcement day. *Crisis* is a dummy variable indicating the period from 1 Jul 2007 through 31 Dec 2009. *Sanction* is the average tone of analysts from the 10 brokerages sanctioned during the 2003 Global Settlement. *ToneHigh* is the average analysts' tone from brokerages with above median co-moving beta, measured at the conference call level. *ToneLow* is the average analysts' tone from brokerages with below median co-moving beta. *ToneAvg* is the average of all analysts' tone. Tones are measured as follows: *Sentiment* is the proportion of (positive – negative) to (positive + negative) words for each analyst-conference call pair. *Litigious* is the proportion of litigious words to total number of words. *Superfluous* is the proportion of superfluous words to total number of words. *Uncertainty* is the proportion of uncertainty words to total number of words. *Gunning_Fog* is calculated as $(0.4 \times \frac{no.\ of\ words}{no.\ of\ sentences} + 100 \times \frac{no.of\ complex\ words}{no.of\ words})$, where words are complex if they have 3 or more syllabus. *Flesch_Kincaid* is calculated as $\left(206.835 - 1.015 \times \frac{no.\ of\ words}{no.\ of\ sentences} - 84.6 \times \frac{no.\ of\ syllabus}{no.\ of\ words}\right)^{-1}$. *Dispest* is the analysts forecast dispersion up to 90 days prior to announcement day. *Nanalyst* is the number of unique forecasts up to 90 days prior to announcement day. *Size* is the natural logarithm of market value. *Bm* is the book to market. Standard errors are clustered by announcement day, *, **, and *** indicate two-tailed statistical significance at the 10, 5 and 1 percent levels, respectively.

Table 6 (Cont'd)

Panel A: Relative, litigious, uncertainty and superfluous tones

Variable	Dependant Variable = CAR (-1,1)							
	Sentiment		Litigious		Uncertainty		Superfluous	
	Bad (<0)	Good (>=0)	Bad (<0)	Good (>=0)	Bad (<0)	Good (>=0)	Bad (<0)	Good (>=0)
Intercept	-1.764 *** (-7.97)	0.924 *** (3.87)	-1.76 *** (-7.81)	0.981 *** (4.26)	-1.739 *** (-7.72)	0.982 *** (4.27)	-1.736 *** (-7.7)	0.969 *** (4.19)
Surp	0.547 (1.6)	0.701 * (1.94)	0.472 (1.39)	0.644 * (1.76)	0.587 * (1.72)	0.62 * (1.68)	0.64 * (1.85)	0.664 * (1.8)
Crisis	-0.389 (-0.74)	1.761 *** (5.47)	-0.725 (-1.39)	1.621 *** (5.09)	-0.81 (-1.54)	1.621 *** (5.09)	-0.81 (-1.54)	1.633 *** (5.13)
Surp * Crisis	-0.185 (-0.39)	-0.511 (-1.03)	-0.104 (-0.23)	-0.52 (-1.04)	-0.162 (-0.34)	-0.5 (-1)	-0.215 (-0.45)	-0.537 (-1.07)
Sanction	-0.166 (-1.35)	-0.24 *** (-2.68)	-0.109 (-0.7)	0.077 (0.69)	-0.098 (-0.77)	-0.061 (-0.7)	-0.361 *** (-3.02)	-0.006 (-0.06)
Sanction * Crisis	0.129 (0.73)	0.183 * (1.75)	0.006 (0.04)	-0.041 (-0.27)	-0.183 (-1.16)	0.041 (0.37)	-0.865 (-0.42)	0.124 (1.13)
ToneHigh	0.513 *** (3.16)	0.169 * (1.69)	-0.118 (-0.76)	-0.145 (-1.06)	0.083 (0.54)	0.082 (0.67)	-0.254 (-1.21)	-0.296 ** (-2.53)
ToneLow	0.294 ** (1.98)	0.078 (0.87)	-0.084 (-0.53)	-0.015 (-0.15)	-0.101 (-0.85)	-0.003 (-0.03)	0.097 * (1.79)	-0.055 (-0.83)
ToneAvg	0.861 *** (4.94)	0.487 *** (5.11)	-0.972 *** (-5.2)	-0.043 (-0.31)	-0.302 ** (-2)	0.086 (0.99)	-0.413 * (-1.94)	-0.372 *** (-3.32)
Dispest	0.58 *** (4.7)	-0.249 *** (-3.46)	0.556 *** (4.09)	-0.268 *** (-3.26)	0.536 *** (4.09)	-0.267 *** (-3.26)	0.526 *** (4.11)	-0.27 *** (-3.25)
Nanalyst	-0.402 *** (-2.67)	0.278 *** (3.66)	-0.388 *** (-2.59)	0.289 *** (3.76)	-0.42 *** (-2.78)	0.288 *** (3.76)	-0.428 *** (-2.83)	0.284 *** (3.73)
Bm	7.626 ** (2.07)	-4.682 (-0.96)	8.611 ** (2.25)	-5.23 (-1.11)	6.471 * (1.74)	-5.336 (-1.13)	6.467 * (1.73)	-5.489 (-1.16)
Size	0.29 (1.46)	-0.764 *** (-6.93)	0.208 (1.07)	-0.816 *** (-7.41)	0.186 (0.96)	-0.823 *** (-7.45)	0.17 (0.87)	-0.815 *** (-7.4)
N	2,221	5,006	2,221	5,006	2,221	5,006	2,221	5,006
Adj. R^2	0.03	0.04	0.03	0.03	0.02	0.03	0.01	0.03
Top cond. Index	4.96	5.80	4.91	5.80	4.90	5.80	4.89	5.80

Panel B: Gunning Fog and Flesch Kincaid scores

Variable	Dependant Variable = CAR (-1,1)			
	Gunning_Fog		Flesch_Kincaid	
	Bad (<0)	Good (>=0)	Bad (<0)	Good (>=0)
Intercept	-1.679 *** (-7.4)	0.981 *** (4.26)	-1.715 *** (-7.59)	0.979 *** (4.24)
Surp	0.628 * (1.79)	0.636 * (1.73)	0.634 * (1.83)	0.63 * (1.72)
Crisis	-0.789 (-1.46)	1.639 *** (5.11)	-0.747 (-1.41)	1.645 *** (5.14)
Surp * Crisis	-0.21 (-0.44)	-0.477 (-0.97)	-0.211 (-0.44)	-0.487 (-0.99)
Sanction	-0.034 (-0.25)	-0.071 (-0.81)	-0.078 (-0.28)	-0.017 (-0.15)
Sanction * Crisis	0.086 (0.45)	-0.087 (-0.67)	0.134 (0.67)	-0.173 (-0.94)
ToneHigh	-0.316 * (-1.88)	-0.083 (-0.71)	-0.456 * (-1.78)	-0.069 (-0.48)
ToneLow	0.079 (0.53)	0.084 (0.86)	-0.024 (-0.08)	0.005 (0.1)
ToneAvg	-0.212 (-1.59)	-0.057 (-0.69)	-0.174 (-0.98)	-0.032 (-0.27)
Dispest	0.546 *** (4.29)	-0.261 *** (-3.3)	0.553 *** (4.35)	-0.264 *** (-3.3)
Nanalyst	-0.439 *** (-2.9)	0.281 *** (3.71)	-0.453 *** (-3)	0.284 *** (3.74)
Bm	6.841 * (1.82)	-5.307 (-1.12)	6.829 * (1.81)	-5.335 (-1.13)
Size	0.191 (0.98)	-0.801 *** (-7.23)	0.18 (0.92)	-0.811 *** (-7.38)
N	2,221	5,006	2,221	5,006
Adj. R^2	0.02	0.03	0.02	0.03
Top cond. Index	4.92	5.84	4.89	5.81

Table 7: The relation between cumulative abnormal returns and brokerage tones during small earnings surprises

The dependant variable is cumulative abnormal returns, measured over the window (-1, 1) centered on conference call date. Coefficients (x100) of standardized independent variables and t-statistics (in parentheses) are reported. *Surp* is the median consensus forecast up to 90 days prior to announcement day. *Crisis* is a dummy variable indicating the period from 1 Jul 2007 through 31 Dec 2009. *Sanction* is the average tone of analysts from the 10 brokerages sanctioned during the 2003 Global Settlement. *ToneHigh* is the average analysts' tone from brokerages with above median co-moving beta, measured at the conference call level. *ToneLow* is the average analysts' tone from brokerages with below median co-moving beta. *ToneAvg* is the average of all analysts' tone. Tones are measured as follows: *Sentiment* is the proportion of (positive – negative) to (positive + negative) words for each analyst-conference call pair. *Litigious* is the proportion of litigious words to total number of words. *Superfluous* is the proportion of superfluous words to total number of words. *Uncertainty* is the proportion of uncertainty words to total number of words. *Gunning_Fog* is calculated as $(0.4 \times \frac{no.\ of\ words}{no.\ of\ sentences} + 100 \times \frac{no. of\ complex\ words}{no. of\ words})$, where words are complex if they have 3 or more syllabus. *Flesch_Kincaid* is calculated as$\left(206.835 - 1.015 \times \frac{no.\ of\ words}{no.\ of\ sentences} - 84.6 \times \frac{no.\ of\ syllabus}{no.\ of\ words}\right)^{-1}$. *Dispest* is the analysts forecast dispersion up to 90 days prior to announcement day. *Nanalyst* is the number of unique forecasts up to 90 days prior to announcement day. *Size* is the natural logarithm of market value. *Bm* is the book to market. Standard errors are clustered by announcement day, *, **, and *** indicate two-tailed statistical significance at the 10, 5 and 1 percent levels, respectively.

