Implications of Bias and Sentiment in the Financial Market

Submitted by Shan Wu to the University of Exeter as a thesis for the degree of Doctor of Philosophy in Finance, July 2016

I certify that all material in this thesis which is not my own work has been identified and that no material has previously been submitted and approved for the award of a degree by this or any other University.

(Signature) ……

Abstract

I investigate how career concerns influence banking analysts' forecasts and find that banking analysts issue relatively more optimistic forecasts early in the year and more pessimistic forecasts later in the year for banks who could be their future employers. This pattern is not observed when the same analysts forecast earnings for banks with no equity research departments. Using the Global Settlement as an exogenous shock on career concerns, I show that this forecast pattern is pronounced after the Settlement. Moreover, I find that analysts benefit from this behaviour as analysts that are more biased in their forecasts towards potential future employers are more likely to move to a higher reputation bank.

Textual analysis of analyst reports is also valuable due to the private information and analysis conveyed in the text. Second paper therefore examines analyst reports with consistent and conflicting signals in terms of qualitative and quantitative outputs. I find that investors react more strongly when the sentiment and earnings forecast bias are consistent. Interestingly, when the tone of report text does not coincide with the earnings forecast, investors place greater weight on the text rather than the EPS forecasts. I also find that consistent reports with both optimistic sentiment and forecast bias have a strong positive market reaction but they are low in forecast accuracy. Markedly, forecasts with pessimistic sentiment have higher accuracy than those of optimistic sentiment. Hence, pessimistic sentiment is a good indicator of the quality of forecast reports.

Finally, in my last paper, I explore whether there is any association between firm-specific investor sentiment and the subsequent tone of firms' quarterly reports. Firm-specific investor sentiment is measured using the methodology from Aboody et al. (2016), which proxies for market confidence relating to a specific firm. Given the potential cost-benefit trade-off in the reporting strategy, I argue and find different responses from managers in their 10-Qs in terms of their investor sentiment. I focus on the tone of optimism, readability and the proportion of uncertain words in the 10-Q filings. For firms with extremely high levels of investor sentiment, managers tend to be more conservative by using less optimistic words to avoid future disappointment. In comparison, in firms with extremely pessimistic investor sentiment, managers tend to use more optimistic and easy to understand language, and minimize their proportion of uncertainty in their 10-Q filings. By doing so, perhaps they are trying to alter their investor sentiment.

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Chapter 1
Introduction

1.1 Motivation and Contributions

The motivation of this thesis is to examine the implications of earnings forecast bias and sentiment of sell-side analyst reports, as well as managers' strategic use of the tone of 10-Q filings based on investor sentiment. First, I contribute to the literature of analyst behaviour by investigating the sources of bias in analyst forecasts (Cowen et al., 2006, Chen and Matsumoto (2006), Guan, Lu, and Wong (2012)). I complement this line of research by documenting a different source of conflict of interest: analyst career concerns. Second, my study extends the analyst literature by evaluating the market reaction to the information in the quantitative and qualitative signals of analyst reports. Using manually collected analyst reports for S&P 500 firms, I provide generalizable results of investor reactions to analyst reports that contain conflicting messages and those that contain consistent messages. Third, I contribute to the research of investor sentiment in behavioural finance by documenting managers' responses to different levels of investor sentiment in terms of 10-Qs tone strategy. To the best of my knowledge, I am the first to apply firm-specific investor sentiment empirically.

1.1.1 Banking analysts: forecast pattern and career concerns

Sell-side analysts are specialists in analysing firm performance. Market participants use analyst reports to help them make investment decisions. I focus on sell-side

analysts who cover investment banks (‘banking analysts’ for short) in Chapter 2. Banking analysts are important information intermediaries and thus important ‘gate keepers’. However, analysts are criticized for strategically distorting their forecasts due to conflicts of interest. Prior literature shows that the conflicts of interest faced by analysts mainly stem from underwriting business (O’Brien, Mcnichols, and Hsiou-Wei (2005) and Arand and Kerl (2015)), the generation of trading commissions (Beyer and Guttman (2011) and Bradley, Gokkaya, and Liu (2015)) and the access to the management team (Lim (2001) and Chen and Matsumoto (2006)). Hong and Kubik (2003) and Ke and Yu (2006) examine analysts’ career concerns. Ke and Yu (2006) focus on the probability of being fired while Hong and Kubik (2003) investigate the likelihood of moving up to better ranked brokerage houses. They find that analysts’ favourable job separation is less sensitive to accuracy but more to forecast optimism, due to brokerage houses’ incentive of trading commissions and underwriting activities. My study in Chapter 2 focuses on a unique conflict of interest faced by banking analysts: job separations. Unlike analysts covering non-bank firms, banking analysts also view other investment banks that they forecast for as potential sources of employment, especially those who work in lower-ranked brokerage houses. Even if a banking analyst does not end up moving to the bank she has covered, keeping a good relationship with the managers from other banks is still important since the network plays an important role in job movement. Moving up to a better-ranked brokerage house gives an analyst the benefits of higher compensation, more research resources and a better

chance to be elected as a star analyst (Sorenson (2013) and Kucheev and Sörensson (2015)).

To examine whether banking analysts curry favour with other investment banks which have sell-side equity research department ('employers' for short), I focus on the pattern in the bias of their forecasts. To disentangle other factors that may influence analysts' forecasts, I hold the analyst constant by requiring that the same analyst is forecasting earnings for employers and non-employers. I find that banking analysts issue forecasts that are relatively more optimistic for employers at the beginning of the year. At the end of the year, the opposite is true; banking analysts issue forecast revisions that are relatively more pessimistic for employers.

I then use the Global Settlement in 2003 as an exogenous shock to examine the effect of career concerns of banking analysts. In general, the Global Settlement mitigates analysts' incentive to curry favour with the firm they cover (Balboa, Gómez-Sala, and López-Espinosa (2009) and Hovakimian and Saenyasiri (2014)), but also decreases job availability due the budget cuts in the research department. I find that before the Settlement, there was no bias difference between forecasting employers and non-employers, but after the Settlement, banking analysts are more biased for their employers relative to non-employers. This suggests that due to the Global Settlement, the increased pressure of job competition exacerbates the walk-down pattern from banking analysts because of their career concerns. It also

suggests that banking analysts do face a unique conflict of interest when forecasting employers and the Settlement did not take this into account.

Thirdly, I examine whether banking analysts benefit from distorting their forecasts. I find that banking analysts with more pessimistic last forecasts are more likely to experience favourable job separations and move to better-ranked brokerage houses. No such an effect is found for non-employer forecasts.

Chapter 2 extends the analyst literature in a number of ways. First, in the literature examining conflicts of interest faced by analysts, I contribute to this by documenting a new source of conflict of interest faced by banking analysts: career concerns. Second, in the literature studying the opaqueness of financial institutions, I complement this line of research by revealing the poor information environment of a financial intermediary.

1.1.2 Consistent and conflicting signals in analyst reports: investor reactions and analyst forecast accuracy

Chapter 2 examines one of the analyst attributes: forecast bias and the implications for such bias: analyst career advancement. Chapter 3 adds another dimension: the qualitative attribute, i.e. the tone of analyst reports. I investigate the implications of these two signals for investors. Anecdotal evidence suggests that textual discussions in analyst reports are valued more than quantitative forecasts for investors, but only a few studies have examined the content of analyst reports

due to data availability and the lack of computer power of linguistic analysis. With all analyst reports forecasting for S&P 500 firms hand-collected and the availability of a financial-specific dictionary from Loughran and McDonald (2011), I analyse the sentiment/tone of analyst reports from 1999 to 2014. This qualitative signal (i.e. the sentiment of analyst report) and the quantitative signal (i.e. the EPS forecast bias) in a report could be consistent or conflicting with each other. I investigate a) whether investors react differently to analyst reports with consistent signals versus those with conflicting signals, b) which signal the market places greater weight on when the qualitative and quantitative signals do not coincide and c) the forecast accuracy difference between analysts' reports with a conflicting signal and those with a consistent signal.

Huang, Zang, and Zheng (2014) find that investor reactions to upward (downward) earnings forecast revisions are stronger when the overall textual opinion of the analyst report is more positive (negative). I focus on the market reaction when earnings forecast bias and textual opinion do not coincide. By ranking analyst sentiment score and earnings forecast bias per firm per year, I observe four types of analyst reports; the first two contain consistent messages and the last two contain inconsistent messages. 1) An O_TO_B analyst report: a report containing an optimistic textual sentiment (O_T) and an optimistic forecast bias (O_B). 2) A P_TP_B analyst report: a report containing a pessimistic textual sentiment (P_T) and a pessimistic forecast bias (P_B). 3) An (O_TP_B) analyst report: a report containing an optimistic textual sentiment (O_T) and a pessimistic forecast bias (P_B). 4) An (P_TO_B)

analyst report: a report containing a pessimistic textual sentiment (P_T) and an optimistic forecast bias (O_B).

I find that investors react more strongly to reports with consistent signals (O_TO_B and P_TP_B reports) than conflicting signals (O_TP_B and P_TO_B reports). Moreover, the intensity of the market reaction to P_TP_B forecasts is stronger than that of O_TO_B reports. Second, I find that when the tone of the report text does not coincide with the earnings forecast bias, investors place greater weight on the tone rather than the earnings forecast bias. This suggests that textual analysis is more important than earnings forecasts when investors use them to make investment decisions. Although I find that consistent reports with both optimistic sentiment and optimistic forecast bias have a strong positive market reaction, further analysis reveals that these reports are associated with lower forecast accuracy. The reports associated with the highest forecast accuracy are those that contain a pessimistic tone (P_TP_B and P_TO_B reports). This suggests that pessimistic sentiment *per se* maybe a good indicator for the quality/credibility of the forecast reports.

There are several contributions in Chapter 3. First, my study extends the sell-side analyst literature by first examining the combination effect of quantitative and qualitative signals from analyst reports, especially when the two signals do not coincide. My findings suggest that investor find that textual discussions of analyst reports are more credible than quantitative measures. Moreover, I find that reports with relative pessimistic sentiment are better in terms of accuracy. Second, my

sample is more generalizable than that of Asquith, Mikhail, and Au (2005) and Twedt and Rees (2012) in terms of sample size, as well as being more objective and easier to replicate than that of Huang, Zang, and Zheng (2014) in terms of tone measurement techniques.

1.1.3 Investor sentiment and the tone of 10-Q filings

Chapter 3 documents that the sentiment of analyst reports has an impact on the market while Chapter 4 examines how investor sentiment influences firm managers' responses when preparing their10-Q filings.

Managers have incentives to maximize their firms' appeal to sentiment-driven investors while maintaining their reputation and integrity. Baker (2011) documents that this sentiment-induced shift in disclosure costs leads to different communication strategies. Managers' disclosure strategy may vary according to different levels of investor sentiment. Chapter 4 investigates whether there is any association between firm-specific investor sentiment and the tone of firms' subsequent quarterly reports. Specifically, I examine how managers respond to investor sentiment by using (1) the optimism of the tone, (2) the readability of the 10-Q filings and (3) the level of inclusion of uncertain information. The measure of firm-specific investor sentiment is adapted from Aboody et al. (2016).

On average, I find that when firm-specific investor sentiment is optimistic (pessimistic), the tone of the subsequent 10-Q filings is optimistic (pessimistic). For

ease of reading, I find that when investor sentiment is optimistic (pessimistic), the subsequent 10-Qs are easier (harder) to read. For the proportion of uncertain words, I find that firms with optimistic (pessimistic) investor sentiment have low (high) proportion of uncertainty in the subsequent 10-Qs. These findings suggest that, on average, the way managers present their 10-Qs is neutral in terms of tone optimism and uncertainty. However, managers could obfuscate the negative statements by increasing the complexity of the text, which is consistent with the obfuscation hypothesis (Courtis (1998)).

I future examine this issue by investigating manager response when firms experience extreme investor sentiment. The prior literature shows that managers recognize the high and low investor sentiment periods and respond to them differently (Brown et al. (2012), Simpson (2013) and Hribar and Quinn (2013)). I compare firms with extremely high investor sentiment to firms with average high investor sentiment and find that managers tend to be more conservative by using less optimistic words to avoid future disappointment when investor sentiment is extremely high. These firms have a low proportion of uncertain words in their 10-Qs but no significant difference in terms of readability. I also compare firms with extremely pessimistic investor sentiment to firms with average low investor sentiment. I find that for firms with extremely pessimistic investor sentiment, managers tend to use more optimistic and easy to understand language, and minimize their proportion of uncertainty in their 10-Q filings when investor sentiment is low. They act differently compared with firms with extremely optimistic

investor sentiment because their priority is to regain investor confidence by providing information in a more positive light. In summary, when preparing corporate filings, managers need to obey SEC laws to provide truthful information, while also acknowledging the level and the change of investor sentiment. Therefore, it appears that managers try to influence investors by using this subtle way of tone management, especially for those firms who experience extreme investor sentiment.

To the best of my knowledge, I am the first to apply firm-specific investor sentiment empirically. The prior literature investigates managers' behavioural difference assuming investors have the same sentiment towards all firms during the same period while we adopt a finer proxy using firm-specific investor sentiment developed by Aboody et al. (2016). Second, I extend the literature by examining the relationship between the tone of financial disclosure and investor sentiment. I focus on whether managers adjust the tone of optimism in the quarterly reports according to different firm-specific investor sentiment. It highlights that the managers may be trying to influence investors using a more subtle soft approach instead of earnings management or earnings guidance. Third, my study complements the investor sentiment literature by investigating the association between firm-specific investor sentiment and tone of uncertainty as well as readability in 10-Q filings.