Variable	Dependant Variable = CAR (-1,1)					
	Sentiment	Litigious	Uncertainty	Superfluous	Gunning Fog	Flesch Kincaid
Intercept	0.106 (0.1)	0.464 (0.46)	0.394 (0.37)	0.33 (0.31)	0.15 (0.14)	0.257 (0.24)
SurpNeg	-1.067 ** (-2.02)	-1.015 ** (-1.95)	-1.043 ** (-1.94)	-1.095 ** (-2.07)	-1.032 ** (-1.97)	-1.096 ** (-2.11)
Crisis	0.039 (0.05)	0.055 (0.07)	0.213 (0.26)	0.028 (0.04)	-0.023 (-0.03)	0.044 (0.05)
SurpNeg * Crisis	3.532 * (1.89)	4.187 ** (1.99)	3.656 * (1.86)	3.839 * (1.88)	4.099 ** (2.23)	3.707 * (1.88)
Sanction	-0.062 (-0.3)	-0.12 (-0.51)	0.103 (0.48)	-0.573 (-1.26)	0.194 (0.96)	0.211 (0.45)
Sanction * Crisis	0.888 *** (3.9)	0.346 (0.8)	-0.279 * (-1.57)	-	0.494 * (1.8)	0.126 (0.32)
ToneHigh	0.291 (1.3)	-0.283 (-1.31)	-0.004 (-0.02)	-0.36 (-0.64)	0.121 (0.43)	0.259 (0.59)
ToneLow	0.238 (1.16)	-0.311 (-1.38)	-0.141 (-0.62)	-0.102 (-0.58)	0.028 (0.11)	0.822 (1.19)
ToneAvg	0.499 ** (2.24)	-0.545 ** (-2.33)	-0.567 ** (-2.18)	-1.063 *** (-2.69)	-0.361 * (-1.64)	-0.542 * (-1.52)
Dispest	1.249 *** (3.8)	1.015 *** (3.24)	1.002 *** (3.38)	1.024 *** (3.45)	0.964 *** (3.48)	1.003 *** (3.33)
Nanalyst	0.371 * (1.77)	0.338 * (1.6)	0.342 * (1.64)	0.341 * (1.62)	0.35 * (1.68)	0.373 * (1.75)
Bm	-3.371 (-0.14)	4.701 (0.21)	3.315 (0.14)	1.453 (0.06)	-2.965 (-0.12)	-1.069 (-0.04)
Size	-1.097 *** (-3.95)	-1.09 *** (-3.86)	-1.057 *** (-3.73)	-1.14 *** (-3.97)	-1.091 *** (-3.79)	-1.131 *** (-3.94)
N	660	660	660	660	660	660
Adj. R^2	0.08	0.05	0.05	0.04	0.05	0.04
Top cond. Index	11.12	11.18	11.10	11.21	11.13	11.23

CHAPTER THREE

Sophisticated Investors' Reactions to Management Earnings Forecasts: Does Credibility Matter?

Abstract

Using a proprietary set of institutional trading data, we investigate how sophisticated investors utilize the information contained in management earnings forecasts characteristics to formulate their trading strategy. We find that these investors' responses to a firm's forecasts are not only increasing in the magnitude of earnings surprise, but also magnified by the firm's prior forecast accuracy. We reveal transient institutions as the principal traders on these forecast characteristics and show that trading strategies using both forecast surprise and prior forecast accuracy are not only profitable to implement, but also outperform those that rely solely on forecast surprise.

JEL Classification: G14, G20, M41

Keywords: Management Earnings Forecast; management credibility; institutional Trading

Sophisticated Investors' Reactions to Management Earnings Forecasts: Does Credibility Matter?

1. Introduction

Thousands of management earnings forecasts are released into the market every year, contributing significant increments to useful accounting information (Beyer, Cohen, Lys and Walther, 2010). Although many studies have shown that forecast characteristics, such as forecast news, prior forecast accuracy, and forecast form have significant impacts on stock returns, analysts' forecasts and bid-ask spreads (e.g., Williams, 1996; Coller and Yohn, 1997; Hirst, Koonce, and Miller, 1999; Libby, Tan, and Hunton, 2006; Han and Tan, 2007; Hutton and Stocken, 2009; Atiase, Res, and Tse, 2010), the literature is so far silent on the consequences of forecast characteristics on the trading responses of informed investors.

Our motivation in this study follows from Bamber, Barron and Stevens (2011)'s argument that trading response to financial disclosures is the most direct evidence of material impact on investors' expectations and investment decisions. While evident that aggregate trading movements must be significant during management forecast events, as implied by the non-trading responses in existing studies, it is not clear whether such public disclosures convey new information to informed investors and therefore elicit trading responses from them as a result.

We argue that a study of informed trading responses to management earnings forecasts is important because of the growing influence of institutions in the US equity market. Institutions currently hold 73% of common stocks, compared to 8% about 50 years ago. With a large fraction of aggregate wealth under their management, institutions are frequently the marginal price-setting agents in the securities markets. Through our analysis of the trading behavior of institutions, we hope to contribute a deeper understanding to the dynamics of stock prices during management earnings forecast events.

Several studies support our assumption that institutions are sophisticated and informed investors: Lo and MacKinlay (1990), Lakonishok, Shleifer and Vishny (1992), Meulbroek (1992), Kim and Verrecchia (1994), Chakravarty and McConnell (1999), Sias and Starks (1997), Koski and Scruggs (1998), Chakravarty (2001), and Hansch and Choe (2007) show that institutional investors are sophisticated investors and their trading can consistently predict future stock returns (Daniel, Grinblatt, Titman, and Wermers, 1997; Grinbalatt and Titman, 1989; Nofsinger and Sias, 1999; Chen, Jegadeesh, and Wermers, 2000; Wermers, 2000). More recently, Irvine, Lipson and Puckett (2007) examine the trading, and trading profits, of institutions prior to the release of analysts' recommendations. They report that institutions trade in the same direction as the analyst recommendations and earn significant profits from their trades. Boehmer and Kelley (2009) find that larger institutional holding leads to better priced stocks. Jegadeesh and Tang (2010) find evidence that institutional investors invest in resources to better gather and process public and private information.

The implications of this study are twofold. First, we validate the importance of management earnings forecast as a source of public information against a more stringent subset of market participants – the informed investors. As institutional investors are informed investors that have the ability to better process publicly available information rather than extract private information (Griffin, Shu and Topaloglu, 2011), management earnings forecasts may be valuable not only in reducing information asymmetry and earnings response inefficiency between firm and investors (Li and Tse, 2008), but in levelling the playing field between informed and uninformed investors as well. The second implication follows from the first: if the informed investors benefit from trading on these events, does forecast news, prior forecast accuracy or other forecast characteristics explain their profitable strategies?

Our study use management earnings forecast data from the First Call database, and institutional trade data from ANcerno Ltd. over the 1998 to 2009 period. To the best of our knowledge, our study is the first to examine institutional trading responses to management earnings forecasts using high-frequency transaction data.[14] We find that institutions' aggregate trading imbalances (average buy minus sell) are significant and increasing in the magnitude of news surprise during management earnings forecast events. We measure news surprise as the difference between management earnings forecast and the median analyst forecast prior to announcement date and find that institutions buy (sell) more on higher positive (negative) surprises.

We then test the explanatory powers of other forecast characteristics on institutional aggregate trading imbalances and find that prior forecast accuracy and size have significant interaction effects on news surprise. Specifically, the more accurate a firm's forecast history and smaller the firm size, the stronger the net trading responses to news surprise. Our results imply that managers can systematically alter institutional investors' prior beliefs about firm earnings through their forecast accuracy, and news surprises of small firms are more surprising even to informed investors.

Within institutional types, transient/short-term institutions are known to be able to access and process both private and public information better than their quasi-indexing and dedicated counterparts (Ke and Petroni, 2004; Ke and Ramalingegowda, 2005; and Yan and Zhang, 2009). We thus investigate the trading imbalances of the different institution types and we find that our results stated so far are indeed driven by transient institutions. Although we use a set of proprietary material to match institution types to ANcerno data (ANcerno keep their clients' identity anonymous except for unique ID codes), our study can be replicated using the matching algorithm in Hu, Ke, and Yu (2009). Both samples provide similar results.

[14] The daily institutional trading data overcome the limitations of quarterly holdings data to allow us to investigate more accurately how institutional investors utilize information contained in management earnings forecast. That is, the quarterly holdings data cannot accurately identify the timing of trades and do not reflect intra-quarter round-trip trades, which results in a significant number of missing trades. Specifically, Elton, Gruber, Blake, Krasny, and Ozelge (2009) and Puckett and Yan (2010) estimate that use of quarterly data fails to capture more than 20% of trades due to intra-quarter round-trip transactions.

Finally, we posit that if transient institutions trade on forecast characteristics, then such information must be profitable on average. We then create portfolios using forecast news and prior forecast accuracy as trading factors, and follow the trades of the typical institution through a hypothetical portfolio whereby security positions are committed during the management earnings forecast announcement window and unwound one day prior to earnings announcement. The added objective of this holding period is to attempt to eliminate the realization risks of forecast errors that are inherent in forecast news and accuracy. Our results show that the holding period returns (net of total trading costs) are significantly positive even after adjusting for size and book-to-market effects. We also find that the two-factor portfolio is more profitable than a single-factor forecast news portfolio. These results suggest that any investor can realistically profit from the public information in forecast characteristics while avoiding realization risks. In addition, we find some evidence that supports existing findings of asymmetric stock price reactions during disclosure events. Specifically, our results suggest that stock price reactions to good news are conditional on prior forecast accuracy whereas bad news are inherently credible (Ng, Tuna, and Verdi, 2010) and post-guidance drifts are larger for firms with lower prior forecast accuracy (Li and Tse, 2008).