1.2 Thesis Structure

The structure of this thesis is as follows. Chapter 2, 3 and 4 are the main research bodies with their own introduction, literature review and hypotheses development, data and methodology, as well as conclusion. Chapter 5 concludes and provides information on future work that I will be conducting.

Chapter 2

Career Concerns of Banking Analysts

2.1 Introduction

Sell-side analysts are important information intermediaries in capital markets and as a result, their research has been under scrutiny. While a large number of studies document that analyst coverage and forecasts have economic consequences (Bailey et al. (2003) and Jackson (2005)), an equally large number of studies document that analyst forecasts are influenced by conflicts of interest (Beyer and Guttman (2011); Cowen, Groysberg, and Healy (2006); Hong and Kubik (2003); Jackson (2005); Richardson, Teoh, and Wysocki (2004); Lim (2001) and Schipper (1991)). In this chapter I concentrate on the banking industry and investigate whether banking analyst forecasts are biased because of their career concerns.

Past studies have documented that analyst forecasts can be biased because of underwriting activities in the investment banking business, the pressure to generate trading commissions, and analysts' career concerns (Dugar and Nathan (1995); Hunton and McEwen (1997); Lin and Mcnichols (1998); Michaely and Womack (1999); Dechow, Hutton, and Sloan (2000); Hong and Kubik (2003) and O'Brien, Mcnichols, and Hsiou-Wei (2005)). In terms of career concerns, past studies have demonstrated that more optimistic analysts tend to experience favourable job separations (Hong and Kubik (2003)) and younger analysts tend to

herd more (Hong, Lim, and Stein (2000)). In these studies, the underlying source of career concerns is the pressure from investment banking and/or the brokerage business to please firms or buy-side portfolio managers respectively.

In this chapter, I concentrate on a different source of conflicts of interest. Banking analysts issue forecasts for firms that constitute a large part of their outside opportunities in terms of employment. These analysts view the banks that they issue forecasts for as potential sources of employment, thereby increasing their incentives to satisfy those clients. This is independent of incentives to generate investment banking business or trading commissions, which exist for all firms they cover.

In order to examine whether this pressure to satisfy future potential employers is influencing analyst forecasts, I examine the pattern in the bias of their forecasts. In my research design, I hold the analyst constant by requiring that the same analyst is forecasting earnings for firms with sell-side equity departments (‘employers’) and for firms with no sell-side equity departments (‘non-employers’). I then show that banking analysts issue forecasts that are relatively more optimistic for employers at the beginning of the year. At the end of the year, the opposite is true; banking analysts issue forecasts that are relatively more pessimistic for employers. Therefore, my research design is similar to a differences-in-difference specification, where I observe the forecasting pattern early and late in the year and I compare this pattern for employers and non-employers for the same set of analysts. I limit

my sample to those analysts who are not employed by the top investment banks and therefore could have relatively greater career concerns. Analysts that are already working for bulge investment banks have greater career opportunities and less incentives to move as they already work at the most reputable banks. Therefore, I treat analysts working at the top banks as a control group that allows me to scale my dependent variable for forecast bias. I report results using both this relative bias variable and an absolute bias variable relative to the earnings of the firm and document similar results.

To further identify the effect of career concerns from forecasting earnings of a potential future employer, I exploit an exogenous shock to future career opportunities. The Global Settlement decreased the budgets for sell-side research significantly and as a result, directly impacted the outside opportunities for sell-side analysts (Cowen, Groysberg, and Healy (2006)). This could lead to an exacerbation of career concerns and as a result a more pronounced walk-down to beatable earnings for employers. On the other hand, after the Global Settlement, the analysts could be more reluctant to substantially bias their forecasts because that might anger other constituents using their forecasts, raising the probability of dismissal. The probability of a promotion at another firm might not look as attractive if analysts are more worried about just keeping their jobs after the Settlement. I find that after the Global Settlement the transition from optimistic to pessimistic forecasts closer to the year-end is stronger. These findings are consistent with

banking analysts' understanding that their forecasts could impact future career opportunities and as a result, provide a walk-down to beatable earnings.

I analyse future job separations to understand whether analysts benefit from such forecasting activity. I find that banking analysts who are pessimistic about their latest forecast are more likely to experience favourable job separations and move to a higher status broker. This result is presented only for analysts that exhibit this behaviour towards employers, which is again consistent with analysts strategically biasing their forecasts because of career concerns.

My identification strategy aims to mitigate the likelihood that other sources of bias, unrelated to a revolving door story, might cause my results. I do so by differentiating both across the types of firms being forecasted (i.e. a bank with or without a research department) as well as across analysts (i.e. employed by a top-bank versus a non-top bank). I show that a walk-down to beatable earnings and upward job mobility is more pronounced when an analyst works for a non-top bank and forecasts earnings of a bank with a research department. It is hard to reconcile these findings with biases due to incentives to generate investment banking business or trading commissions, which should be presented in both types of forecasted firms or analysts. For example, bias arising from incentives to generate investment banking business should be strong for banks with or without research departments and it should be less pronounced after the Global Settlement. Similarly, incentives to generate trading commissions should be as strong for

analysts working at top banks and when forecasting earnings for banks without research departments. Of course, if for example, investment banking business or trading commissions are significantly higher for banks with research departments and analysts in non-top banks have stronger incentives to bias their forecasts to generate investment banking business or trading commissions that could explain my results. However, in my matched sample, banks with and without research departments exhibit very similar market capitalization, valuation ratios, analyst following, share turnover, and risk; all variables that could be related to investment banking or trading commission sources of bias. Moreover, reduced competition, due to brokerage house closures, following the Global Settlement could explain my results (Hong and Kacperczyk (2010)). I address this concern by examining whether the pattern I document holds for firms in which analyst coverage did not decrease after the Global Settlement and therefore the competition effect is not at play. I find similar results for this subsample.

My results contribute to a body of literature that investigates the sources of bias in analyst forecasts (Cowen, Groysberg, and Healy (2006)). I complement this line of research by documenting a different source of conflict of interest. Effectively the conflict I document here relates to the 'revolving-door' phenomenon, which has been investigated in relation to audit partners (Menon and Williams (2004); Geiger, Lennox, and North (2008)), SEC lawyers (deHaan et al. (2015)), and credit rating analysts (Cornaggia, Cornaggia, and Xia (2016)). I show that this effect

generalizes in settings outside auditing and, consistent with Cornaggia, Cornaggia, and Xia (2016), affects information intermediaries more broadly.

The results contribute also to a literature that seeks to understand whether financial institutions are more opaque and therefore characterized by higher information asymmetry and more information risk (Morgan, 2002; Flannery et al., 2004). Given that sell-side analyst activity significantly improves the information efficiency of capital markets, my results suggest that the career concerns banking analysts are facing will contribute to the poor information environment of financial institutions.

The chapter proceeds as follows. In Section 2.2, I review the related literature and form the hypotheses of this study. Section 2.3 describes the data and the research design. Section 2.4 details the descriptive statistics and the results. I conclude in Section 2.5.

2.2 Literature Review and Hypotheses Development

2.2.1 Forecast bias of bank and non-bank analysts

2.2.1.1 Optimistic bias and the incentives

If analyst forecasts are formed objectively and errors arise from unforeseen events, there should not be any trend over time in the distribution of earnings surprises. Similarly, if analyst forecasts are unbiased, there is no reason to think that the distribution of surprises should differ across different types of firms or industries.

However, the existence of an optimistic bias in analyst forecasts is well documented in many studies (Fried and Givoly (1982); Brown et al. (1987); O'brien (1988);Klein (1990); Affleck-Graves, Davis, and Mendenhall (1990); Boni and Womack (2002) and Malmendier and Shanthikumar (2014)).

The evidence of forecast bias has led many studies to propose and test incentive-based explanations. For example, analysts have incentives to maximize the trading volume in the stock they cover to increase trading commissions (Jackson (2005); Cowen et al., 2006; Beyer and Guttman (2011) and Brown et al. (2015)). Bilinski et al. (2016) show that analysts facilitate short-term institutional investors with profitable trades by issuing biased target prices. Similarly, evidence suggests that analysts from brokerage houses that have underwriting relationships with a firm tend to issue more optimistic forecasts (but not less accurate) than unaffiliated analysts (Dugar and Nathan (1995); Hunton and McEwen (1997); Lin and Mcnichols (1998); Michaely and Womack (1999); Dechow, Hutton, and Sloan (2000); O'Brien et al., 2005 and Ljungqvist et al. (2007)).

Similarly, analysts are likely to take into account the impact their forecasts may have on their relationship with management (to increase investment banking business or to curry favour with management to obtain and maintain access to private information) by issuing favourable (Schipper (1991) and Lim (2001)) or beatable (Richardson, Teoh, and Wysocki (2004)) earnings forecasts. Chen and Matsumoto (2006) show that managers provide more information to those analysts

who issue favourable recommendations. Solomon, Soltes, and Sosyura (2014) and Brown et al. (2015) show that private communication and good relationships with firm managers benefit analysts' careers.

2.2.1.2 Inter-temporal pattern

Other literature examines the inter-temporal pattern in analyst forecast bias and finds a trend from optimism to pessimism within both the quarterly and annual forecasts (Cowen et al., 2006; Richardson et al., 2004; Ke and Yu (2006)). Cowen et al. (2006) document for a sample of forecasts issued from 1996 to 2002 that 180 day+ forecasts are positively biased, 91 to 180-day forecasts are unbiased, and 0- to 90-day forecasts are negatively biased. Similarly, Richardson et al. (2004) document the optimistic to pessimistic pattern (or 'walk-down') of both annual and quarterly forecasts and Ke and Yu (2006) find that annual forecasts are on average optimistic and quarterly forecasts are pessimistic. In terms of management guidance, Cotter, Tuna, and Wysocki (2006) find that analyst forecasts for guiding firms are significantly less optimistic than the control sample after the guidance is issued. The consensus analyst forecast is 1.7 times as likely as the control sample to be pessimistic after the guidance is issued. Baik and Jiang (2006) and Bartov, Givoly, and Hayn (2002) have similar results.

2.2.1.3 Banking analyst vs Non-banking analyst

Banking analysts may face more conflicts of interest than non-bank analysts. First, investment banks work together as they syndicate bonds and loans for each other.

Ljungqvist, Marston, and Wilhelm (2009) show that investment banks have strong business ties among each other and banks syndicated with other banks that are themselves better networked for underwriting mandates. Second, since they forecast their own industry, writing unfavourable reports of other banks may indicate a poor situation of the whole industry and eventually may affect investors' confidence in their own banks. Hence, they have the incentive to talk up their own industry.

The third conflict of interest is the analyst career concerns. Hong and Kubik (2003) point out that analysts face fierce career competition, which is supported by Ke and Yu (2006), who find that 15% of analysts were fired from prestigious brokerage houses between 1983 and 2000. These findings suggest that the incentive of bank analysts' forecast bias could stem from their career concerns, since competitor banks are their potential employers. Unlike other analysts, banking analysts issue forecasts for firms that constitute a large part of their outside opportunities in terms of employment. These analysts may view the banks that they issue forecasts for as potential sources of employment, thereby increasing their incentives to satisfy those clients, independent of incentives to generate investment banking business or trading commissions for their own employers that should exist when making forecast for all firms they cover. If this is true then an analyst who forecasts both employers and non-employers will have stronger career incentives (resulting in a greater need to curry favour with the managers from these potential employers), and therefore are more likely to bias their forecasts for the potential employers (i.e.

investment banks) relative to the non-employers they cover. This leads to my first hypothesis:

> ***H1:*** *The change in the bias of the forecasts over time from optimistic to pessimistic is greater when forecasting earnings of employers relative to non-employers.*

2.2.2 Exogenous shock: Global Analyst Research Settlement

To further explore the effect of analyst career concerns I employ the Global Settlement as an exogenous shock. The Global Settlement was initiated to curb the biased research produced by brokerage houses and resulted in ten of the largest banks paying nearly $1.4 billion in fines. Among other provisions, the Global Settlement created a “Chinese Wall” between the research divisions and the investment banking divisions of brokerage houses. This regulation changed the way brokerage firms profit from analyst activity and thereby increased the level of competition in the sell-side analyst labour market. Importantly, these provisions prohibited the explicit cross-subsidization of research activities from underwriting activities, drastically altering the demand for sell-side analysts at investment banks. This regulatory shock changed the labour market landscape. As Cowen et al. (2006) note, investment banks decreased their spending on equity research by more than 40% as compared to 2000 levels, which reduced the analyst head count on average by 15% to 20% and cut analysts’ compensation by a third or more. This significant increase in competition in the sell-side analyst labour market allows me

to test the effect of analysts-related future career concerns on their forecast bias. The sign of this effect of increasing or reducing analyst bias, however, is unclear. It could be the case that, following the Global Settlement, forecast biases have decreased as analysts have switched their focus to one of keeping their current job rather striving for promotion at another investment bank. Under this scenario, analysts may take fewer risks and be reluctant to issue significantly biased forecasts just in case it annoys their clients and thereby increases the likelihood of dismissal.[1] An alternative scenario is that following the Global Settlement, analyst career concerns may have been exacerbated and consequently analysts may have stronger incentives to walk down their forecasts to beatable earnings. This may be particularly true for my sample, as the Global Settlement was focused more on the top banks (which were the subject of the Settlement) than the medium and low tier banks. Ultimately, the effect of the Global Settlement on analyst career concerns is an empirical question and leads to my second hypothesis:

> ***H2:*** *The bias of the forecasts over time from optimistic to pessimistic due to career concerns changes following the Global Settlement.*

2.2.3 Analyst career concerns

The literature discussed above suggests that managers prefer optimism in beginning-of-period and pessimism in end-of-period analysts' forecasts (Richardson, Teoh, and Wysocki (2004), Cotter, Tuna, and Wysocki (2006) and

[1] I would like to thank the anonymous reviewer for highlighting this possible scenario.

Cowen, Groysberg, and Healy (2006)), but this leaves open the question of why analysts appear to cooperate with management and issue forecasts that are consistent with their preferences.

Compared with examining analysts' forecasts, there are a limited number of studies investigating whether forecast bias is associated with an analyst's career advancement (Mikhail, Walther, and Willis (1999); Hong and Kubik, 2003;Horton and Serafeim (2009) and Lourie (2015)). Bradley, Gokkaya, and Liu (2015) show that pre-analyst work experience of sell-side analysts leads to favourable career outcomes: higher probability of becoming star analysts, but I examine analysts' job separation. The closest paper to mine is that of Hong and Kubik (2003), who find that the association between accuracy and turnover varies with the analysts' level of optimism and affiliation status. The turnover decisions of affiliated analysts depend less on accuracy and more on optimism than those of unaffiliated analysts. My study focuses on analysts that move up to better ranked brokerage houses or move down to lower ranked brokerage houses. Compared with Ke and Yu (2006), who only use data before the Regulation Fair Disclosure in 2001, I also explore the effect after 2001. Furthermore, Ke and Yu (2006) focused on the incentive of accessing management's private information whilst I investigate the motivation of favourable job separation.

The revolving-door literature also provides evidence that career incentives may cause individuals to lose objectivity in their assessment of potential future

employers. Lourie (2015) investigates the forecast bias of analysts who leave the profession and are subsequently hired by firms the analyst had previously covered. He finds that prior to their new employment, analysts provide more optimistic recommendations and higher target prices for the firms that subsequently hire them, although he finds no systematic forecast earning bias for these firms. Cornaggia, Cornaggia, and Xia (2016) investigate the revolving door phenomenon, in relation to credit rating analysts and find that transitioning credit rating analysts become more favourable to their future employers prior to their transitions. They conclude that these conflicts of interest at the analyst level distort credit ratings.

If analysts are biasing employers' forecasts because of future career incentives then following the findings of Hong and Kubik (2003), I would expect such analysts to benefit from this activity and thereby experience more favourable job separations. This leads to my third hypothesis:

> ***H3:*** *Analysts who provide more biased earnings forecasts for employers are more likely to experience favourable job separations.*

2.3 Data and Methodology

2.3.1 Sample of analysts

I obtain data on all individual analysts' forecasts of annual earnings per share from the Institutional Brokers Estimate System (I/B/E/S) Detail File. For a sample period from 1999 to 2006, I identify all banks with investment arms. This identification

starts with the SIC codes 60-62,[2] and the Bloomberg categorization of investment services, but in order to be confident in my identification process, I also use the information disclosed in the banks' annual reports and websites to validate my identification. I start from the year 1999 because the Institutional Broker Estimate System (I/B/E/S) Price Target file with analyst names starts from 1999. I use this file to match the analyst code with the analyst name and also the brokerage house code with the brokerage house name. I do not include observations post 2006 due to the financial crisis, although I find that my results are not sensitive to extend the sample period to 2014, excluding the financial crisis.[3] From this sample, I extract sell-side analysts that follow both firms with sell-side equity departments (for convenience, I term these 'employers') and firms with no sell-side equity departments (again for convenience, I term these 'non-employers'). Requiring that the same analysts make forecasts across both groups mitigates the probability that differences in the results are driven by differences in the types of analysts making the forecasts. Moreover, since I find that over 90% of the investment bank sample is within the S&P 500, I also limit my analysis to S&P500 firms only; this again mitigates the probability that differences in the results are driven by differences in the types of firms being forecasted. However, if I relax both of these requirements the results continue to hold. An alternative sample uses analysts with forecasts for both investment banks and other banks (mainly commercial banks). Compared

[2] I do not however classify those firms with a SIC code of 6099 (commercial banks) and 6111 (credit and debit card issuer) as employers.

[3] The global financial crisis is commonly believed to have begun in July 2007, and given I am investigating both the first and last analyst forecasts, I limit the sample period to the end of 2006.

with the main sample, these latter firms operate in a more similar setting and therefore have more similar risks. The control variables of market value and book to market ratio are from Compustat. Equity return data is available on CRSP.

I consider only the last and first forecast for each analyst-firm pair during the twelve months of the annual earnings release date reported by I/B/E/S period. The reason I look at first and last forecast revisions is that investors normally appraise firms at three points in time: in response to the (a) initial analyst forecast, (b) revised analyst forecast, especially forecast revision shortly before the actual earnings announcement and (c) the actual earnings announcement. Econometrically speaking, I could only choose one observation per firm per year per year. Otherwise, cross-correlation problems could arise due to multiple observations from the same analyst. This is also consistent with prior literature (Hong et al., (2000); Richardson et al., (2004); Kim et al., (2011)). I exclude observations with forecast horizons shorter than one month and longer than one year (Clement and Tse (2005)) and also exclude those observations with negative price-to-book ratios and stock prices less or equal to one dollar, thereby ensuring that illiquid stocks do not influence my results. I also drop firms followed by fewer than three analysts, as my forecast bias measure requires intra firm-year variation (Clement and Tse (2003) and Kerl and Ohlert (2015)). Furthermore, I drop analysts with only one forecast per year since I observe analysts' first and last forecasts. Consistent with Clement and Tse (2003), I eliminate the scaled forecast bias in the top and bottom one percent of revisions to reduce the effect of outliers.

Given my focus is on analysts' career concerns, I exclude from my sample all analysts who are employed by the top brokerage houses as these analysts will have lower career concerns as they already work for a top brokerage[4] house and they are less likely to bias their forecasts to satisfy potential future employers. If this assumption is incorrect and analysts at top investment banks have equally strong incentives to walk-down expectations this would bias my analysis against finding any results. Thus, my sample only captures those analysts who have stronger incentives to satisfy potential future employees and move up the brokerage house echelons. This results in an overall unique sample of 228 individual analysts who issue forecasts in the same year for both employers and non-employers. The additional firm-specific data is obtained from Compustat.

2.3.2 Measuring forecast bias

To measure analyst optimism I adopt a similar approach to prior literature(Jacob, Lys, and Neale (1999); Clement (1999); Hong and Kubik, 2003; Cowen et al., 2006; Walther and Willis (2013)). My first measure compares the optimism of a given analyst's forecast for a particular firm and time period to the mean optimism of all analysts employed by the top brokerage houses who make forecasts for the same firm and time period within a comparable forecast horizon. This requires me to exclude those firms followed by fewer than three analysts from the top brokerage houses as my forecast bias measure requires intra firm-year variation (Clement

[4] Although I exclude the analysts from the top brokerage houses from the sample I do use their forecasts to determine the relative forecast bias.

and Tse (2003); Kerl and Ohlert (2015)). Note, this constraint reduces the number of firm-year observation but not the number of individual analysts. This relative performance metric controls for any firm or time-specific factors that affect forecast optimism. I define forecast optimism of the analyst *i* for firm *j* in year *t* (FB_{ijt}) as the signed difference between the forecast and the actual earnings per share (EPS). Where:

$$FB_{ijt}=Forecast\ EPS_{ijt}-Actual\ EPS_{ijt}$$

and to control for the firm-year effects the demeaned version of FB_{ijt} is[5]:

$$Rel\_DFB_{ijt}=\frac{\left[FB_{ijt}-Avg(TopFB_{jt})\right]}{\left|Avg\left(TopFB_{jt}\right)\right|}$$

My second measure, consistent with Walther and Willis (2013), is an absolute forecast bias based on the signed forecast error as a percentage of share price:

$$Abs\_DFB_{ijt}=\left[\frac{FB_{ijt}}{P_{jt}}\right]\times 100$$

where P_{jt} is the share price from firm *j* for year *t* issued 10 trading days before the forecast release date.

[5] I deflate the variable with the absolute mean of the top analyst's forecast error for each firm-year since Clement (1999) shows that this procedure reduces heteroscedasticity.

If either Rel_DFB_{ijt} or Abs_DFB_{ijt} is positive, then the analyst forecast is optimistically biased (positively biased) whereas if it is negative then the analyst forecast is pessimistically biased (negatively biased). I calculate two Rel_DFB_{ijt} (and two Abs_DFB_{ijt}) one for each time period, the first forecast and last forecast revision analyst *i* makes for firm *j* in year *t*.

2.3.3 Modelling forecast bias between employers and non-employers

To test H1, that employer forecasts are relatively more biased than non-employer forecasts, I estimate the following cross-sectional regression with an indicator variable *EMPLOYER* that equals one if the analyst is forecasting earnings of a future employer and zero otherwise:

$$Rel\_DFB_{ijt} \text{ (or } Abs\_DFB_{ijt}) = \alpha + \beta_1 EMPLOYER + \beta_2 Earn\_Std_{ijt} + \beta_3 Ln(MV_{jt}) + \beta_4 Ln(BTM_{jt}) + \beta_5 Ln(Follow_{jt}) + \beta_6 F\_Horizon_{ijt} + \beta_7 dayElap_{ijt} + \beta_8 fr_{ijt} + \beta_9 Firm\_Exp_{ijt} + \beta_{10} Gen\_Exp_{ijt} + \beta_{11} Num\_Co_{ijt} + \beta_{12} Num\_Ind_{ijt} + \beta_{13} Num\_Ana_{ijt} + \beta_{14} Year\_F.E + \varepsilon_{ijt} \quad (1.1)$$

I estimate model (1.1) for both the first forecast and last forecast the analyst makes for firm *j* at time *t*. If employer forecasts are relatively more biased than non-employers' forecasts then I would expect β_1 to be significantly different from zero. I expect β_1 to be positive and significant for the first forecast and negative and significant for the last forecast. Equation (1.1) includes a number of control variables proposed in the prior literature that are also likely to be related to forecast

bias. I also include as year fixed effects (*Year_F.E.*). Robust standard errors are clustered at the firm and analyst pair.

2.3.4 The control variables

Control variables are standardized the same way as forecast bias. I include analyst characteristics and firm characteristics following the prior analyst literature (Clement and Tse (2003), Lehavy, Li, and Merkley (2011) and Walther and Willis (2013)).

$$Characteristic_{ijt} = \frac{Raw\_Characteristic_{ijt} - \overline{Raw\_Characteristic_{jt}}}{\overline{Raw\_Characteristic_{jt}}}$$

Analyst Characteristics Proxies

Proportional Forecast Horizon ($F\_Horizon_{ijt}$)

Forecast Horizon (FH_{ijt}) is the number of days between analyst *i*'s estimation and firm *j*'s earning announcement in year *t* (year t based on forecast period end date in I/B/E/S). It is a proxy for forecast timeliness.

$$F\_Horizon_{ijt} = \frac{FH_{ijt} - \overline{FH_{jt}}}{\overline{FH_{jt}}}$$

Where $FH_{ijt} = \left| ForecastDate_{ijt} - EarningsAnnouncementDate_{ijt} \right|$

Days Elapsed ($dayElap_{ijt}$)

Days Elapsed is the number of days since a prior forecast from any analyst forecast for the same firm for the same year. The measure of the days is calculated as the days between analyst *i*'s forecast of firm *j*'s earnings in year *t* and the most recent preceding forecast of firm *j*'s earnings by any analyst, minus the average number of days between two adjacent forecasts of firm *j's* earnings by any two analysts in year *t*, with this difference scaled by the average days between two adjacent forecasts of firm *j*'s earnings in year *t*.

Forecast Revisions (fr_{ijt})

Clement and Tse (2005) include the number of reports of firm *j* written by analyst *i* in year *t*. It is reasonable to say that an analyst revises the report because she acquires some more valuable information that turns out to be inconsistent with the conclusion she made before. Therefore, higher accuracy is expected for high forecast frequency analysts.

The measure of analyst *i*'s forecast frequency for firm *j*, calculated as the number of firm *j* forecasts made by analyst *i* following firm *j* in year *t* minus the average number of firm *j* forecasts for analysts following firm *j* in year *t*, with this difference scaled by the average number of firm *j* forecasts issued by analysts following firm *j* in year *t*.

Number of companies followed (Num_co_{ijt})

Following the methodology of Clement & Tse (2005), I measure the number of firms by counting firms tickers the analysts issued forecasts for using the I/B/E/S database.

The measure of the number of firms analyst *i* follows in year *t* is calculated as the number of firms followed by analyst *i* following firm *j* in year *t* minus the average number of firms followed by analysts who follow firm *j* in year *t*, with this difference scaled by the average number of firms followed by analysts following firm *j* in year *t*.

Number of industries followed (Num_Ind_{ijt})

The measure of the number of industries analyst *i* follows in year *t* is calculated as the number of two-digit SICs followed by analyst *i* following firm *j* in year *t* minus the average number of SICs followed by analysts who follow firm *j* in year *t*, with this difference scaled by the average number of two-digit SICs followed by analysts following firm *j* in year *t*.

Number of Analysts Working in a Brokerage House (Num_Ana_{ijt})

Num_Ana_{ijt} is a proxy for brokerage house size. It is calculated as the number of analysts in the brokerage house. Large brokerage houses tend to have better access to resources.

Proxy for Portfolio Complexities

Firm Size ($Ln(MV)_{jt}$)

Larger firms have more complex businesses and higher variation than those of smaller ones. Therefore, firm size is incorporated here following Kothari, Li, and Short (2009). It is the natural log of firm *j*'s market value at the end of year *t*.