Our study contributes to two lines of literature. First, it adds to the literature on management earnings forecasts, with new evidences that such disclosures are useful sources of public information even to informed investors. Second, our results add to a large and growing body of empirical research that shows that institutional investors are sophisticated investors, by showing that transient institutions can infer additional information about the quality of firm earnings and devise them into profitable trading strategies during management earnings forecasts.

The rest of the study is organized as follows. Section 2 reviews prior research and develops the hypotheses. Section 3 discusses the research design. Section 4 reports the results, with robustness tests presented in Section 5. Section 6 concludes.

2. Background and hypothesis development

2.1. *Trading reactions around earnings disclosures*

Beaver (1968) explain the reason why trading reactions of informed investors should be studied using trading volume. He posits that volume changes reflect differential beliefs among individual investors while price change is an aggregated measure of market expectation. Small price changes do not readily reveal the differences between earnings disclosures that are uninformative and those that drive large disagreements. On the other hand, earnings disclosures are deem to be informative once investors change their shareholdings in response, of which the most direct measure is trading volume.

Consistent with this theory, Bamber and Cheon (1995) show evidences of differing magnitudes of price and volume reactions (high volume with little price changes and low volume with large price changes) during earnings announcements. Kandel and Pearson (1995) also find abnormal trading volume to earnings announcements that induce no changes to stock price. The importance of analyzing disclosures through the lens of volume reactions are further substantiated in Cready and Hurtt (2002). They show evidences that volume reactions are more powerful than price reactions in interpreting market responses.

2.2. *The management earnings forecast environment*

The comprehensive framework of Hirst, Koonce and Venkataraman (2008) characterizes the management earnings forecasts literature into three components: antecedents, characteristics, and consequences. Antecedents are factors that managers consider before deciding whether to issue a forecast, such as regulatory environment, analyst/ investor needs (Ajinkya, Bhojraj and Sengupta, 2005) and litigation risks (e.g., Kasznik and Lev, 1995). Characteristics are the attributes of earnings forecasts, such as news (e.g., Hutton and Stocken, 2009), accuracy (e.g., Chen, 2004; Rogers and Stocken, 2005), form (e.g., Han and Tan, 2007) and duration (e.g., Waymire, 1985). Managers appear to have the most control over forecast characteristics. Once they decide to issue a management earnings forecast, managers possess a high degree of choice over forecast characteristics to alter market expectations. Consequences are the outcomes of earnings forecasts such as changes in stock returns (e.g., Anilowski, Feng and Skinner, 2007), analysts' forecasts (e.g., Beyer, 2009), cost of capital (Coller and Yohn, 1997), reputation (Graham, Harvey and Rajgopal, 2005), signal of management quality (Trueman, 1986) and litigation risks (Skinner, 1994; Field, Lowry and Shu, 2005).

Managers provide management earnings forecasts on a voluntary basis and such disclosures are less regulated than mandatory disclosures such as earnings announcements. Regulations such as the Private Securities Litigation Reform Act (PSLRA) enacted in 1996 further protect firms from being easily sued for optimistic forecasts, raising concerns over disclosure credibility. Generally, forecast characteristics such as news, prior forecast accuracy and form are easily observable signals of disclosure credibility that are capable of predicting or inflicting significant consequences to management earnings forecasts. This stream of literature so far suggest that forecast characteristics such as news and prior forecast accuracy are particularly persistent in explaining stock market reactions (e.g., Williams, 1996; Rogers and Stocken, 2005; Li and Tse, 2008; Hutton and Stocken, 2009; Ng, Tuna and Verdi, 2010), while market reactions to forecast forms and horizons are mixed (Baginski, Conrad and Hassell, 1993; Pownall, Wasley and Waymire, 1993; Atiase, Supattarakul and Tse, 2005). In this study, we add informed trading responses as a new dimension of forecast consequences to forecast characteristics of management earnings forecasts.

2.3. *Management earnings forecast characteristics*

2.3.1. *Earnings News*

Earnings news is the most commonly used forecast characteristic in the management earnings forecasts literature. Good news refers to earnings forecasts that exceed market expectations, bad news forecasts fall below market expectations and confirming forecasts are in line with market expectations (e.g., Penman, 1980; Kaznick and Lev, 1995; Cotter, Tuna, and Wysocki., 2006; Hutton and Stocken, 2007).

Prior to a management earnings forecast announcement, we assume institutions to be holding an optimal portfolio based on their investment needs. In this state, institutions have no incentives to trade due to the absence of new information. Unless the institutions have knowledge of, or predict the forecast news in advance, the release of surprisingly good or bad earnings news in this state will exceed their expectations and trigger trading responses. Correspondingly, we should observe a change in institutional trading volume that is consistent with and increasing in the magnitude of surprise, as predicted by Kim and Verrechia (1991)'s model and consistent with the results of other empirical studies in different earnings disclosure settings (e.g., Atiase and Bamber 1994; Bamber and Cheon 1995; Bhattacharya 2001; Bailey, Li, Mao, and Zhong, 2003; Hope, Thomas, and Winterbotham, 2009).

Hypothesis 1: Institutions buy (sell) on positive (negative) forecast surprises, with increasing responses to larger surprises.

2.3.2. *Disclosure credibility*

Mercer (2004) defines disclosure credibility as *investors' perceptions of the believability of a particular disclosure*. The voluntary and unaudited features of management earnings forecasts naturally raise concerns about forecast credibility and investors are influenced by many factors when deciding if a forecast is believable. Our main motivation in this paper is to provide a broad first look at the effects of disclosure credibility on informed trading responses and thus conveniently model the incentives, business environment and management ability to forecast accurately as a persistent trend (Williams, 1996; Hirst, Koonce, and Miller, 1999; Ng, Tuna, and Verdi, 2010; Hutton and Stocken, 2009). Correspondingly, we expect institutional investors, as informed investors, to exhibit higher levels of responsiveness to forecast news issued by firms with higher prior forecast accuracy.

We also consider the disclosure credibility of those forecast characteristics that investors can directly observe (form and duration), may affect pre-announcement trading (analyst following), and influence contemporaneous trading responses (analyst dispersion, and firm size). We do not propose a definite hypothesis for forecast form due to mixed results in existing literature (see Pownall et al., 1993; Atiase et al., 2005; Hirst et al., 1999; Libby et al., 2006), but we control for all of the above forecast characteristics in our empirical model.

Hypothesis 2: Prior forecast accuracy increases the effect of forecast surprises on trading responses, after controlling for other forecast characteristics.

2.4. *Differences in institutional types*

Yan and Zhang (2009) find that changes in short-term institutional ownership are predictive of future returns while long-term institutional holdings are not. Using a separate classification by Bushee (2001), Ke and Petroni (2004) find that transient institutions tend to sell more shares in the quarter before bad news breaks in strings of consecutive earnings increase. Both studies attribute the performance of the transient institutions to private informational advantages. Ke and Ramalingegowda (2005) find that transient institutions are able to earn abnormal returns from exploiting post-earnings announcement drift. In that study, they do not find conclusive evidence of transient institutions trading on private information, thus implying that transient institutions are excellent responders to public information. Hu, Ke, and Yu (2009) find that transient institutions are able to detect the underlying motivation behind small negative earnings surprises and make informed trading responses instead of overreacting to such information as perceived by many studies.

The literature on institutional trading so far suggest that transient institutions are either better at, or more concerned about, gathering and processing information than other institution types. These results are also consistent with the basis of Bushee (2001)'s institutional investors' trading classifications: transient institutions are short-term investors with high portfolio turnover and diversified portfolio, whose trading responses are driven by short-term trading profits considerations; while quasi-indexing and dedicated institutions are long-term stable investors, motivated by longer-term dividends or capital appreciation (Porter (1992), Dobryzynski (1993)).

We posit that if transient institutions are as responsive to earnings disclosures as suggested by the trading literature, then they should be just as responsive to management earnings forecasts if H1 is true. Based on the findings of current institutional trading literature, we also hypothesize that transient institutions are more responsive to management earnings forecasts than the quasi-indexing or dedicated institutions.

Hypothesis 3: In terms of trading responses, transient institutions are more sensitive than other types of institutions to the forecast characteristics of management earnings forecasts.

The next hypothesis thus follows: if transient institutions consistently trade on forecast characteristics, then such strategies are expected to be profitable on average. Further, if H2 is true, then prior forecast accuracy must add beneficial trading information to forecast news. This implies that a two-factor trading strategy that considers both forecast news and prior forecast accuracy should be superior to a single-factor trading strategy that considers only forecast news.

Hypothesis 4: Trading on forecast characteristics during management earnings forecasts are expected to be profitable on average. If H2 is true, then a two-factor trading strategy should outperform a single-factor trading strategy that uses only forecast news.

3. Sample and research design

3.1. *Sample development*

We obtain a sample of 41,447 management earnings forecasts from the First Call Company Issued Guidelines (CIG) database that are released between January 1, 1998 and December 31, 2009. Our selection includes only point and range quarterly unadjusted EPS forecasts of firms listed on NYSE, AMEX or NASDAQ.[15] We exclude forecasts before 1998 due to non-availability of ANcerno data. The sample excludes non-discontinuity events and annual forecasts due to significant differences in forecast precision between quarterly and annual frequencies (Baginski and Hassell 1997; Kasznik, 1999; Chen, 2004; Hribar and Yang, 2010).

We merge our First Call sample with the unadjusted actual EPS from I/B/E/S, and remove observations with missing analyst estimates within 90 days prior to announcement day (3,947 observations) and actual earnings more than 120 days from end of reporting quarter (105 observations).[16] We then remove all observations except for the last forecast made for the reporting quarter (8,462 observations).

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[15] CIG values in the First Call CIG database are reported on unadjusted basis.

[16] We use analyst forecasts and actuals from I/B/E/S instead of First Call for two reasons. First, CIG values from First Call are provided on an unadjusted basis but the database's actuals and forecasts are split-adjusted, which

We use this sample of 28,933 observations to develop measures of prior forecast accuracy. However, our hypothesis requires examining stock returns and institutional trading, for which we extract a subsample of 6,656 observations. This sample excludes confounding earnings events where management forecasts occur within five days centered on an earnings announcement date (16,028 observations), missing firm size and book-to-market data (253 observations), stock prices that are less than $1 so as to avoid illiquid and volatile stocks (61 observations), stocks with less than 10% institutional holdings and 5% change in quarterly institutional holdings (8 observations), missing trading data from ANcerno (5,638 observations) and lastly, all management earnings forecasts that occur prior to the date of earnings announcement for the previous fiscal period (289 observations).

We summarize the sample selection process in Table 1.

3.1.1. *Institutional trading data*

Our institutional trading data comes from ANcerno Ltd. (formerly Abel/Noser Corporation), a leading consulting firm that monitors and analyzes execution costs for institutional investors. Other studies that have used ANcerno data include Lipson and Puckett (2007), Goldstein, Irvine, Kandel, and Wiener (2009), Chemmanur, He, and Hu (2009), Hu, Ke, and Yu (2009), Goldstein, Irvine, and Puckett (2011), Anand, Irvine, Puckett, and Venkataraman (2012) and Pucket and Yan (2011).

The data covers a large sample of equity transactions from January 1998 to December 2009. This sample includes the exact date, execution price, order size, number of shares traded, commissions paid, whether the trade is a buy or a sell and unique identity codes of the institutions initiating the trades.

would lead to 'rounding off' measurement errors (Payne and Thomas 2003). Second, I/B/E/S has a more comprehensive coverage of brokers/analysts than First Call.

The ANcerno database captures all the trading data directly from the Order Delivery System (ODS) of their clients, which include pension plan sponsors, money managers and brokers. In record, ANcerno clients and their money managers are anonymous, but identifiable by unique identity codes. Client codes and client types identifies the ANcerno clients and their associated institution type (pension plan sponsor, money manager or brokerage). ANcerno clients can make trades on their own or through an external money manager. In both cases, the managers making these trades are given unique manager codes, which are different numbers from the client codes even if the institutions are the same.

In the case whereby a money manager trades on behalf of a pension plan sponsor who does not subscribe to ANcerno, the trades will be tagged to: the money manager's client code, the money manager's manager code, and then classified as money manager trades instead of pension fund trades. If both institutions are ANcerno clients, then the trades will be tagged to: the pension plan sponsor's client code, the external money manager's manager code, and then classified as pension fund trades. Also, the manager code is unique to a money manager and does not differentiate between their different financial products and services.

To minimize the error that we capture long-term strategic trades of a transient-type money manager trading on behalf of their pension clients, we select only the subsample of trades classified as money manager trades. Consistent with the notion that money managers typically do not engage other money managers, we find that trades classified as money manager trades seldom have more than one unique pair of manager to client code.

Regarding concerns about the representativeness of the ANcerno sample, Anand et al., (2012) and Puckett and Yan (2011) do not find significant differences in the characteristics of the stocks held and traded by institutions in the ANcerno and 13F database except that ANcerno institutions tend to be larger than the average 13F institution.[17]

3.1.2. *Institutional investors' trading classification*

We rely on the institutional investors' trading classifications from Brian Bushee to distinguish between the types of institutions in the ANcerno database. This classification scheme, as described in Bushee (2001), is constructed based on the quarterly institutional ownership data in the 13F database. This trading classification has been used in Bushee and Noe (2000), Collins, Gong, and Hribar (2003), Ke and Petroni (2004), Ke and Ramalingegowda (2005), and Hu, Ke, and Yu (2009).

Although Bushee provides annual trading classifications in the sample, the classification for each institution is highly stable over time, with year-to-year correlations of more than 0.80. Therefore, most studies using the trading classification assign the "permanent classification" (most frequent type) to each institution in their sample. However, some investment managers do change their trading orientation over time and we attempt to balance between stability and accuracy by assigning each institution the most frequent classification for the time period covered in our study.

We possess a proprietary list of ANcerno manager details that allows us to match the manager codes with their respective institution classifications through the 13F database. Using this list, we are able to match 613 manager codes out of the full listing of 1,047 manager codes in the ANcerno database, covering 60% of the total order volume in the sample. The proportion of transient-quasi-dedicated institutions in our sample is 44% - 53% - 3%, which is close to the proportion in the full classifications list (38% - 57% - 5%).

[17] Form 13F is a mandated quarterly filing with the Securities and Exchange Commission (SEC), required of institutional investment managers with over $100 million in investment assets. The 13F database contains information about the amount and changes in quarterly institutional investment holdings.

We present the summary statistics of our matched institutional trading sample in Table 2. Our sample consists of 350,101 trades during the three-day event windows of 6,656 management earnings forecasts over a 12 year period. Consistent with the proportion of transient institutions in our sample, transient institutions make up 44% of institutional participation and their trades account for 37% of all trades. As expected of institutions, we observe large order values (mean = $184,874) accompanied by large order sizes (mean = 7,988 shares). Transient trade sizes and values are significantly 22% smaller than the non-transient institutions, but relatively consistent over the years. Interestingly, non-transient trades have declined by almost 50% from the earlier years of the sample. This trend suggests that management earnings forecasts have become relatively less important events to non-transient institutions than transient institutions.

3.2. *Research design*

3.2.1. *Institutional trading during management earnings forecast*

To test our first hypothesis that institutions react to management earnings forecasts by buying more on larger forecast surprise (and vice-versa), we compare the average trading response to the different levels of forecast surprise. We use the order size variable in the ANcerno database rather than traded volume because the former fully captures the trading intentions of the managers. Traded volume on the other hand, will not include trades that cannot be fulfilled due to factors (such as aggressive price jumps) exogenous to the managers' intentions.

We compute trading imbalance (MF_Imbalance) as a measure of institutional response in the following manner (where subscript i denotes management earnings forecast event, k denotes institution, and t denotes the time period):

$$MF\_Imbalance_i = \frac{(\sum^k BUY_{k,[t-1,t+1]} - \sum^k SELL_{k,[t-1,t+1]})/3}{mean(\sum VOL_{i,[t-365,t-3]})} \tag{1}$$

We trim trading volume at 0.5 percentile on both ends to remove potential outliers, and aggregate the average institutional buy orders minus sell orders over the three-day event window centered on the day of management earnings forecast announcement. Following which, we divide the figure by 3 to obtain the daily average imbalance for each management earnings forecast event. We scale this figure by the daily average CRSP volume from 365 through 3 days before the event to control for non-announcement period trading (Ali, Klasa, and Li, 2008). The resulting figure can be interpreted as a percentage of the average daily CRSP volume. Positive imbalance implies that institutions are buying on average, and vice-versa. In the total absence of trading incentives, such as no new information, trading imbalance is theoretically zero. Trading imbalance can also be zero when the amount of disagreement results in an equal proportion of buy and sell orders.

We compute the amount of forecast surprise (News) in the following manner (where subscript i denotes management earnings forecast event, and t denotes the time period):

$$NEWS_{i,t} = \frac{\left(CIG_{i,t} - MEDEST_{i,t-1}\right)}{Price_{i,t-2}} \tag{2}$$

We define the variables as follows: NEWS is the amount of forecast surprise. CIG is the acronym for Company Issued Guideline, which is the management earnings forecast (unadjusted EPS) recorded in the First Call database. This figure can be in the form of a range forecast and we adopt the midpoint of this range as the EPS forecast for the event. MEDEST is the median I/B/E/S consensus analyst forecasts from the set of latest forecast by individual analysts from 90 days through 1 day before the event. Price is the stock price of the firm issuing the management earnings forecast. We scale the forecast surprise by the stock price 2 days prior to event and winsorize the final sample at 1% to remove potential extreme values. The resulting figure is expressed as a percentage of the firm's stock price and can be interpreted as good news (positive), bad news (negative), or confirming news (zero).

For H1, we sort the events into quintile portfolios by surprise. We attempt to avoid a look-ahead bias by using the distribution of the prior year's forecast surprises to determine the quintile cut-offs for the current year's forecast surprise (Foster, Olsen, and Shevlin, 1984; Ng, Tuna, and Verdi, 2010). We then compare the mean imbalance across the quintiles of forecast surprise.

3.2.2. *Institutional trading on disclosure credibility*

If institutional investors are concerned about disclosure credibility, our prediction in hypothesis 2 says that prior forecast accuracy is informational to trading. To test this hypothesis, we estimate the following OLS regression (event subscripts are suppressed), adjusted for firm clustering and calendar year fixed effects.

$$MF\_IMBALANCE = \alpha + \beta_1 NEWS + \beta_2 ACCURACY + \beta_3 (NEWS \times ACCURACY) + \sum \beta_j Control_j + \sum \beta_k NEWS \times Control_j \quad (3)$$

We define the variables as follows: The dependent variable MF_IMBALANCE, as defined in (1), is the average daily trading imbalance generated over the three-day event window and expressed as a percentage of the average daily CRSP volume. NEWS is the amount of forecast surprise as defined in (2). ACCURACY is defined as follows (where subscript i denotes event, subscript n denotes number of prior quarters, and subscript t denotes the time period):

$$ACCURACY_i = -\frac{1}{n}\sum_{i-1}^{i-n}\left(\frac{\left|CIG_{i-n,t} - ACTUAL_{i-n,t}\right|}{Price_{i-n,t-2}}\right) \quad (4)$$

This measure appears in many studies involving prior forecast accuracy (e.g., Chen, Francis, and Jiang, 2005; Hutton and Stocken, 2009; and Ng, Tuna, and Verdi, 2010). We calculate this figure as the negative of the average absolute forecast errors of a firm's prior forecasts and scaled by stock price two days prior to event day. If a firm's string of management earnings forecasts have zero forecast error, this accuracy measure will be 0. Forecast errors in a firm's history will be reflected as a negative number, with larger negative values signifying larger errors. We compute this measure using a horizon of four quarters prior to the current fiscal period. Sensitivity tests with prior eight, twelve and all quarters reveal similar results.