Book-to-Market Ratio ($Ln(BTM)_{jt}$)

Book-to-market ratio is a proxy for the growth or riskiness of the firm. Growth firms have more unrecorded, intangible assets, whose valuation depends heavily on future profitability. $Ln(BTM)_{jt}$ is the natural log of the ratio of book value of equity to market value of firm *j* at the end of year *t*.

Number of Analysts Following ($Ln(Follow_{jt})$)

$Ln(Follow_{jt})$ is measured as the natural log of analysts following firm *j* in year *t*. It is proxy for firm size and potential profitability from the brokerage house aspect.

Standard Deviation of Prior Earnings ($Earn\_Std_{jt}$)

Gu and Wu (2003) find that forecast errors are greater for firms with more volatile earnings. I use the standard deviation of a firm's 5-year earnings to control for the relation between the firm's earning volatility and analysts' forecast errors.

Proxy for Analyst Ability

Analyst Experience

Analysts' experience is a proxy for their ability. Clement (1999) finds that both general and firm-specific forecasting experiences have a positive relationship with forecast accuracy, but the relationship with firm-specific experience is stronger.

Firm-specific Experience ($Firm\_Exp_{ijt}$)

The measure of analyst *i*'s firm-specific experience is calculated as the number of years of firm-specific experience for analyst *i* following firm *j* in year *t* minus the average number of years of firm-specific experience for analysts following firm *j* in year *t*, with this difference scaled by the average years of firm-specific experience for analysts following firm *j* in year *t*.

General Experience (Gen_Exp_{ijt})

The measure of analyst *i*'s general experience is calculated as the number of years of experience for analyst *i* following firm *j* in year *t* minus the average number of years of experience for analysts following firm *j* in year *t*, with this difference scaled by the range of years of experience for analysts following firm *j* in year *t*.

To examine the effects of the Global Settlement and test hypothesis 2, I re-run equation (1.1) separately for periods before and after the Global Settlement. However, to control for the possibility that any results are driven by changes in the

composition of the analysts' pool (and not by analysts changing their behaviour) after the Global Settlement, my sample for this analysis is restricted to only those analysts that appear in both periods.

2.3.5 Propensity score matching

Propensity score matching (hereafter PSM) is a widely used technique to find a treatment group and a control group with similar characteristics, mitigating the effect of selection bias. The advantage of PSM is that it is effective at selecting observations that are closely matched (Minutti-Meza (2013)). I employ the PSM technique to match one employer firm with one non-employer firm for the same analyst in the same year. This could minimize the difference between employer firms and non-employer firms and therefore isolate the effect of career concerns from other factors. Banks with and without investment arms could be different in their risks, opaqueness or size. Following Anolli, Beccalli, and Molyneux (2014), I calculate propensity scores based on z-score (proxy for insolvency risk), and standard deviation of monthly return (proxy for total risk), market value, book-to-market ratio and bid-ask spread.

Although the construction of such risk proxies can be influenced by accounting conventions/policies that differ across banks and countries, the Z-score has been widely used in the literature (Iannotta, Nocera, and Sironi (2007); Laeven and Levine (2009); Liu and McConnell (2013) and Anolli, Beccalli, and Molyneux

(2014)). It is calculated as a risk metric including net accounting income, total assets and total equity.

$$Z-score_{jt} = \frac{\sum_{q=1}^{4}[2\pi_{jq}/(A_{jq}+A_{jq-1})]/n + \sum_{q=1}^{4}[(E_{jq}+E_{jq-1})/(A_{jq}+A_{jq-1})/n]}{s_{ROA_{jt}}}$$

where π_{jq} is net accounting income after taxes of firm j in each quarter q of year t; A_{jq} is total assets; E_{jq} is total equity; s_{ROAjt} is the estimated standard deviation of ROA.

I also match it based on analysts' related variables: the number of analysts following the firm and the firm-specific experience of the analysts following the firm.

2.3.6 Measuring brokerage house status

To investigate the impact of forecast bias on job separation I obtain a sample of all analysts who moved brokerage houses during 1999-2006. This yields a total of 886 analysts. I am unable to identify the exact name of the brokerage house (since I/B/E/S simply provides a code for each brokerage house not the name[6]) the analyst works for and therefore I am not able to measure the brokerage house status using an external ranking system, such as the one published by *Institutional Investor* and used in prior studies (Hong and Kubik, 2003). However, Hong and Kubik (2003) find that an alternative measure of brokerage house status based on the size of a brokerage house is highly correlated to the *Institutional Investor*

[6] I was unable to obtain the Broker Transaction file, which would enable me to identify the brokerage houses' name.

ranking system and their results are not sensitive to this alternative status measure. Following Carter and Manaster (1990) and Huang et al, 2014, I measure the status of the brokerage house based on the number of analysts from each brokerage house. To replicate Hong and Kubik's (2003) proportions of brokerage houses identified as high, medium and low status, I identify a high-status house as a brokerage house with a house size in the top 3% each year. Low-status is any brokerage house size below the average house size each year and the remaining are identified as middle-status houses. I classify as high status the top 3% of brokerage houses in terms of number of analysts employed. Consistent with Hong and Kubik (2003), who report that approximately 29% of their sample analysts are identified as employed by high status brokerage houses, I find approximately 31.5% of my sample analysts are identified as being employed by high-status houses. Moreover, I find that approximately 22.2% and 46.3% of analysts worked in low-status houses and median-status houses respectively, which again is consistent with the proportions reported by Hong and Kubik (2003).[7]

2.3.7 Modelling forecast bias and job separation

I estimate the following ordinal logit specification to test H3:

$$Move\_status_{t+1} = \beta_1\ BIAS_{ijt} + \beta_2 EMPLOYER + \beta_3\ BIAS_{ijt} * EMPLOYER + \beta_4 Gen\_Exp_{ijt} + \beta_5 Num\_Co_{ijt} + \beta_6 Accuracy + \beta_7 Status\ F.E. + \beta_8 Year\ F.E + \varepsilon_{ijt} \quad (1.2)$$

Move_status takes a discrete value of -1, 0, 1, or 2, depending on whether the

[7] I find however, my results are not sensitive to either a 1% increase or decrease of this identification metric.

analyst has moved that year to a higher or lower status house and the size of the jump made. For example, analyst *i* who moves up to a higher status brokerage house (i.e. is promoted) in year *t* is given the value 1 if it involves one movement up the hierarchy of brokerage house status (i.e. low status to middle status) and the value of 2 if the move up represents a move of two hierarchies (i.e. low status to high status). An analyst who moves down one hierarchy or two will be given a value of -1 or -2. However, because I limit the sample to those analysts moving from medium-status and low-status brokerage houses the maximum drop in hierarchy possible is -1 (medium to low). *Move_status* equals 0 if analyst *i* moves within the same hierarchy status. Consistent with Hong and Kubik (2003), I do not classify a status movement for the analyst if it is only the brokerage house that changes status during the year since the analysts has not experienced a job separation and I also exclude brokerage houses which merged during the year.

I follow a similar methodology to that of Hong and Kubik (2003) and measure a relative forecast bias for each firm the analyst forecasts in each year (*Rel_DFB*) (i.e. relative to the average bias of analysts from top brokerage houses) and then average across the stocks that the analysts from top brokerage houses cover, which gives a bias measure for analyst *i* in year *t*. However, this relative bias measure will be noisy for analysts that only follow a few firms in a year. Therefore, consistent with Hong and Kubik (2003), I create the measure *Rel_BIAS,* which is the average of the analyst's forecast biases in year *t* and the two previous years. For those analysts that forecasted both employers and non-employers, I measure

separate *Rel_BIAS* for their employers' forecasts and their non-employer forecasts.[8] For those analysts covered only non-employers, the *Rel_BIAS* measure is based on all firms covered.[9] I also construct *Abs_Bias* in a similar manner. Due to data limitation, I am unable to identify the position and hierarchy of an analyst in the brokerage house. I assume analysts experience favourable job separation when they move to better-ranked brokerage houses, which is also consistent with the prior literature.

In addition, I also control for general experience in terms of the number of years the analyst has been forecasting for (*Gen_Exp*), the number of firms the analysts follows during the three year window (*Num_Co*) and whether the analysts is in the top decile of forecast accuracy during the period the *BIAS* is calculated (*Accuracy*). Additionally, I also include indicator variables for the status of the brokerage house the analyst currently works for, as well as year fixed effects.

I estimate model (1.2) for both the first and last forecast the analyst makes for firm *j* at time *t*. If the forecast bias for employers is more important for job separation relative to a non-employer forecast then I would expect β_3 to be significantly different from zero.

[8] The results are not sensitive to excluding the non-employer forecasts for those analysts forecasting both employer and non-employer.

[9] Since I am unable to identify the brokerage house name that an analyst works for (as I do not have access to a Broker Transaction file) I am unable to directly link an analyst who moved to a particular investment bank that she had previously covered. Given I argue that biased forecast help the analysts build relationships with prospective employers then a banking analyst will always provide a more pessimistic forecast irrespective of whether they ultimately work for a specific investment bank they cover or not.

2.4 Results

2.4.1 Descriptive Statistics

Table 1.1 Panel A reports analyst characteristics before standardization. The distributions are consistent with prior studies, such as that of Clement and Tse (2003). For example, every analyst issues an average of four forecast revisions per firm per year and follows about twenty one firms per year. The number of industries an analyst follows decreases from five from Clement and Tse (2003) to two in my sample due to the data selection process. I also report distributions for the scaled variable in Panel B. The variables are scaled to range from zero to one, but preserve the relative positions of each observation within a firm-year.

I report correlations among the analysts' forecast bias and analyst forecast and firm characteristics in Panel C. *EMPLOYER* is positive and significantly correlated to bias for the first forecast and negative and significantly correlated to bias for the last forecast. *EMPLOYER* is also significantly correlated to a number of firm and standardized analyst characteristics, specifically a positive correlation is noted for firm size (*Ln(MV)*), book-to-market (*Ln(BTM)*), and analysts following (*Ln(Follow)*); a negative correlation is noted for earnings dispersion (*Earn_Std*), forecast frequency (*fr*) and analysts' general experience (*Gen_Exp*). Consistent with prior research, I find the firm characteristics of earning dispersion, firm size, book-to-market and analysts' following to be significantly correlated to forecast bias. The correlations among forecast characteristics and forecast bias are not significant,

except for forecast horizon and forecast revisions. None of the analyst characteristics are significantly correlated with forecast bias.

2.4.2 Forecast bias for employers versus non-employers

Table 1.2 Panel A presents estimates of equation (1.1), where the dependent variable is relative forecast bias (*Rel_DFB*) in columns 1 and 2 and absolute bias (*Abs_DFB*) in columns 3 and 4, for the analyst's first or last forecast. The coefficient on the indicator variable *EMPLOYER* for both the first forecast (column 1) and last forecast (column 2) is economically and statistically significant. Specifically, the coefficient on *EMPLOYER* for the first forecast is positive, indicating an optimistic forecast, and significant at the five percent level. The size of the *EMPLOYER* coefficient indicates that the average relative first forecast bias for employers is 17.7% more optimistic than for non-employers. In contrast, for the last forecast the coefficient on *EMPLOYER* is negative, indicating a pessimistic forecast, and is significant at the ten percent level. The size of the *EMPLOYER* coefficient indicates that the average last relative forecast bias (*Rel_DFB*) for employers is 36.9% more pessimistic than for non-employers. These results provide support to hypothesis one that analysts are more biased with respect to employers' forecasts than non-employers' forecasts and that this bias follows an optimistic to pessimistic pattern documented in prior studies (Richardson et al., 2004, Ke and Yu, 2006; Bradshaw et al., 2014). The alternative bias measure *Abs_Bias* (column 3 and 4) provides a similar pattern to *Rel_Bias*. The first

forecast bias for employers is 12.7% more optimistic and significant at the one percent level, whilst the last forecast bias for employers is 18.6% more pessimistic and significant at the one percent level.

These findings are consistent with my argument that analysts who forecast earnings of both employers and non-employers will have stronger career incentives with respect to their employer forecast and a greater need to curry favour with these managers. In unreported results, I find the analysts' first employer forecast is significantly more accurate than their first non-employer forecast, whilst the last employer forecast is not significantly different compared with the last non-employer forecast. Thus, the optimism I observe for the first employer forecast cannot be attributed to the difficulty of the task (Bradshaw, Lee, and Peterson (2016)).

Among the non-standardized control variables in columns (3) and (4) the coefficient estimates for earning dispersion (*Earn_Std*) and book-to-market *Ln(BTM)* are positive and significantly different from zero for both the first and last forecast analyses. In addition for the first forecast, forecast revision (*fr*), analyst firm experience (*Firm_Exp*) and general experience (*Gen_Exp*) and number of industries followed (*Num_Ind*) are significantly different from zero. For the last forecast analysis, the number of analysts covering the firm (Ln (Follow)), forecast horizon (*F_Horizon*), number of firms followed (*Num_Co*) and industries covered (*Num_Ind*) by the analysts are significantly different from zero.

2.4.2.1 Only banks

I test the sensitivity of these results to alternative samples. First, from my main sample, I focus only on analysts with forecasts for banks with and without investment arms (mainly commercial banks, therefore excluding other financial institutions). Certainly, these latter firms operate in a more similar setting and therefore have more similar risks and regulations compared to firms that provide non-financial services. The results are reported in Table 1.2 Panel B. I find for both measure of bias a similar pattern, *EMPLOYER* is positive and significant, with a coefficient of 0.182, for the first forecast when bias is *Rel_Bias* (Column 1) and negative and significant, with a coefficient of 0.430, for the last forecast (Column 2). For the *Abs_Bias* the *EMPLOYER* is positive and significant, with a coefficient of 0.141 (Colum 3) and negative and significant, with a coefficient of 0.272, for the last forecast (Column 4). The results are therefore not sensitive to this alternative sample.