To determine the necessary control variables for (3), we now discuss variables that are known to influence forecast characteristics or trading behavior.

3.2.2.1. *Forecast form and duration*

Management earnings forecasts can come in qualitative or quantitative forms. Quantitative forms are usually point, range, minimum or maximum estimates. Although forecast precisions are associated with managerial certainty (Hassell, Jennings, and Lasser, 1988; Hirst et al., 1999; Hughes and Pae, 2004), the stock price and analyst reactions to forecast form is so far mixed. As a control variable (FORM), we indicate a point forecast as 1, and 0 otherwise.

Baginski and Hassell (1997) find that disclosures issued earlier in the fiscal period tend to be less accurate. We measure duration (DURATION) as the number of days between end of reporting quarter and forecast announcement date.

3.2.2.2. *Analyst following and dispersion*

O'Brien and Bushan (1990) find that analyst following affects levels of institutional shareholdings. Larger analyst following is associated with higher levels of information production and disclosure by the firm (Lang and Lundholm, 1996). We posit that institutions may also gather such information from private sources such as brokerage analysts (Irvine, Lipson and Puckett, 2007), and adjust their trades outside the management forecast window.

Depending on whether firms disclose more during or before management earnings forecast, higher levels of analyst following may either increase or attenuate the effect of news surprise on trading imbalance. In a separate study on the association of analyst following on forecast accuracy, Dhole, Mishra, and Sivamakrishnan (2010) find that larger analyst following increases the likelihood of a downward bias in management earnings forecasts. Thus, analyst following appears to correlate with trading activity as well as news surprise and we aim to avoid this potential omitted variable bias by controlling for the number of unique analysts (NANALYST) used to calculate our measure of median I/B/E/S consensus forecast.

Based on Kim and Verrechia (1997)'s model that revisions in differential belief spurs trading, larger analyst forecast dispersions increase trading activities during disclosure events (Atiase and Bamber, 1994). However, analyst dispersions could also be a measure of the informational differences between the informed and uninformed investors (Barron, Stanford, and Yu, 2009). If so, we may or may not observe significant effects of analyst dispersion on institutional imbalances during earnings surprises. We thus control for analyst dispersion (DISPERSION) and measure this variable as the standard deviation of the analyst forecasts used in our median I/B/E/S consensus estimate.

3.2.2.3. *Firm size*

Bamber (1987) finds that small firms garner more trading volume than large firms during earnings announcements, although the trend seems to have reversed in recent years (Barron et al., 2009). The latter result could probably be explained by the fact that larger firms usually provide more detailed disclosures and tend to be more accurate in their forecasts (Ajinkya, Bhojraj, and Sengupta, 2005; Bhojraj, Libby, and Yang, 2010). However, it is also plausible that the informational content in the earnings disclosures of large firms are proportionately smaller than their smaller counterparts (e.g., Atiase, 1985; Bamber, 1986), which makes the surprises of small firms even more surprising. Conditional on the level of surprise, trading reactions should then be decreasing in firm size. We control for this size effect (SIZE) by taking the natural logarithm of the firm's market value.

3.2.3. *Trading differences between institutional types*

For our third hypothesis, we re-run equation (3) on the subset of transient, quasi-indexing and dedicated institutions to test if transient institutions are more sensitive to the information disclosed by forecast characteristics than other institution types.

3.2.4. *Trading by different institutional types*

Our final prediction says that if transient institutions trade on news surprise and prior forecast accuracy, then such strategies are expected to be profitable on average. To test this claim, we assign institutional trades into quintile portfolios sorted by forecast characteristics and measure the holding-period net profit of round-trip trades from the forecast announcement window to one day before earnings announcement. We choose this holding period for two reasons. First, we do not wish to confound the returns predictability of forecast characteristics with earnings announcement effects. Second, our choice of holding period avoids the realization risks of forecast errors that are inherent in forecast characteristics. Regardless how accurate a firm's prior forecasts are, there is always a non-negative probability that it will make an error subsequently.

We now outline the way we derive net profits, which is similar to the method used by Puckett and Yan (2011). For every participating institution in our sample of management earnings forecast events, we use the execution price to calculate the holding period returns for each round-trip trade initiated during the three day event window. We then calculate the abnormal return by subtracting the corresponding size and book-to-market (2 x 3) benchmark return obtained from Professor Kenneth French's website.[18] We subtract the trading costs,

[18] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

which consist of round-trip commissions and implicit trading costs (e.g. price impact) to obtain the net profit of the trade. A large order may take multiple orders or days to fulfil and we calculate the implicit trading costs for each buy trade as the execution price minus the volume-weighted average price of the same trading day; and for each sell trade as the volume-weighted average price minus the execution price.

We identify all the management earnings forecast events that transient institutions participate in and remove potential outliers that have per trip commissions and implicit trading costs of more than 10%, and raw returns outside the range of [-0.5, 0.5]. We then form quintile portfolios by forecast surprise using the method outlined before, and also double sort the forecast surprise portfolios into another quintile portfolio by prior forecast accuracy. Finally, we calculate the equal-weighted net profit for each set of portfolios to compare their trading performances.

4. Empirical results

4.1. *Institutional trading reactions to forecast news*

Table 3 presents the cumulative abnormal returns (size and book-to-market adjusted) and the institutional trading imbalances around the 3-day event window. The cumulative abnormal returns, a measure of aggregate market response, increases monotonically from -12.1% (t-statistics = 32.5) for the most negative news surprise to 6.7% (t-statistics = 22.4) for the most positive news surprise. This result affirms the significance of the information content in our management earnings forecasts sample (Waymire, 1984).

Our measure of trading imbalance in Table 3 increases monotonically from -3.47% (t-statistics = 2.3) for the most negative forecast surprise to 1.73% (t-statistics = 2.1) for the most positive forecast surprise. This implies that on average, institutions react to forecast news by buying on good news and selling on bad news.

The skewness of both the cumulative abnormal returns and trading imbalances towards bad news is obvious. We find that the abnormal returns of the extreme bad news quintile are almost twice that of the extreme good news. Our results support but do not distinguish between the extensive evidences of bad news being more credible than good news (Jennings, 1987; Skinner, 1994; Hutton, Miller, and Skinner, 2003; Rogers and Stocken, 2005; Ng et al., 2006), or good news are more likely to be leaked out earlier than bad news thereby inducing the market to react prior to announcement (Kothari, Shu, and Wysocki, 2005).

We also observe that the trading imbalances for ranks 3 and 4 are not significantly different from zero. However, rather than a reduced incentive to trade due to absence of information, we find that the total order volume for the middle ranks are in fact 3% to 10% higher than average (not shown), consistent with the predicted outcome of investor disagreement (Bamber, Barron, and Stober, 1997). Thus, the differences between the abnormal imbalances between the extreme and middle ranks are more likely to be driven by higher levels of consensus among institutional investors rather than reduced trading incentives. We confirm that this level of consensus is not systematically driven by firm credibility as the two extreme ranks are not associated with higher levels of prior accuracy.

4.2. *Disclosure credibility and institutional trading*

Table 4 presents the results of our disclosure credibility measures on institutional trading. Our objective is to examine the disclosure credibility of the forecast news and thus present only the results of the interaction variables of the other forecast characteristics with NEWS. [19] Model 1 shows the results of equation (3) without the control variables, while model 2 shows the results of equation (3) in full. Coefficients are interpreted in percentage form. As predicted, the coefficient on NEWS is significant and positive in both models. In Model 1, the daily

[19] We note that the coefficients of the single variables (ACCURACY, FORM, DURATION, NANALYST, DISPERSION and SIZE) are statistically insignificant.

average trading imbalance in the absence of forecast news (NEWS = 0) is both economically and statistically insignificant (intercept = 0.15). Every percentage increase in news surprise increases trading imbalance by 4.51%, which corresponds to a 30-fold increment on the intercept term (4.51/0.15). In Model 2, this coefficient remains positive and significant after controlling for other forecast characteristics (coefficient = 45.43, t-statistics = 3.0). We find that the large coefficient of NEWS in Model 2 is solely attributable to the control variable NEWS * SIZE. Given that the coefficient on SIZE is small and insignificant, we note that the large NEWS coefficient in model 2 is the combined result of a huge range of firm sizes in our sample and a strong influence of the SIZE effect on trading imbalance to NEWS.

We find, consistent with hypothesis 2, that the coefficient on NEWS * ACCURACY is significantly positive for both models. Assuming linearity holds, the interaction can be interpreted in the following manner for Model 1: For every level of forecast surprise, every percentage increase in prior forecast accuracy will add 2.52 to the NEWS coefficient. However, we caution the use of this simplistic linear interpretation due to a possible non-linear influence of prior forecast accuracy on NEWS and MF_IMBALANCE (Hutton and Stocken, 2009). Regardless, we find evidence that higher prior forecast accuracy increases trading response to forecast news.