2.4.2.2 Propensity score matching for employers and non-employers

Second, I employ propensity score matching (PSM) and use a one-to-one matched pair design to identify for each analyst an employer and a non-employer. My matching algorithm uses variables typically related to analyst forecast accuracy and firm-specific variables highlighted in the banking literature (Flannery, Kwan, and Nimalendran (2004) and Anolli, Beccalli, and Molyneux (2014)). Specifically, I match on a number of firm characteristics, namely, book-to-market (*BTM*), size (*MV*), bid-ask spread (*Qspread*), stock turnover (*Turnover*), stock return volatility

(*Total Risk*), insolvency risk (*Zscore*) and analysts' related variables: number of analysts following the firm (*Follow*) and the firm-specific experience of the analyst following the firm (*Firm_Exp*). I also investigate the sensitivity of my results by creating a sub-sample of banks with and without equity departments. For this sub-sample, I match on all variables noted above along with one additional firm-specific variable, return-on-assets (*ROA*). I include this additional variable given that the accounting is similar for this sub-sample of firms, unlike for the full sample. In the matching process, I set caliper equals to 0.001 and neighbour equals to 1 with common support. I included five-year senior CDS spreads (proxy for credit risk) initially, but the number of observations dropped significantly because the data starts from year 2003. Although the results still hold, I do not include it.

Table 1.3 (Panels A and B) reports the mean difference in covariate values for the first and last forecasts using the full sample and the banking sub-sample respectively. I assess the balance with reference to the bias reduction and t-test (columns 7 and 8). As Oakes and Kaufman (2006) suggest, the standardized bias below 10% after matching is desirable. Both panels reveal the impact of the matching process. In Panel A (full sample), other than *Firm_Exp* and *Qspread* (and *BTM* for first forecast sample), all covariate mean differences pre-matching are statistically significant (consistent with the correlations noted above) but after matching only *Total Risk* (for the first forecast sample) and *BTM* still differ significantly, although their residual bias is below 10%. The bank sub-sample, Panel B, provides a similar picture with the majority of covariate means differing

significantly pre-match (for both first and last forecast samples) and only a few covariate means differ significantly after the match, again all the residual biases are below 10%.

Panel C reports the regression estimates using the matched samples for the full sample. Consistent with the prior results, using either *Rel_DFB* or *Abs_DFB* the variable of interest, *EMPLOYER,* is positive and significantly different for the first forecast at 5% and 1% levels respectively (columns 1 and 3) and negative and significantly different for the second forecast at 5% level (columns 2 and 4). The size of the *EMPLOYER* coefficient (column 1) indicates that the average relative first forecast bias for employers is 20.4% more optimistic than for non-employers and the last forecast bias is 75.2% more pessimistic than for non-employers (column 2). Similarly, for the banking sub-sample (Table 1.3, Panel D) the first forecast is positive and significant at the 1% (for both the relative and absolute forecast biases) and negative and significant at the 5% and 10% for the last relative forecast bias and absolute forecast bias respectively.

2.4.2.3 Non-linear controls

Lastly I test the sensitivity of the results by controlling for firm-specific and analyst's specific characteristics in non-parametric analysis. I recast all the control variables as indicator variables according to the quintile in which the value of the variables falls. Therefore, instead of controlling for firm specific experience with a linear variable, I include four indicator variables as controls. Table 1.4 presents these

results, which are consistent with the prior findings and thus the results are therefore not sensitive to this alternative specification.

2.4.3 Exogenous shock: Global Settlement

Table 1.5 presents the results of the impact of the Global Settlement on analysts' career concerns and hence their forecast bias. Columns (1) and (2) are pre Global Settlement period and columns (3) and (4) are for the post-settlement period, for first and last forecasts respectively. As noted earlier, for this analysis I only include those analysts that are in both the pre and post periods. This is to exclude the potential explanation that analysts are different before and after the Global Settlement. I find for the first forecast the *EMPLOYER* coefficient is positive both before and after Global Settlement, but only becomes significant after Settlement. This indicates that following the Global Settlement employer analysts' first forecast is 23.6% relatively more optimistic than non-employers, unlike the pre-settlement period when it was only 5% relatively more optimistic than non-employers. For the last forecast analysis, I find in both periods that the *EMPLOYER* coefficient is negative. However, following the Global Settlement, the last forecast is 55.4% relatively more pessimistic than non-employers and statistically significant, compared to the prior period when it was 9.2% relatively more pessimistic. These findings are consistent with the Global Settlement increasing analyst incentives to bias their forecast and as a result provide an even steeper walk-down to beatable earnings. Moreover, to the extent that the Global Settlement mitigates other

sources of conflict of interest, one would expect to find the opposite result.

However, reduced competition due to brokerage house closures following the Global Settlement could explain my results (Hong and Kacperczyk (2010)). Therefore, I re-run the model (1.1), but exclude from the pre and post sample those firms who experienced a decrease in analyst coverage following the Settlement. This new sample thereby reduces the possibility of the competition effect, noted by Hong and Kacperczyk (2010), from influencing my results. The results are reported in Table 1.5 Panel B. I find similar results to those of the main sample (Table 1.5 Panel A).

I use *Rel_DFB* not *Abs_DFB* because the global settlement also has an impact of the analyst view of investment banking and analysts are pessimistic about banks relative to non-banks following the Global Settlement. If I use the absolute measure, it is difficult to ascertain whether the bias is driven by career concerns or by a general pessimistic view of the banking sector as the Global Settlement may have an impact on the firms' profitability and price. Therefore by choosing the relative measure, I remove the general pessimism following the Global Settlement.

Overall, the results suggest that the exacerbation of career concerns prevents any decrease in bias from potentially mitigating other conflicts of interest, consistent with the intention of the Settlement.

2.4.4 Robustness check

2.4.4.1 Opaqueness

Some researchers assert that banks are more opaque, so banks are more difficult to forecast. Morgan (2002) claims that what is different about banks lies in the opacity of a bank's portfolio because lending to opaque borrowers may cause opaque banks. However, based on the literature of equity market microstructure, Flannery, Kwan, and Nimalendran (2004) state that if banks were relatively difficult for outsiders to understand, their shares should exhibit distinctive trading characteristics in variables such as their bid-ask spreads, the "adverse selection" component of those spreads, their trading volume, and maybe their return volatility. Although some may claim that banks are more difficult to forecast due to the risks taken by banks, Anolli, Beccalli, and Molyneux (2014) document that bank-specific risks did not influence forecasting abilities before the 2008 financial crisis.

Therefore, I compare the microstructure of investment banks and compare groups to explore whether investment banks are more opaque, which leads to a greater difficulty with forecasting, compared with non-bank firms. In this sub-sample, I choose non-employer firms with an equity market value closest to employer firms and a stock price within in 25% of the price of investment banks matched from the proper trading venue of NASDA and NYSE/AMEX, which is consistent with Flannery, Kwan, and Nimalendran (2004). I select all firms on the CRSP that

survived the entire calendar year and are re-selected at the start of each calendar year.

Table 1.6 compares the microstructure of investment banks and the non-bank group (hereafter “control group”) with a similar stock price and equity value. I find no evidence that banks are more opaque than non-banks. For each variable, mean values and the statistical significance of the difference between banks and non-banks groups are presented. To assess the economic importance of these differences, a proportional (*Prop’al*) difference for each bank–nonbank pair is calculated, equal to the difference between the two firms’ values (the non-bank’s value minus the bank’s value), divided by their mean value.

The first two rows in Table 1.6 confirm that the control group’s market values and prices closely resemble the banks’. The first row (*markv*) also illustrates the large size difference between the NASDAQ and NYSE subsamples: the typical NYSE-traded banks are four times larger than their NASDAQ counterpart. Most of my bank samples are traded in NYSE and the difference of return volatility (*std*), trading volume between banks and control group in NYSE are not statistically significant. *qspread* and *jspread* describe bid–ask spreads and their components. The proportional difference is statistically insignificant, indicating that banking firms are unusually not opaque to market investors. Since I match the sample on the basis of equity market value and price, each firm in a pair has a similar number of shares outstanding, and thus the difference between the turnover (*tover*) of the

control group and the bank is large.

2.4.4.2 Forecast Accuracy

I also compare forecast accuracy of analysts forecasting employer firms and non-employer firms from equation (1.3). It is it the same methodology as investigating forecast bias, but accuracy is the absolute value of Rel_DFB_{ijt} . One possible explanation for analysts to be more optimistically biased towards employers is that employer firms are more difficult to forecast (Bradshaw, Lee, and Peterson (2016)). Therefore, I compare the forecast accuracy of employers and non-employers.

$$\begin{aligned} Accuracy_{ijt} &= \alpha + \beta_1 EMPLOYER + \beta_2 earn\_std_{ijt} + \beta_3 Ln(MV_{jt}) + \beta_4 Ln(BTM_{jt}) \\ &+ \beta_5 Ln(Follow_{jt}) + \beta_6 F\_Horizon_{ijt} + \beta_7 dayElap_{it} + \beta_8 fr_{ijt} + \beta_9 Firm\_Exp_{ijt} \\ &+ \beta_{10} Gen\_Exp_{it} + \beta_{11} Num\_Co_{ijt} + \beta_{12} Num\_Ind_{ijt} + \beta_{13} Num\_aAna_{jt} + \beta_{14} Year\_F.E + \varepsilon_{ijt} \end{aligned} \tag{1.3}$$

Table 1.7 presents the estimation of equation (1.3), where the dependent variable is relative forecast accuracy (absolute value of Rel_DFB). In the first forecast of column 1, I find analysts are more accurate at forecasting employers than non-employers, with the coefficient of $EMPLOYER$ being positive and significant. In the last forecast of column 3, there is no difference in accuracy between forecasting employers and non-employers, with the coefficient of $EMPLOYER$ insignificant. The results show that banking analysts are more accurate in the initial forecast, thus the optimism I observe for the first employer forecast cannot be attributed to the difficulty of the task.

2.4.5 Forecast bias and job separation

Table 1.8 Panel A reports the percentage of analysts who work in high-status and low-status brokerage houses. Consistent with Hong and Kubik (2003), I find approximately 31.5% of analysts worked in high-status brokerage houses each year. High-status brokerage houses in aggregate should not employ the majority of analysts; otherwise, there would be little meaning to being considered a prestigious house. Table 1.8 Panel B reports the summary statistics of those analysts in the I/B/E/S database who leave their brokerage house but stay in the profession. About 6% of analysts changed brokerage houses each year during the 1999-2006 period. Of these movers approximately 7% were analysts who covered employers (column 2). As a fraction of these movers, about 51% moved up the hierarchy, about 30% moved down the hierarchy and the remaining were lateral movers. These percentages were very similar to the all analyst sample (Column 1).

Taking a slightly different look at these job separation patterns, on average during the period approximately 16% of bank analysts moved from either high-status or low-status brokerage houses. The biggest movers are from mid-status houses, where nearly 68% of bank analysts moved from this group. Again these percentages are similar to the all analyst sample.

Table 1.8 Panels C and D present the results of estimations from the ordinal logit model, equation (1.2), for the various job separation measures involving movements along the brokerage house hierarchy. As noted earlier, the sample I

use only includes those analysts from the medium and low-tier brokerage houses. In Panel C, column 1, the *Rel_BIAS* relates to the first forecast bias, in column 3 it relates to the last forecast bias. I find the first forecast bias is not associated with job separation along the brokerage house hierarchy, and that analysts who forecast employers are not significantly different from other analysts, since the coefficient on the interaction variable (*EMPLOYER*BIAS*) is not significantly different from zero. However, I find the last forecast bias (column 3) for analysts who forecast employers is associated with job separation along the brokerage hierarchy. Specifically, the coefficient on the interaction variable (*EMPLOYER*BIAS*) is negative, indicating that analysts who issue pessimistic forecasts for employers are relatively more likely to move up the brokerage hierarchy, compared to analysts who forecast non-employers. This result supports my hypothesis that analysts who bias their employer forecasts are more likely to experience favourable job separations. Panel D presents results using *Abs_BIAS* and again I find the results are consistent.

Given that interaction terms do not have a straightforward interpretation in nonlinear models as in linear models, I follow Ai and Norton (2003) and estimate marginal effects for different cells. Moreover, I report odds ratios for all estimated coefficients. I note that no odds ratios can be calculated for the interaction effect but rather I report the ratio of the odds ratio for the interaction effect. Figure 1 shows the marginal effect for a unit change in bias for movements up or down the hierarchy based on whether the analyst makes forecasts for an employer or non-

employer in the last forecast. As can be seen, non-employer bias does not affect movements. For non-employers, the marginal effect is 0.09% (z-stat=0.26) for downward movement and -0.25% (z-stat=-0.26) for upward movement as an analyst's bias increases. In contrast, for employers, the marginal effect is -1.51% (z-stat=-2.63) for downward movement and 7.28% (z-stat=2.07) for upward movement as an analyst's bias increases. Therefore, more biased analysts in forecasts for employers are significantly more likely to be promoted by moving to higher reputation banks.

2.5 Conclusion

I investigate how career concerns of analysts that forecast the performance of potential future employers influence their forecasts. I find evidence of a walk-down to beatable earnings when forecasting earnings of future employers but not of firms that are unlikely to be future employers. Moreover, this pattern is more pronounced after the Global Settlement, which exacerbated career concerns of analysts by limiting their outside opportunities. Consistent with career concerns about future employment biasing forecasts, I find that bias in potential future employers' forecasts leads to favourable career outcomes. No such effect is found for bias in non-employer forecasts. I find a source of conflict of interest for analysts, which are also discussed in other settings, such as auditing. The generalizability of the phenomenon to the analyst setting is important as it suggests that other information intermediaries might be affected by such conflicts.