The coefficient of NEWS * NANALYST (t-statistics = 2.0) shows that the net effect of forecast news on trading imbalance increases by 0.37% per increase in analyst. This result supports our first notion that larger analyst following is associated with increased disclosure *during* management earnings forecast events. If the increased disclosures occur before the event, institutions may react to the information outside of the event window and the coefficient for this interaction term will turn negative.

Lastly, we find the coefficient of NEWS * SIZE to be significantly negative, implying that institutional investors react more to smaller firms of the same level of surprises as compared to their larger counterparts. Our results show that a 1% increase in firm size reduces NEWS effect by 0.03%, adding support to existing findings that earnings news conveys a proportionately larger amount of information for smaller firms (e.g., Atiase, 1985; Bamber, 1986).

4.3. *The trading responses of transient, quasi-indexing, and dedicated institution types*

Table 5 compares the results of equation (3) on the different types of institutions based on the institutional trading classification by Bushee (2001). The coefficients on NEWS for transient and quasi-indexing institutions are positively significant, but the magnitude of response of quasi-indexing institutions is weaker (3.85 versus 2.94 for model 1, and 45.43 versus 26.64 for model 2). NEWS, however, do not explain trading imbalance of dedicated institutions. Our results are loosely consistent with Bushee and Noe (2000)'s finding that transient and quasi-indexing institutions react to increased disclosure levels but dedicated institutions do not. The weaker responses of quasi-indexing institutions in our sample also support their suggestion that quasi-indexing institutions are more concerned about monitoring than short-term trading opportunities.

Our results suggest that only transient institutions react to the prior forecast accuracy measure NEWS * ACCURACY (coefficient=2.55 and 2.99, t-statistics=2.2), implying that these short-term investors increase their shareholdings in firms that are better predictors of future earnings during management earnings forecast events. We do not find statistically significant trading reactions from the quasi-indexing or dedicated institutions, although the coefficients on NEWS * ACCURACY for the former are consistent and economically significant (coefficient=0.93 and 1.16).

The coefficient on NEWS * FORM is negatively significant for quasi-indexing institutions (coefficient= -5.07, t-statistics= 2.0), but positive and economically significant for transient (coefficient= 1.92, t-statistics= 0.9) and dedicated institutions (coefficient=2.29, t-statistics=

1.5). Although statistically insignificant, transient and dedicated institutions appear to increase trading responses to higher levels of managerial certainty (Hassell, Jennings, and Lasser, 1988; Hirst et al., 1999; Hughes and Pae, 2004). In contrast, quasi-indexing institutions buy and sell less on higher forecast precision during positive and negative surprises respectively. A possible explanation is that the market conditions allowing firms to exhibit higher forecast certainty for the contemporaneous fiscal period are systematically linked to the quasi-indexing institutions' diversifying strategies. This may increase the expectations of the quasi-indexing managers and cause a reaction (or over-reaction) prior to the management earnings forecast events, thereby causing FORM to be negatively associated with trading imbalance during the management earnings forecasts. We do not attempt to unravel this issue in this study and will leave this question for future research.

Coefficients of NEWS * SIZE are significantly negative (transient = -3.26, quasi-indexing = -1.77) and in similar magnitudes for both institutional types (transient = 3.26/45.43, quasi-indexing = 1.77/26.64). The results are consistent with those in Table 4, and add to our finding that transient and quasi-indexing institutions are more sensitive to the proportion of informational content revealed in earnings forecast than dedicated institutions.

In sum, we find that the aggregate results in Table 4 are primarily driven by the transient institutions, with weaker supporting responses by quasi-indexing institutions. In contrast, none of our forecast characteristics in the model explains the trading imbalances of dedicated institutions.

4.4. *Profitability of trading strategy on forecast news and prior forecast accuracy*

Our objective in this section is to analyze the predictive profitability of forecast news and prior forecast accuracy. Table 6 and 7 show the trading performance of portfolios sorted by forecast news, and by forecast news and prior forecast accuracies. These are hypothetical portfolios constructed by aggregating the institutional trades committed during the three day event window and unwinding these positions one day before earnings announcements. In Table 6, for a sell strategy across NEWS, we find that the abnormal returns (measured as the holding period return less size and book-to-market benchmark returns) increases monotonically from -4.08% for the '*most positive*' quintile to 2.65% for the '*most negative'* quintile. Correspondingly, for a buy strategy across NEWS, we find that the abnormal returns increase from -3.12% for the '*most negative*" quintile to 4.37% for the '*most positive*' quintile. This implies that the most profitable trading strategies are to buy on extreme positive surprises and to sell on extreme negative surprises. Trading otherwise would be strictly less profitable, with maximum losses for buying on extreme negative surprises and selling on extreme positive surprises.

Although abnormal returns suggest that trading in the direction of forecast surprise results in higher level of profits than otherwise, some may argue that round-trip commissions could reduce the returns to trivial levels of profitability. In addition, market reactions may rapidly move prices during extreme forecast surprises, resulting in negative price impacts to large trades that require multiple trades or days to fulfil. Consistent with these arguments, we find that total trading costs are significantly higher for the profitable portfolios: buy trades in the '*most positive*' quintile (0.76%, t-statistics = 8.2) and sell trades in the '*most negative*' quintile (0.87%, t-statistics = 8.9). In contrast, the average total trading cost for the other quintiles is 0.21%. Even so, the trading costs for the profitable portfolios do not seem high enough to significantly negate trading profits. Net of trading costs, the profits for buying and selling on the '*most positive*' quintile and '*most negative*' quintile are 2.86% (t-statistics = 7.6) and 0.92% (t-statistics = 2.2) respectively. These results thus support our prediction that investors can realistically earn positive net profits from forecast news, by trading in the direction of forecast surprise.

To answer the second part of H4, we now focus on the two most profitable quintiles (buy on most positive surprise and sell on most negative surprise) and double sort each quintile into another quintile portfolio by prior forecast accuracy. We do not present the tables of all these 25 portfolios and will summarize and discuss our key findings here. We find that, consistent with our earlier results, average total trading costs are higher for the most profitable news quintiles (0.74% for '*most positive*', 0.82% for '*most negative*', 0.29% for other news quintiles). Abnormal returns are generally increasing in prior forecast accuracy for the '*most positive*' quintile, with the '*most credible*' portfolio outperforming the '*least credible*' portfolio by 1.7% (4.9% versus 3.2%). The only difference lies in the '*most negative*' quintile for which we find the largest abnormal returns for the '*least credible*' (3.7%) and '*most credible*' (4.2%) portfolio, against other in-between portfolios (1.2%), thereby implying a U-shape returns curve instead of a monotonic one. Initially surprising, we find that our results can be explained as the net effect of two forces: higher prior forecast accuracy increases the magnitude of stock price reactions around the event window (e.g., Hutton and Stocken, 2009), and lower prior forecast accuracy increases post-forecast drift (Li and Tse, 2008; Ng, Tuna, and Verdi, 2010). In other words, firms with higher forecast credibility experience a larger stock price adjustment at event date, whereas less accurate firms experience a larger drift during the post-forecast period. As to why this effect is not pronounced for the good news quintile, our explanation is that bad news are generally more credible than good news (e.g. Hutton, Miller, and Skinner, 2003) and good news are informative only when the issuing firm has a credible forecast track record (Ng et al., 2010). In other words, good news issued by inaccurate firms convey much smaller information content, which may then attenuate investor response and reduce both the price reactions on event day and post-guidance drift. Nevertheless, for the purpose of our study, we compare the differences between the most credible and least credible portfolios for the extreme quintiles of forecast news. We note that this setup bias against our results.

Table 7 Panel A presents the trading performance of the extreme quintiles sorted by both forecast news (‘*most positive*’ and ‘*most negative*’) and prior forecast accuracy (‘*most credible*‘ and ‘*least credible*’). The average total trading costs for the portfolios are similar (0.78% to 0.93%), with slightly higher costs for the ‘*most positive*’ quintile (0.11%). We find that prior forecast accuracy matters to abnormal returns, with the ‘*most credible*’ quintile outperforming the ‘*least credible*’ quintile by 1.74% and 0.57% (t-statistics= 9.9 and 3.0) for the ‘*most positive*’ and ‘*most negative*’ quintile respectively. Net of trading costs, the ‘*most credible*’ quintile outperforms the ‘*least credible*’ quintile with a net profit difference of 1.88% and 0.62% (t-statistics= 11.4 and 3.4) for the ‘*most positive*’ and ‘*most negative*’ quintile respectively. The results show that our measure of prior forecast accuracy, conditional on extreme forecast surprises, do exhibit higher profitability for the portfolios with high prior accuracy.

Panel B of Table 7 confirms our prediction that a two-factor portfolio (forecast news and prior forecast accuracy) outperforms a single-factor portfolio (forecast news only). Abnormal returns for the two-factor portfolio are 0.48% and 1.58% higher (t-statistics= 4.9 and 12.8) than the single-factor portfolio, for the ‘*most positive*’ and ‘*most negative*’ quintiles respectively. Net of trading costs, the two-factor portfolios continue to generate larger net profits than the single-factor portfolio: 0.25% (t-statistics= 2.53) for the ‘*most positive*’ quintile and 1.75% (t-statistics= 13.4) for the ‘*most negative*’ quintile.

5. Robustness checks

There are two main concerns about our study, which are selectivity and replication issues. First, we re-estimate equation (3) with the full sample of ANcerno institutions and obtain similar results. Second, we follow the matching algorithm in Hu, Ke, and Yu (2009) to derive an alternative sample of transient, quasi-indexing and dedicated institutions. This algorithm identifies ANcerno managers through the similarities in their quarterly holding changes with the 13F database. Using this method, we obtain 148 institutions of which 66% appear in our sample, thus allowing us to perform a partial out-of-sample test of this study. We also note that the proportion of institutional distribution in the alternative sample is similar to our sample as well as the full sample by Brian Bushee. We re-run all our models using the alternative sample and the results do not alter our inferences.