Analyst forecast accuracy (unsigned) and bias (signed) are related, but they do not subsume each other. If as suggested by my results that, given biased banking analysts have greater opportunities to move to higher status investment banks, does this imply that investment banks are employing poor quality analysts? The answer I believe is no as the analysis in Table 1.7 suggests the quality of the analysts forecasts for investment banks relative to non-investment banks forecast is no worse and in some cases is better. Specifically, I do not find that banking analysts forecast accuracy is of a lower quality for their investment banks forecast relative to their non-investment bank forecasts. This is consistent with Lim (2001) and Jacob, Rock, and Weber (2008) who show that higher levels of optimism bias does not necessarily imply reduced accuracy. Indeed, an analyst could trade off some amount of bias in their forecasts in exchange for access to additional information that improves their accuracy.

My findings should be of interest to investors and policy makers who want to know the incentives that drive biased forecasts. Jackson (2005) shows that retail investors find it difficult to debias analysts' forecasts. My findings, that the walk-down pattern exists in banking industry, could help small investors identify and correct for such bias, thereby obtaining more informative forecasts. For securities regulators, my findings may help them to scrutinize factors which lead analyst to strategically distort their forecasts. Although the Global Settlement reduces the frequency of issuing buy recommendations (Balboa et al (2009)), my results show

that the Settlement did not mitigate conflicts of interest faced by banking analysts. It is possible that such biased forecasts for banking industry have implications for an efficient market and could lead to the mispricing of banks but I suspect only in the short-run.

Chapter 3

Analyst reports with consistent and conflicting signals: market reaction and forecast accuracy

3.1 Introduction

Recent research finds that the sentiment of the analyst report provides incremental information beyond the quantitative measures such as target prices or earning forecasts (Asquith, Mikhail, and Au (2005), Twedt and Rees (2012) and Huang, Zang, and Zheng (2014)). The textual discussion is an important part of an analyst report because it provides investors with the analysis and justification behind the forecast figures the analyst has arrived at. This private information and the analyst's understanding of the stocks contained in the discursive element of the report are found to be valuable to investors. Specifically, Huang et al. (2014) finds that when the sentiment of the analyst report is optimistic (pessimistic), investors react more strongly to upward (downward) earnings revisions. This finding focuses primarily on those analyst reports that contain consistent signals between the qualitative and quantitative elements of the report. However, it is unclear how investors will react to conflicting signals between these two elements and therefore I investigate investor reactions to analyst reports which contain conflicting signals and those that contain consistent signals.

Specifically, I focus on the sentiment (i.e. qualitative measure[10]) and earnings forecast bias (i.e. quantitative measure) of analyst reports. I investigate the following three questions: First, does the market react differently to analyst reports which contain consistent signals compared to those with conflicting signals? Second, when the analyst textual discussion and earnings forecast bias do not coincide, which attribute do investors place greater weight on? Lastly, is there any difference in terms of forecast accuracy between those analysts' reports that contain a conflicting message and those that have a consistent message?

I therefore group the analyst reports into the four possible combinations of quantitative and qualitative messages. The first two contain consistent messages and the last two contain inconsistent messages:

1. A report containing an optimistic textual sentiment (O_T) and an optimistic forecast bias (O_B), resulting in an O_TO_B analyst report.
2. A report containing a pessimistic textual sentiment (P_T) and a pessimistic forecast bias (P_B), resulting in a P_TP_B analyst report.
3. A report containing an optimistic textual sentiment (O_T) and a pessimistic forecast bias (P_B), resulting in an (O_TP_B) analyst report.
4. A report containing a pessimistic textual sentiment (P_T) and an optimistic forecast bias (O_B), resulting in an (P_TO_B) analyst report.

Investors spend millions of dollars subscribing to the full analyst reports even though they have access to analyst quantitative outputs. Survey evidence from Brown et al. (2015) suggests that textual analysis of analyst reports could be more

[10] I use textual discussion, text, sentiment and qualitative measure interchangeably.

valuable than the final EPS forecasts or stock recommendations because they provide detailed analyses with a lower probability of being affected by conflicts of interest. Yet the existing literature focuses almost exclusively on the quantitative properties such as target price, earnings forecasts and stock recommendations while only a few studies have examined the qualitative attributes of the analysts' reports. This was highlighted by Bradshaw (2011), who advocates that there should be more studies investigating elements other than the analysts' quantitative output. Certainly, there is evidence that investors value the analysis of the analyst reports far more than their final conclusions (The Institutional Investor magazine, 2011). We answer Bradshaw (2011) call by examining the market reaction to the interaction effect of quantitative and qualitative attributes in analyst reports.

I manually collected all sell-side analyst reports of S&P500 firms from 1999 to 2014. From these I measure the sentiment of analyst reports using the Loughran and McDonald (2011)[11] methodology. I then compare the market reaction to analyst reports which contain consistent signals (O_TO_B and P_TP_B reports) and those which contain conflicting signals (O_TP_B and P_TO_B reports). Although, Huang et al. (2014) find that investors react to optimistic (pessimistic) earnings forecast revisions more intensively when they are supported by optimistic (pessimistic) text, the focus of my research is based in part on the persuasion theory, which suggests that there may be some incremental benefit from having conflicting signals, in so far as a proper amount of negative argumentation could improve analyst credibility (Crowley and

[11] I use LM hereafter.

Hoyer (1994)). My first empirical test finds that investors react more strongly when the sentiment of textual discussion and earnings forecast bias are consistent relative to those reports containing inconsistent signals. In other words, O_TO_B and P_TP_B reports have a stronger market reaction than O_TP_B and P_TO_B reports.

Focusing on the conflicting reports, I investigate which conflicting signal investors put greater weight on, the text or the forecast bias. I find that when the tone of the text does not coincide with the earnings forecast bias, investors place greater weight on the tone rather than the forecast bias, i.e. an O_TP_B report has a positive reaction while a P_TO_B report has a negative reaction. It suggests that, although more costly, investors believe the textual information disseminated by analysts is more valuable than their final numerical conclusion. This is consistent with Brown et al. (2015) argument that the model and analysis behind the final EPS forecasts are important[12].

Although I find that consistent reports with both optimistic sentiment and optimistic forecast bias have a strong positive market reaction, further analysis reveals that these reports are associated with lower forecast accuracy. The reports associated with high forecast accuracy are those that contain a pessimistic tone (P_TP_B and P_TO_B reports). This suggests that pessimistic sentiment *per se* maybe a good indicator for the quality/credibility of the analyst reports. Furthermore, of these two types of reports - P_TP_B and P_TO_B reports, I find those with relatively pessimistic sentiment, but an optimistic earnings bias (P_TO_B) are associated with the highest

[12] This is also consistent with the discussions I had with analysts and fund managers.

forecast accuracy. Compared with P_TP_B reports, P_TO_B reports show two-sided argumentation, which indicates analyst awareness of both positive and negative aspects of the stock they cover.

My study complements the analyst literature by examining the interaction effect of different signals contained in analyst reports, especially when those signals do not coincide. I believe I am the first to show that investors react differently to analyst reports with conflicting and consistent signals. More importantly, within those reports which contain conflicting signals, investors place greater weight on the textual analysis relative to the forecast numbers. In addition, I complement the literature on analyst forecast accuracy by investigating which combinations of quantitative and qualitative attributes in analyst reports enjoy the highest accuracy. I find that reports with pessimistic sentiment are more credible because they are associated with a high accuracy. Lastly, I complement the research in the textual analysis of analyst reports by providing large sample evidence, compared with Asquith, Mikhail, and Au (2005) and Twedt and Rees (2012), who conducted pilot tests by using non-random and small sample sizes. The dictionary-based technique enables me to measure the tone of analyst reports more objectively and makes it easier to replicate, compared with the machine learning technique applied by Huang, Zang, and Zheng (2014).

Section 3.2 discusses relevant prior studies and develops the hypotheses; Section 3.3 provides the dictionary-based approach for sentiment analysis; Section 3.4

presents data and the methodology being applied in this chapter; Section 3.5 discusses the empirical results and Section 3.6 concludes.

3.2 Literature Review and Hypotheses Development

3.2.1 Market reaction to the different combinations of the sentiment and the EPS forecast bias of the analyst reports

3.2.1.1 Sentiment of financial disclosures

With the development of linguistic software, researchers have tried to understand how the sentiment of financial disclosures influences the market. The qualitative information that has been analysed by textual sentiment researchers in finance comes predominantly from three sources: **a)** public corporate disclosures (Schleicher and Walker (2010), Li (2010), Feldman et al. (2010), Rogers, Buskirk, and Zechman (2011), Davis and Tama-Sweet (2012), Price et al. (2012), Jegadeesh and Wu (2013), Kravet and Muslu (2013), Ferris, Hao, and Liao (2013), Merkley (2014), Muslu et al. (2015) and Davis et al. (2014), Tama-Sweet (2014) and Blau, DeLisle, and Price (2015)), **b)** media articles (Tetlock, Saar-tsechansky, and Macskassy (2008), García (2013), Engelberg, Reed, and Ringgenberg (2012), Schumaker et al. (2012), Yu, Duan, and Cao (2013), Chen et al. (2013) and Rees, Sharp, and Twedt (2015)), and **c)** social media posts and personal correspondence (Chen et al. (2014), Hillert, Niessen-Ruenzi, and Ruenzi (2014) and Wang et al. (2015)).

It has been shown that the sentiment of financial disclosure can significantly affect the capital market response to the release of other types of information by conditioning the market expectations. Davis, Piger, and Sedor (2012) investigate language used in firm earning press releases. They find a positive relationship between the sentiment of earnings press releases and future ROA. Furthermore, they find that market responds to the sentiment of the earnings press release. Additionally, Jegadeesh and Wu (2013) find that the tone of positive words in the annual report is positively correlated with the market reaction. Earning conference calls is another area where researchers have examined managerial choice of words. Using a sample of 10,062 conference call transcripts during 2003-2005, Matsumoto, Pronk, and Roelofsen (2011) find that both the manager's presentation and the Q&A sections of the conference call add information beyond the preceding press release. Since all of their conference calls occurred during the trading session, the authors were able to measure the market's immediate reaction (i.e., abnormal absolute returns) to each portion of the call. Although Matsumoto et al. (2011) do not measure the sentiment of the earnings conference call, they do create a list of financially oriented words. The list contains mostly financial jargon terms such as leasing, ROA, ROI, cash, costs, and prepayment. They find that firms with stronger prior accounting operating performance use more financially oriented words during management presentations, compared to those with weaker accounting operating performance.

The tone used in media reports has also been analysed. Liu and McConnell (2013) examine the media influence on 636 acquisitions with negative announcement reactions from investors during 1990-2010. They find that managers are sensitive to their reputational capital. They report that both the level of media attention (measured by number of articles) on the proposed acquisition and the tone of the corresponding news articles (measured as a percentage of LM negative words[13]) can significantly affect the probability of abandoning the deal. Having more articles with a negative tone is associated with managers being more likely to drop the proposed acquisition.

Other studies such as that by Hillert, Niessen-Ruenzi, and Ruenzi (2014) investigate the tone of mutual fund letters during 2006-2012 after controlling for past performance and fund characteristics. They document that the tone of the mutual fund letter directly affects money flows. A more negative tone in the shareholder letter is linked with significantly lower net flows into the open-end mutual fund.

So far, only three studies have examined the sentiment of analyst reports. They all find that textual analysis of analyst reports provides incremental information and is priced by market. Asquith, Mikhail, and Au (2005) conducted a preliminary study by manually computing the sentiment score for 193 analyst reports. Their seminal study concludes that the tone of analyst reports can explain market reactions.

[13] Loughran and Mcdonald (2011) negative words

However, it must be noted that their sample is non-random as they only include top-ranked analysts.

Twedt and Rees (2012) examine the tone and detail of analyst reports. Tone is measured by General Inquirer. Detail is measured by complexity (Fox Index), length, and visual aids. They find that the ranking of these two qualitative attributes, tone and detail, provides incremental information beyond the standard deviation between analysts' stock recommendation and that of consensus, as well of the standard deviation between analysts' earnings forecasts and that of consensus. They also document that the tone and complexity of analyst reports help explain cross-sectional variation in investors' reactions around the issuing dates of reports. Twedt and Rees (2012) selected 2,057 analyst reports from 2006 and only examine the analysts' initiation reports because they manually read each report, which is very time-consuming.

Huang, Zang, and Zheng (2014) substantially extend the sample and are the first to apply the machine learning approach to calculate the sentiment of analyst reports. They find that investors react stronger to negative sentiment than to positive sentiment. They also argue that investors value the reports more if the reports focus on non-financial topics and are written more assertively and concisely. They utilize the machine learning method, which is viewed as more accurate but more labour intensive, less objective and therefore less generalizable. In the machine learning method, a researcher manually classifies words into different

categories after reading some analyst reports. Unfortunately, different people usually have different views towards the tone of a sentence, which introduces consistency problems in replicating the results. Their study finds that the text of reports facilitates investors to make decisions when it is consistent with the quantitative measure. I complement and add to this paper by comparing the market reaction to reports with consistent signals and conflicting signals. Furthermore, I also explore within the conflicting reports which signal provides the greatest incremental information to investors.