A number of studies point out that management often use analyst expectations as a benchmark (e.g., Ajinkya and Gift, 1984; Waymire, 1984) and the empirical test for such a prediction often use a relative forecast accuracy measure (Williams 1996, Hutton and Stocken, 2009). We calculate relative forecast accuracy as the difference between management bias and analyst bias, and re-estimate equation (3) using this new measure. We also observe that existing literature on prior forecast accuracy use many different estimation periods for their accuracy measures. Accordingly, we re-estimate equation (3) using prior two years (8 quarters), three years (12 quarters) and all years. Our results are robust to all these new specifications.

Lastly, we test our models on a subsample period that excludes earnings pre-announcements. Earnings pre-announcement is the period in between the end of the fiscal period and earnings announcement. Managers are expected to have a firmer grasp on their earnings performance since the fiscal period has concluded, and management earnings forecast issued within this period are expected to be more credible. We do not find any evidence that earnings pre-announcements are driving our results.

6. Summary and conclusion

This paper benchmark the usefulness of the information content in management earnings forecasts against a group of informed market participants – the institutional investors. Using high-frequency transaction data from ANcerno Ltd, we find that institutions trade in the direction of forecast surprises and in larger magnitudes to firms with higher prior forecast accuracy.

Using the institutional investors' trading classifications from Brian Bushee, we predict and find that transient institutions are more sensitive than quasi-indexing institutions to the information content in the characteristics of management earnings forecasts, while dedicated institutions do not respond to these characteristics in a significant way.

Given that transient institutions respond to forecast news and prior forecast accuracy, we predict and find that such forecast characteristics do generate abnormal returns over a holding period that spans from the management earnings forecast window to one day prior to earnings announcement. The selection of such a holding period avoids confounding effects from earnings announcements and realization risks of forecast errors. With the detailed trade by trade information in the ANcerno database, we find that the residual profits, net of actual commissions and implicit trading costs, are positive and economically significant. Lastly, we find that a two-factor portfolio, sorted by forecast surprise and prior forecast accuracy, is more profitable than a single-factor one sorted by forecast surprise only.

In conclusion, this study provides new evidence that management earnings forecast convey useful information to informed investors. Our results also suggest that any investor can realistically improve their investment profits by considering the characteristics of forecast news and prior forecast accuracy in management earnings forecasts.

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Table 1: Sample Selection

This table presents the sample selection criteria for our study. Management forecasts data are obtained from the First Call Historical Database. Actual earnings and analyst forecast data are obtained from I/B/E/S. Institutional trading data are obtained from ANcerno Ltd. Our sample period runs from January 1, 1998 to December 31, 2009. We exclude non-discontinuity events and retain the last forecast for the fiscal period.

	No. of events
All quarterly point and range EPS forecasts of common stocks listed in NYSE, AMEX and NASDAQ	41,447
Non-missing Analyst Forecasts	37,500
Actual date less than 120 days from end of Reporting Quarter	37,395
Last forecast for the fiscal period end	28,933
Non-Confounding events	12,905
Non-missing firm size and book-to-market data	12,652
Stock price more than $1	12,591
More than 10% institutional holdings and 5% change in quarterly institutional holdings	12,583
Missing Ancerno trade	6,945
Events after prior earnings announcements	6,656
Final Sample	**6,656**

Table 2: Descriptive Statistics for Institutional Trading Data

Institutional trading data are obtained from ANcerno Ltd, from January 1, 1998 to December 31, 2009. We separately match a list of known manager codes with Thomson 13F and classify these institutions into transient and non-transient institutions based on the institutional investors trading classification sample by Brian Bushee. Transient institutions are short-term investors, while the non-transient institutions (quasi-indexing and dedicated) are long-term investors. We calculate Total Institutions (event cumulative) by summing the number of distinct institution participation for each event, for all events, within the year. Average order size and value refers to the average number of shares and their corresponding value for each institution order initiated.

	All Matched Institutions				Transient Institutions				Non-transient Institutions			
Year	**Total Institutions (event cumulative)**	**Total no. of trades**	**Average order size**	**Average order value**	**Total Institutions (event cumulative)**	**Total no. of trades**	**Average order size**	**Average order value**	**Total Institutions (event cumulative)**	**Total no. of trades**	**Average order size**	**Average order value**
1998	39	80	3,635	98,895	22	43	4,324	104,795	17	37	2,698	92,154
1999	2,378	15,557	9,942	213,787	1,273	7,902	7,596	171,681	1,105	7,655	16,131	424,345
2000	3,004	22,128	9,702	227,553	1,546	9,588	6,736	171,409	1,458	12,540	13,486	388,325
2001	6,012	39,654	9,179	211,076	4,404	26,774	7,953	176,141	1,608	12,880	14,204	370,980
2002	5,857	39,299	10,287	220,285	3,444	18,355	8,989	186,656	2,413	20,944	13,879	328,219
2003	4,915	32,926	9,112	200,966	1,934	11,929	7,378	165,713	2,981	20,997	11,588	279,310
2004	5,430	48,107	8,593	213,934	1,597	10,384	9,481	241,586	3,833	37,723	10,050	272,185
2005	3,702	24,235	8,068	204,054	829	3,288	10,441	325,778	2,873	20,947	7,560	195,493
2006	4,145	37,720	6,019	165,265	1,515	9,346	8,102	237,553	2,630	28,374	5,581	154,643
2007	3,704	27,911	6,361	186,461	1,202	7,548	8,591	280,908	2,502	20,363	5,886	175,639
2008	4,198	38,437	7,218	146,577	874	6,686	7,189	146,621	3,324	31,751	7,310	160,529
2009	3,326	24,047	7,740	129,636	1,705	16,737	5,937	122,544	1,621	7,310	10,831	191,649
Average	**3,893**	**29,175**	**7,988**	**184,874**	**1,695**	**10,715**	**7,726**	**194,282**	**2,197**	**18,460**	**9,934**	**252,789**

Table 3: Cumulative Abnormal Returns and Trading Imbalances around Management Earnings Forecasts Events

This table presents the cumulative abnormal returns (*CAR*) and trading imbalances (*MF_IMBALANCE*) around the three-day management earnings forecast announcement window, centered on announcement date. *NEWS* is calculated as (CIG value- Consensus median Analyst Forecast) divided by stock price two days before event day. We rank *NEWS* from 1 – 5 with 1 indicating the most negative and 5 the most positive surprise. *CAR* is obtained by differencing the stock's cumulative return over the three-day event window, against the corresponding size and book-to-market benchmark (2 x 3) obtained from Professor Kenneth French's website. The benchmark portfolios are formed by intersecting two portfolios formed on market equity and three portfolios formed on the book-to-market ratio (as of end June for every year). The size breakpoint is the median NYSE market equity and the book-to-market ratio breakpoints are the 30th and 70th percentile of the NYSE. *MF_IMBALANCE* is calculated as the average net (buy – sell) over the three-day event window, scaled by traded stock's daily average CRSP annual volume. Numbers in parentheses are t-statistics. *, **, and *** indicate two-tailed statistical significance at the 10, 5, and 1 percent levels, respectively.

NEWS Rank	N	**CAR (%)**	**MF_IMBALANCE (%)**
5 (Most positive)	1,114	**6.70 ***** **(22.4)**	**1.73 **** **(2.1)**
4	1,190	-0.09 (-0.3)	0.45 (0.6)
3	1,640	**-1.40 ***** **(-6.8)**	0.33 (0.6)
2	1,311	**-8.16 ***** **(-23.0)**	**-2.40 **** **(-2.0)**
1 (Most negative)	1,401	**-12.10 ***** **(-32.5)**	**-3.47 **** **(-2.3)**
Total	6,656		

Table 4: Institutional Trading Responses to Forecast Characteristics

This table presents the OLS regressions that investigate the effect of forecast characteristics on institutional trading responses around the management earnings forecast announcement window. The dependent variable is trading imbalance (*MF_IMBALANCE*), which is calculated as the average net (buy – sell) over the three-day event window, scaled by traded stock's daily average CRSP annual volume. *NEWS* is calculated as (CIG value-Consensus median Analyst Forecast) divided by stock price two days before event day. *ACCURACY* is calculated as the mean of (-1 x |CIG value – Actual EPS|) for the prior four quarters. *FORM* is a dummy variable with 1 for point forecast and 0 otherwise. *DURATION* is calculated as the (Fiscal Ending Period Date – Management Forecast Announcement Date). *NANALYST* refers to number of analysts in the calculation of the median consensus forecasts (within 90 days prior to Management Earnings Forecast Announcement Date). *DISPERSION* is calculated as the standard deviation of the analyst forecasts used to compute the consensus estimate. *SIZE* is the natural logarithm of market value. We include all single variables and year fixed effects in the OLS regression but only report the coefficients of the variables of interests and their interaction terms. Numbers in parentheses are t-statistics, adjusted for one-way clustering by firms. *, **, and *** indicate two-tailed statistical significance at the 10, 5, and 1 percent levels, respectively.