3.2.1.2 Forecast bias

There is an extensive literature on analyst forecast bias indicating that it has economic incentives beyond pure judgement error. The most important two reasons for conflicts of interest are underwriting relationships (Dugar and Nathan (1995); Lin and Mcnichols (1998); Michaely and Womack (1999); and Dechow, Hutton, and Sloan (2000)) and the generation of trading commissions (Jackson (2005); Cowen, Groysberg, and Healy (2006); Beyer and Guttman (2011) and Bradley, Gokkaya, and Liu (2015)). For example, O'Brien, McNichols, and Lin (2005) find that banking ties increase an analyst's reluctance to reveal negative news. Similarly, Arand and Kerl (2015) demonstrate that the aggregate number of simultaneous business ties with a reported firm is positively associated with the optimism level in the target prices and in the recommendations. Maintaining a good relationship with managers also creates forecast bias. Lim (2001) finds that

analysts tend to be optimistically biased in order to secure management access. Moreover, Hong and Kubik (2003) document that underwriter analysts who issue more optimistically biased earnings forecasts are more likely to experience favourable career outcomes. These studies investigate analyst incentives to optimistically bias their forecasts. Recent research identifies analysts' incentives to walk-down their forecast revisions and pessimistically bias their last forecasts. Cotter, Tuna, and Wysocki (2006), Ke and Yu (2006) and Pinello (2008) argue that managers prefer beatable forecasts and therefore negative forecast bias facilitates firms to beat market expectations. Due to the equity incentives of management teams, some studies find a positive relationship between negative forecast bias shortly before earnings announcement dates and net sellers of stock after an earnings announcement. This game is examined by Richardson, Teoh, and Wysocki (2004); Cheng and Warfield (2005); Cheng, Warfield, and Ye (2011); Bergstresser and Philippon (2006); Cheng and Kin (2006); Tama-Sweet (2014). Examining the relationship between forecast bias and task difficulty, Bradshaw, Lee, and Peterson (2016) find that analysts tend to issue optimistically biased forecasts when they are less certain about their forecasts. Their finding supports the argument that pessimistically biased forecasts are more credible.

3.2.1.3 Market reaction

Several studies investigate market reaction when investors take into account the analysts' incentives mentioned above. Barber, Lehavy, and Trueman (2007)

demonstrate that the market reacts stronger to recommendations made by independent analysts than by affiliated analysts. Focusing on buy recommendations, Lin and Mcnichols (1998) find that the market does not react to favorable recommendations made by affiliated analysts, suggesting investors' awareness of analysts' strategic bias. Iskoz (2002), Malmendier and Shanthikumar (2007), Mikhail, Walther, and Willis (2007) and Malmendier and Shanthikumar (2014) compare reactions from large and small investors and find that the large investors discount recommendations, in particular affiliated ones, while small investors do not.

While these studies above examine investor reactions to recommendations around earnings announcement dates, others investigate the market response to earnings forecast bias. Kasznik and McNichols (2002) find that for those firms with low analyst following and institutional ownership, investors react stronger to positive earnings surprises (i.e. meeting or beating consensus forecast). Hirshleifer et al. (2008) focus on retail investors. Their study documents that retail investors tend to buy stocks after extreme negative and positive earnings surprises. Malmendier and Shanthikumar (2014) extend the study and show that small investors react more positively than larger investors to (meet or beat) earnings news, but do not consider the specific quantity of good news or bad news. Ivkovic and Jegadeesh (2004) focus on forecast revisions and find that the market reacts strongly to forecast revisions in the week after the earnings announcement. However,

Altınkılıç, Balashov, and Hansen (2013), using intraday returns, do not find analysts' forecast revisions informative.

3.2.1.4 Consistent signals vs. conflicting signals

Engelberg (2008) states that making investment decisions based on a synthesis of information, although more costly, is more reliable than investing based on a single indicator. Opdyke (2002) and the Securities and Exchange Commission (2010) advise investors to not just rely on analyst summary outputs since they might be strategically distorted due to conflicts of interest. Francis and Sofferf (1997) examine how investors react to two indicators interactively. They examine both analyst stock recommendations conditional on the earnings forecast and vice-versa. Francis and Soffer (1997) find lower precision of favourable recommendations. Consequently, they find that investors put more weight on earnings forecasts when buy recommendations are issued. Winchel (2015) also examines the interaction effect of two attributes of analyst reports by running experiments with 40 MBAs. She studies the presence of a causal explanation and positive conclusions. She finds that investors react strongly to an optimistic analyst report when the report provides unambiguous positive arguments. In contrast, when ambiguous optimistic arguments are presented, investors give more credit to two-sided argumentation. Both these studies show that investors do not rely on one attribute in analyst reports but the interaction effect.

So overall, the above findings would suggest investors are likely to react more intensively to reports with consistent signals (O_TO_B and P_TP_B), especially given the findings of Huang et al. (2014), who find that the market reacts more strongly when the text support the quantitative outputs, compared with quantitative outputs only. However, investors may react more intensively to reports with conflicting signals (O_TP_B and P_TO_B reports). These two-sided argumentation reports could be more credible to investors because they contradict analysts' institutional incentives and show analyst effects in providing both positive and negative aspects of the covered firms (Winchel (2015)). Therefore, it is an empirical question as to whether the market reacts differently to the types of analyst reports. This leads to my first hypothesis:

> ***H1:*** *Market reactions to analysts' reports containing conflicting signals will be different to those containing consistent signals.*

3.2.1.5 Text vs. bias

Some investors prefer to look at the final outputs such as EPS forecasts and do not fully read the complete analyst reports (Huang et al, (2014)). These investors may pay more attention to the conclusions due to time constraints. Therefore, investors may react more to EPS forecasts and use them directly while reacting less to the text of full analyst reports since they are too time-consuming to read and costly to obtain.

On the other hand, it is also possible that the market reacts more strongly to the textual discussion of analyst reports. Investors spend millions of dollars to subscribe to full analyst reports while they already have access to analyst earnings forecasts or recommendations via news services. This extra payment suggests that investors value more the written reports since analysts' final numerical outputs are more likely to be influenced by conflicts of interest (Guan, Lu, and Wong (2012), Kadan et al. (2009), Agrawal and Chen (2005), Chan, Karceski, and Lakonishok (2007)). Therefore, when analyst earnings forecasts are not consistent with their textual discussion, investors might show a greater reliance on the textual discussion of analyst reports. In addition, surveys from Institution Investor[14] magazine show that buy-side analysts and fund managers value both private and proprietary information conveyed in the sell-side analyst reports as well as the analysts' interpretation of this information. This is confirmed by Soltes (2014) and Brown et al. (2015), who find that analyst reports are more valuable if private discussions with management are mentioned. Some investors could prefer to use information they believe is trustworthy to make their own decisions, without relying on the analyst EPS forecasts. Final quantitative outputs are merely aggregations of all the information, assumptions, analysis and biases of the analysts. Investors may adjust the assumptions and or biases and use alternative valuation models based on the financial and non-financial information which the analysts have provided (Institutional Investor (2011)). Using their professional resources, the

[14] For details, see various October issues of the Institution Investor magazine.

information gathered by analysts can be more valuable for investors than the analysts' final quantitative outputs. Moreover, psychology literature also shows that a proper amount of negative argumentation could improve credibility (Crowley and Hoyer (1994) and Elsbach and Elofson (2000)). Therefore, I hypothesize that:

> ***H2:*** *If the sentiment of the textual discussions contained in the analyst reports does not coincide with their forecast bias, then investors will react more to the sentiment relative to the forecast bias.*

3.2.2 Forecast accuracy of the different combinations of the sentiment and the EPS forecast bias of the analyst reports

3.2.2.1 Determinants of forecast accuracy

Prior literature investigates the accuracy of analyst reports focusing on analyst characteristics, their incentives and other factors that influence forecast accuracy and the subsequent benefits of accurate forecasts. Clement (1999) and Jacob, Lys, and Neale (1999) find that analyst experience, portfolio complexity, forecast horizon, forecast revisions and broker size are determinants of analyst forecast accuracy. Mikhail, Walther, and Willis (1999) provide evidence that low accuracy leads to a higher probability of analyst turnover. Walther and Willis (2013) find that analysts are quite optimistic and least accurate when market confidence is high, while Ertimur, Sunder, and Sunder (2007) find that more accurate analysts make more profitable recommendations.

3.2.2.2 Pessimistic sentiment and forecast accuracy

Hong, Lim, and Stein (2000), Hugon and Muslu (2010) and Huang et al. (2014) find that pessimistic information contained in analyst forecasts receive more intense investor reactions. Analysts may have the incentive to hype the stocks they cover (Lin and Mcnichols (1998), O'Brien, Mcnichols, and Lin (2005), Jackson (2005), Ljungqvist et al. (2007) and Bartholdy and Feng (2013)) because optimistic reports are likely to be driven by conflicts of interest such as trading commissions (Cowen, Groysberg, and Healy (2006)) and management relationship (Mayew (2008)). Therefore, reports with pessimistic text are less likely to suffer from strategic bias and may be of a higher quality. In addition, Bradshaw, Lee, and Peterson (2016), supported by the cognitive psychology literature, find a significant association between analyst forecast optimism and the difficulty of the task. Therefore, unlike analysts with an optimistic outlook, analysts with a pessimistic sentiment might be more credible and confident in their information since the forecasting task is simply less difficult. Furthermore, O'Brien, McNichols, and Lin (2005) and Kadan et al. (2009) examine the conflicts of interest faced by analysts. They find that the affiliated analysts are reluctant to reveal negative news or downgrade those firms with investment banking ties. This leads to my third hypothesis:

> ***H3:*** *If the analyst's report contains a pessimistic textual discussion it is associated with higher forecast accuracy relative to a report containing an optimistic textual discussion.*

3.3 The Method of Textual Analysis

3.3.1 Different techniques

Textual analysis is a multi-disciplined study, involving computational linguistics, statistical language processing, information retrieval and content analysis. In early financial text research, Bryan (1997) and Callahan, Cook, and Smith (2004) conducted sentiment analysis on small-size samples based on manually coded data. This method enjoys the advantages of being more precise, detailed and tailored to the specific research setting. However, the disadvantages are obvious; it is very time-consuming and is only therefore only appropriate for small samples.

The improvement of computer knowledge recently, however, now enables researchers to conduct textual analysis with larger samples. The most common content analysis methods includes the dictionary-based approach and machine learning. In the dictionary-based approach, different wordlists are available. In addition, there are two word frequency measures: equal-weighting and inverse document frequency weighting. Henry and Leone (2016) use both content analysis methods and compare these two word frequency approaches, and overall advocates for a dictionary-based approach, an equal-weighting scheme with a financially-specific wordlist. I therefore apply this method to my current study.

3.3.1.1 The dictionary-based method

The working principle for this method is that it maps each text file with counts on dictionary-supplied categories. That is, it indentifies and counts word frequencies, matching them against words. People can customise which dictionaries they use. This approch has at lease three benefits: First, the output results are continuous rather than categorical, which increases the power of analysis; second, the measure is normalized by word count, which allows for comparisons between disclosures of vastly different lengths; and finally, the process is objective, which means it can be applied to large quantities of text, and provides results that are replicable by other researchers.

Diction, General Inquirer and Linguistic Inquiry and Word Count are the most commonly used types of software to apply this technique. Their working principles are the same. The major difference in these software types is that they have different dictionaries. Diction uses a series of thirty-three dictionaries (word-lists) to search text passages for different semantic features such as, e.g., *praise, satisfaction*, or *denial*, while General Inquirer uses the Harvard-IV-4 Psychological Dictionary with Lasswell dictionaries. In recent years, Diction software has gained more popularity in accounting and finance research since it accepts a larger number of files within a single project (Demers and Vega (2010), Rogers, Van Buskirk, and Zechman (2011), Loughran and Mcdonald (2011), Ferris, Hao, and Liao (2013) and Demers and Vega (2014)).

3.3.1.2 The machine learning method

Machine learning involves one or more algorithms reading a training set and writing a ‘model’ containing its statistics. Specifically, researchers first manually classify words into ‘positive’, ‘negative’ or other training sets. Then, a selection of sentiment analysis algorithms such as the Naïve Bayesian algorithm is then trained on the training corpus. The algorithm ‘learns’ the sentiment classification rules from the pre-classified data set, and apply these rules out-of-sample to the whole context. Finally, sentiment measures can be derived using various combinations of the classifications used in the training corpus.

Compared with the dictionary-based approach, machine learning is more time-consuming and costly because the training set must be manually classified. It also leads to another disadvantage of a lack of objectivity and generalizability since different researchers may get a different training set for the same context. Although Li (2010) claims that machine learning has a higher accuracy than the dictionary-based approach, the “Black Box” nature and the difficulty of replications limit its development.

Li (2010) uses the Naïve Bayesian algorithm to study the relationship between the MD&A section of the 10-K and subsequent earnings and shows that the sentiment of the forward-looking statements (FLS) in the MD&A are positively related to future earnings for the firm. Buehlmaier (2013) uses the machine learning approach to gauge tone in newspaper articles regarding US merger

announcements and finds that positive media content about the acquirer predicts takeover success. Huang, Zang, and Zheng (2014) measure analyst report sentiment using Naïve Bayesian machine learning and find that an analyst's report text has predictive value in terms of determining future earnings growth in the subsequent five years.

3.3.1.3 The choice of wordlist

It is important to select a proper wordlist to perform an accurate sentimental analysis using the dictionary-based approach. Four different dictionaries are commonly used by researchers: Harvard's General Inquirer (GI), Henry (2008), Diction & Loughran and McDonald (2011).

1. *Harvard's General Inquirer (GI)*

The Harvard General Inquirer wordlist is a group of lists used historically in the sociology and psychology literature. It combines Harvard-IV-4 Psychological Dictionary with the Lasswell dictionaries, which contains 4,187 negative words. However, this wordlist may not be appropriate for textual analysis of financial disclosure.