	Dependent Variable = MF_IMBALANCE	
Independent Variable	Model (1)	Model (2)
Intercept	0.15 (0.3)	-0.13 (0.0)
NEWS	**4.51 ***** **(3.0)**	**46.56 ***** **(3.3)**
NEWS * ACCURACY	**2.52 **** **(2.0)**	**3.36 **** **(2.4)**
NEWS * FORM		-2.78 (-1.1)
NEWS * DURATION		0.08 (1.3)
NEWS * NANALYST		**0.37 **** **(2.0)**
NEWS * DISPERSION		0.02 (0.2)
NEWS * SIZE		**-3.26 ***** **(-3.2)**
Adjusted R2	0.81%	1.88%
Number of Firm Clusters	1,069	1,029
Number of Observations	4,281	4,149

Table 5: Trading Response Differences between Institutional Types

This table presents the OLS regressions that investigate the effect of forecast characteristics on institutional trading responses around the management earnings forecast announcement window. The institutions are classified according to the institutional investors trading classification sample by Brian Bushee. Trading imbalance (*MF_IMBALANCE*) is calculated as the average net (buy – sell) over the three-day event window, scaled by traded stock's daily average CRSP annual volume. *NEWS* is calculated as (CIG value- Consensus median Analyst Forecast) divided by stock price two days before event day. *ACCURACY* is calculated as the mean of (-1 x |CIG value – Actual EPS|) for the prior four quarters. *FORM* is a dummy variable with 1 for point forecast and 0 otherwise. *DURATION* is calculated as the (Fiscal Ending Period Date – Management Forecast Announcement Date). *NANALYST* refers to number of analysts in the calculation of the median consensus forecasts (within 90 days prior to Management Earnings Forecast Announcement Date). *DISPERSION* is calculated as the standard deviation of the analyst forecasts used to compute the consensus estimate. *SIZE* is the natural logarithm of market value. We include all single variables and year fixed effects in the OLS regression but only report the coefficients of the variables of interests and their interaction terms. Numbers in parentheses are t-statistics, adjusted for one-way clustering by firms. *, **, and *** indicate two-tailed statistical significance at the 10, 5, and 1 percent levels, respectively.

	Transient		Quasi-Indexing		Dedicated	
Independent Variable	Model (1)	Model (2)	Model (1)	Model (2)	Model (1)	Model (2)
Intercept	-0.29 (-1.0)	-3.50 (-0.8)	0.56 (1.3)	3.76 (0.8)	-0.83 (-1.5)	-8.04 (-1.7)
NEWS	**3.85 ***** **(3.3)**	**45.43 ***** **(3.0)**	**2.94 *** **(1.8)**	**26.64 *** **(1.8)**	-0.81 (-1.0)	-11.27 (-1.0)
NEWS * ACCURACY	**2.55 **** **(2.2)**	**2.99 **** **(2.2)**	0.93 (1.1)	1.16 (1.0)	1.58 (0.2)	-2.09 (-0.1)
NEWS * FORM		1.92 (0.9)		**-5.07 *** **(-2.0)**		2.29 (1.5)
NEWS * DURATION		0.10 (1.7)		0.01 (0.2)		0.00 (-0.1)
NEWS * NANALYST		0.28 (1.4)		0.23 (1.3)		0.13 (0.4)
NEWS * DISPERSION		0.10 (0.9)		-0.05 (-0.7)		0.04 (0.9)
NEWS * SIZE		**-3.26 ***** **(-2.9)**		**-1.77 *** **(-1.7)**		0.40 (0.6)
Adjusted R2	1.94%	4.28%	0.31%	0.75%	-0.39%	3.21%
Number of Firm Clusters	870	841	983	950	46	46
Number of Observations	2,942	2,866	3,865	3,760	90	90

Table 6: Abnormal Returns, Trading Costs, and Net Profits of Portfolio Strategy using Single Forecast Characteristics Factor: Forecast News

This table presents the holding-period net profit of round-trip trades from the forecast announcement window to one day before earnings announcement. Institutional trades are aggregated over the three-day management earnings forecast event window by buy and sell for each *NEWS* rank. We rank *NEWS* from 1 – 5 with 1 indicating the most negative and 5 the most positive surprise. *Abnormal Returns* are calculated as the holding period returns (based on execution price) less the corresponding size and book-to-market benchmark (2 x 3) obtained from Professor Kenneth French's website. The benchmark portfolios are formed by intersecting two portfolios formed on market equity and three portfolios formed on the book-to-market ratio (as of end June for every year). The size breakpoint is the median NYSE market equity and the book-to-market ratio breakpoints are the 30th and 70th percentile of the NYSE. *Total Trading Costs* include round-trip actual commissions and implicit trading costs. Implicit trading costs are calculated as the execution price minus the volume-weighted average price of the same trading day (for buy trade) and the volume-weighted average price minus the execution price (for sell trade). We calculate *Net Profits* as *Abnormal Returns* less *Total Trading Costs*. Numbers in parentheses are t-statistics. *, **, and *** indicate two-tailed statistical significance at the 10, 5, and 1 percent levels, respectively.

NEWS Rank		N	Abnormal Returns (%)	Total Trading Costs (%)	Net Profits (%)
5 (Most Positive)	Sell	882	-4.08 *** (-10.2)	-0.30 *** (-3.2)	-3.48 *** (-8.9)
	Buy	877	4.37 *** (10.8)	0.76 *** (8.2)	2.86 *** (7.6)
4	Sell	812	-0.72 * (-1.8)	0.17 ** (2.1)	-1.06 *** (-2.9)
	Buy	811	0.92 ** (2.4)	0.23 *** (2.8)	0.46 (1.2)
3	Sell	1,232	-0.30 (-1.2)	0.26 *** (5.1)	-0.82 *** (-3.4)
	Buy	1,245	0.29 (1.1)	0.10 ** (2.1)	0.08 (0.3)
2	Sell	725	0.79 * (1.8)	0.69 *** (7.7)	-0.59 (-1.4)
	Buy	734	-0.93 ** (-2)	-0.17 * (-1.9)	-0.60 (-1.4)
1 (Most Negative)	Sell	720	2.65 *** (6.2)	0.87 *** (8.9)	0.92 ** (2.2)
	Buy	732	-3.12 *** (-6.9)	-0.36 *** (-3.9)	-2.39 *** (-5.4)

Table 7: Trading Performance of Portfolio Strategy using Two Forecast Characteristics Factors: Forecast News and Prior Forecast Accuracy

This table presents the holding-period net profit of round-trip trades from the forecast announcement window to one day before earnings announcement. Panel A shows the results for a two-factor portfolio sorted by forecast news and prior accuracy. Panel B shows the results of the difference in trading performance between the two-factor portfolio and a single-factor portfolio sorted by forecast news only. Institutional trades are aggregated over the three-day management earnings forecast event window by buy and sell for each *NEWS* and *ACCURACY* rank. We rank *NEWS* from 1 – 5 with 1 indicating the most negative and 5 the most positive surprise. We rank ACCURACY from 1 – 5 with 1 indicating the *least credible* and 5 the *most credible*. *Abnormal Returns* are calculated as the holding period returns (based on execution price) less the corresponding size and book-to-market benchmark (2 x 3) obtained from Professor Kenneth French's website. The benchmark portfolios are formed by intersecting two portfolios formed on market equity and three portfolios formed on the book-to-market ratio (as of end June for every year). The size breakpoint is the median NYSE market equity and the book-to-market ratio breakpoints are the 30th and 70th percentile of the NYSE. *Total Trading Costs* include round-trip actual commissions and implicit trading costs. Implicit trading costs are calculated as the execution price minus the volume-weighted average price of the same trading day (for buy trade) and the volume-weighted average price minus the execution price (for sell trade). We calculate *Net Profits* as *Abnormal Returns* less *Total Trading Costs*. Numbers in parentheses are t-statistics. *, **, and *** indicate two-tailed statistical significance at the 10, 5, and 1 percent levels, respectively.

Panel A: Two-Factor Portfolio sorted by Forecast News and Prior Forecast Accuracy

		Abnormal Returns (%)			**Total Trading Costs (%)**			**Net Profits (%)**		
NEWS Rank		Least Credible (Rank 1)	Most Credible (Rank 5)	Difference (2) - (1)	Least Credible (Rank 1)	Most Credible (Rank 5)	Difference (2) - (1)	Least Credible (Rank 1)	Most Credible (Rank 5)	Difference (2) - (1)
5 (Most Positive)	Buy	3.09 ** (2.2)	4.85 *** (5.3)	1.77 *** (9.9)	0.93 *** (2.9)	0.87 *** (4.1)	-0.06 (-0.2)	1.23 (1.0)	3.11 *** (3.4)	1.88 *** (11.4)
1 (Most Negative)	Sell	3.67 *** (3.0)	4.23 *** (3.7)	0.57 *** (3.0)	0.81 ** (2.5)	0.78 *** (3.0)	-0.03 (-0.1)	2.05 * (1.9)	2.67 ** (2.2)	0.62 *** (3.4)

Panel B: Performance of Single-Factor Portfolio against Two-Factor Portfolio using Most Credible Strategy

NEWS Rank		Abnormal Returns (%) Single Factor (Forecast News)	Abnormal Returns (%) 2 Factor (Forecast News & Most Credible)	Abnormal Returns (%) Difference (2) - (1)	Total Trading Costs (%) Single Factor (Forecast News)	Total Trading Costs (%) 2 Factor (Forecast News & Most Credible)	Total Trading Costs (%) Difference (2) - (1)	Net Profits (%) Single Factor (Forecast News)	Net Profits (%) 2 Factor (Forecast News & Most Credible)	Net Profits (%) Difference (2) - (1)
5 (Most Positive)	Buy	4.37 *** (10.8)	4.85 *** (5.3)	0.48 *** (4.9)	0.76 *** (8.2)	0.87 *** (4.1)	0.11*** (4.79)	2.86 *** (7.6)	3.11 *** (3.4)	0.25 *** (2.53)
1 (Most Negative)	Sell	2.65 *** (6.2)	4.23 *** (3.7)	1.58 *** (12.8)	0.87 *** (8.9)	0.78 *** (3)	-0.09 *** (-3.2)	0.92 ** (2.2)	2.67 ** (2.2)	1.75 *** (13.37)