Prior literature examines whether sentiment provides incremental information content using GI. The common theme in the literature is the slow diffusion by investors of soft information. Tetlock (2007) finds that pessimistic sentiment of the Wall Street Journal column temporarily lowers the level of the Dow Jones Industrial

Average, but the economic meaning is limited, with only one standard deviation increase in pessimism leading to an 8.1 basis points decline in the Dow the following day. Tetlock, Saar-tsechansky, and Macskassy (2008) and Engelberg (2008) examine firm-specific news and earnings announcements in the Dow Jones News Service and find that negative sentiment is associated with lower subsequent earnings and stock prices respectively. Kothari, Li, and Short (2009) use more sources of financial disclosures and demonstrate that disclosure tone affects both stock return volatility and analyst forecast error dispersion. Hanley and Hoberg (2010) study the tone of the initial prospectus (Form S-1). IPOs with more informative content in their S-1 have lower offer price revisions and first-day returns.

2. Diction

Diction has 35 different dictionary subcategories. It defines optimism as “language endorsing some person, group, concept or event or highlighting their positive entailments” and the Diction formula for net optimism is [praise + satisfaction + inspiration]-[blame + hardship + denial].

The Diction wordlist provides a general measure of tone and has been used in many contexts, including earnings announcements (Davis, Piger, and Sedor (2012); Demers and Vega (2010); Bligh and Hess (2007); Yuthas, Rogers, and Dillard (2002)); presidential speeches (Bligh, Kohles, and Meindl (2004)); corporate annual reports (Yuthas, Rogers, and Dillard (2002); Davis and Tama-Sweet (2012)); and other business communications (Ober and Zhao (1999)).

Davis and Tama-Sweet (2012) and Davis, Piger, and Sedor (2012) both examine the sentiment of corporate disclosure and subsequent return on assets (ROA). Davis and Tama-Sweet (2012) find that the more pessimistic the MD&A tone of Form 10-K, the lower is the subsequent ROA while Davis, Piger, and Sedor (2012) find that the positive tone of earnings press releases is positively associated with ROA. Focusing on shareholder litigation, Rogers, Van Buskirk, and Zechman (2011) find that one standard deviation increase in net Diction optimism is related to a 52% increase in being sued by shareholders.

3. Limitations of Harvard and Diction wordlists

In relation to business text, the Harvard General Inquirer wordlist misclassifies some words as negative which are commonly used in corporate filings, such as *tax, cost* and *capital*. Words such as *cancer* and *crude* do not convey negative sentiment in the oil and pharmaceutical industries, but the Harvard General Inquirer wordlist identifies them as negative words. The Diction wordlist has similar problems. It categorises words such as *respect* and *necessary* as positive words, but they usually do not have a positive meaning when managers describe future or current operations.

Several research papers have demonstrated the limitation of measuring sentiment of financial documents using the GI and Diction wordlists. Applying the GI wordlist to news articles, higher optimistic sentiment is associated with higher pessimistic sentiment since Heston and Sinha (2013) find a positive correlation (0.51) between

the proportion of positive and negative words. In contrast, Heston and Sinha (2013) find a more sensible negative relationship between the frequency of positive and negative words using Loughran and McDonald (2011) wordlist. Loughran and McDonald (2011) argue that around 75% of negative words from the Harvard wordlist do not exhibit negative sentiment in Form 10-K. Li (2010) fails to find a relationship between the tone of the MD&A section of 10-Ks using GI and Diction.

4. Henry (2008)

Neither GI nor Diction wordlists are designed for a financially-specific context. Henry (2008) claims that a general wordlist likely omits words that would be considered positive or negative in the context of financial disclosure and includes words that would not. For example, GI classifies *shares*, and *outstanding*, as positive words, and *tax* as a negative word.

Henry (2008) developed dictionaries specifically for financial contexts. Her wordlist was created by examining earnings press releases for the telecommunications and computer services industries. The weakness of her wordlist is the limited number of words in the list. Compared with the Harvard General Inquirer, which has more than 4,100 negative words, Henry's list only contains 85 negative words. Some common negative words such as *loss*, *impairment* and *adverse* are surprisingly not included in the list. Price et al. (2012) demonstrate that Henry's list is better than that of the Harvard General Inquirer by examining the tone of earnings conference calls. Price et al. (2012) find that an optimistic Q&A tone predicts higher stock

returns. Doran, Peterson, and Price (2012) look at the real estate investment trust (REIT) and find a positive association between the tone of the conference calls and stock return during the conference calls.

5. *Loughran & Mcdonald (2011)*

Similar to Henry (2008), Loughran and McDonald (2011) build their own financial specific dictionary. As argued by Loughran and McDonald (2011), standard dictionaries fail to account for the nuances of finance jargon, and thus the categorization. They built this wordlist by examining word usage in a larger sample of 10-Ks during 1994-2008 and their list was created based on the most likely interpretation of the business environment. Loughran and McDonald (2011) wordlist contains 354 and 2,329 positive and negative words respectively. A recent review paper by Kearney and Liu (2014) claims that Loughran and McDonald (2011) wordlist has become predominant in more recent studies. Words such as *greater*, *beneficial* and *successful* are categorized as LM positive words, but words such as *trust, secured* and *outstanding* are not included in LM positive words.

The LM wordlist is the most commonly used dictionary in the accounting and finance literature. García (2013) finds that the sentiment of two financial columns in the New York Times (1995-2005) can predict future stock returns, particularly during recessionary periods. Solomon, Soltes, and Sosyura (2014) find that investors chase funds with high past returns only if the funds received media coverage of their holdings. Chen et al. (2014) focus on Seek Alpha, which contains

articles and comments posted by investors. They find that investor opinions provide incremental information since they have predictive power for future stock returns and following earnings surprises. In the research of sentiment of analyst reports, Twedt and Rees (2012) find that a more positive tone in an analyst report is linked with higher stock returns on and around the analyst report issue dates.

3.3.1.4 Term weighting

Apart from wordlists, the choice of the weighting scheme is the second most important factor influencing a tone score. Equal weighting and frequency weighting are two weighting schemes. The magnitude of an equally-weighted tone measure is increasing in the proportion of all words appearing in a document that is classified as positive versus negative. The magnitude of frequency weighting is decreasing in the frequency with which any given positive or negative word appears in any document within the specific sample of documents, whether or not the word has been correctly classified.

Therefore, an equally weighted measure is unrelated to the composition of the sample, but frequency weighted measure is completely dependent on the composition of documents in the sample and can vary dramatically depending on which and how many other documents are in the sample. The majority of the literature (e.g. Loughran and McDonald (2011), Henry and Leone (2016) and Kothari, Li, and Short (2009)) advocate an equal weighting scheme. In my study, I

therefore employ the Loughran and McDonald (2011) wordlist and measure using the equal weighting scheme.

3.4 Data and Methodology

3.4.1 Data matching

3.4.1.1 Analyst estimates

Analyst estimates data is collected from the Institutional Broker Estimate System (I/B/E/S) for S&P500 firms from 1999 to 2014. The Detail and Price Target tape of the database are utilised to download the original data. The earliest year of I/B/E/S data is 1999. Other stock price and accounting data is collected from CRSP and COMPUSTAT. Consistent with Clement and Tse (2005), I retain observations with stock prices greater than $3 per share, firms with more than 3 analysts following, positive book-to-market ratio and all variables are winsorized at a one percent level, top and bottom.

3.4.1.2 Analyst reports

Analyst reports are obtained from Thomson Research Investext® for S&P500 firms from 1999 to 2014. Investext is a collection of full-text analyst research reports from over 980 of the world's leading financial firms, including Goldman Sachs, Morgan Stanley JPMorgan, and Credit Suisse and covering more than 30,000 firms worldwide. Using the analysts' full names contained in I/B/E/S/ forecasts

output, I match the analyst reports obtained from Investext. Reports are downloaded by specifying the time period, firm, resource type, and analysts' full names. 118,527 analyst reports from 3,397 analysts are successfully analysed by Diction and matched to the analysts' names from I/B/E/S. If the report is written by more than one analyst, I view the report as belonging to every one of the analysts and match them to I/B/E/S[15].

The sentiment analysis of the analyst reports is conducted using the Diction linguistic software[16]. I convert all analyst reports from the pdf format to txt format and import them into Diction. Diction allows a customised dictionary, so Loughran and McDonald (2011) wordlist is imported to calculate the sentiment score.

Table 2.1 describes the sample selection process for the sample used in Chapter 3. An initial sample of 118,527 analyst reports was collected from Investext. Consistent with Clement and Tse (2005), I retain observations with stock prices greater than $3 per share, firms with more than 3 analysts following, and firms with positive book-to-market ratio. I/B/E/S, CRSP and COMPUSTAT are also used to collect the control variable. Consistent with Huang et al., 2014, I include earnings forecast revision (*ef_rev*), which is the earnings forecast difference between current revision and last revision, consequently this resulted in all the first reports being dropped. Finally, the 2008 financial crisis period is also dropped due to the large

[15] My result still holds if I view the report as belonging to the first author who is usually the senior.
[16]See http://www.dictionsoftware.com/testimonials/#academicsoftware for detail.

amount of extreme forecasts and high volatility during this period. All these adjustments result in a final sample of 20,734 observations.

3.4.2 Measure of cumulative abnormal returns

Consistent with Bonner, Hugon, and Walther (2007) and Huang, Zang, and Zheng (2014), I calculate market reaction to the sentiment of analyst reports using cumulative market-adjusted (value-weighted) abnormal return over the five-day[17] window centred on the forecast report date (-2 day to +2 day).

3.4.3 Measure of four types of analyst reports

To capture the combined quantitative measure (i.e. tone of analyst reports) and qualitative measure (i.e. earnings forecast bias) contained in the analyst reports, I consider the four possible combinations for each analyst report (denoted O_TO_B, O_TP_B, O_TP_B, O_TP_B). This design is similar to that of Ke and Yu (2006), who also have four combinations of analyst earnings forecast biases that capture the intertemporal pattern of each analyst's earnings forecasts. In my design, O_TO_B reflects a report with a consistent optimistic signal, in other words, an analyst report that contains both an optimistic sentiment in their textual discussion and an optimistic earnings forecast bias, relative to other analysts who cover that same firm during the same year; P_TP_B represents an analyst report that contains both a pessimistic textual sentiment and a pessimistic earnings forecast bias, relative to

[17] The result continues to hold if I change this to a three-day event window (-1 day to +1 day).

other analysts who cover that same firm during the same year; O_TP_B reflects a report with inconsistent signals, an optimistic sentiment in their text discussion together with a pessimistic earnings forecast bias, relative to other analysts who cover that same firm in the same year; and finally, P_TO_B denotes the analyst reports which contain a pessimistic sentiment in the textual discussion and an optimistic earnings forecast bias, relative to other analysts who cover that same firm in the same year.

Following Loughran and Mcdonald (2014), sentiment is defined as the difference between the number of positive and negative words, scaled by the total number of words.

$$sentiment_{ijt} = \frac{PositiveWords_{ijt} - NegativeWords_{ijt}}{TotalWords_{ijt}}$$

Consistent with Sidhu and Tan (2011), Hribar and McInnis (2012) and Bradshaw, Lee, and Peterson (2016), I measure earnings bias as the difference between forecasted earnings and actual earnings, scaled by the absolute value of actual earnings.

$$bias_{ijt} = \frac{forecastedEPS_{ijt} - actualEPS_{jt}}{|actualEPS_{jt}|}$$

Reports are categorized as having optimistic (negative) sentiment if their sentiment scores are above (below) average, compared with other reports forecasting the same firm in the same year (i.e. O_T or P_T). Similarly for earnings bias, reports with above (below) average forecast bias are defined as optimistic (pessimistic)

earnings bias, compared with other forecasts covering the same firm in the same year (i.e. O_B or P_B). I define optimism and pessimism both relative to peer analysts, because the actual earnings are not known at the time investors read their reports. By definition, it controls for any firm or industry specific differences.

3.4.4 Measure of forecast accuracy

Following Clement and Tse (2003), forecast accuracy is measured as below:

$$accuracy_{ijt} = \frac{AFE\max_{jt} - AFE_{ijt}}{AFE\max_{jt} - AFE\min_{jt}}$$

$$AFE_{ijt} = \left| ForecastedEPS_{ijt} - ActualEPS_{jt} \right|$$

Analyst forecast accuracy ($accuracy_{ijt}$) is defined as the maximum absolute forecast errors for analysts following firm *j* in year *t* minus the absolute forecast errors for analyst *i* following firm *j* in year *t*, scaled by the difference between the maximum and minimum absolute forecast errors for analysts following firm *j* in year *t*. By definition, accuracy is bounded from 0 (for the least accurate forecast) to 1 (for the most accurate forecast) for easy comparison between different firms and industry.

3.4.5 Empirical model

3.4.5.1 Different signals from analyst reports

To test H1, that the market reaction to analysts' reports containing conflicting signals will be different to those containing consistent signals, I estimate model (2.1) where CAR_{ijt} refers to cumulative market-adjusted (value-weighted) abnormal returns over the period beginning two days before the analyst forecast date and ending two days after the analyst forecast date[18]. The reason that I include two days before the forecast date is that I/B/E/S may have one or two days' error when recording the analyst forecast date or controlling for some information leakage. O_TO_B, O_TP_B, P_TO_B and PP_B denote four types of analyst reports with the first letter representing textual sentiment and the second letter representing the bias of earnings forecast. *mix* is a dummy variable which equals 1 when the analyst's report contains conflicting signals (O_TP_B and P_TO_B reports), and equals 0 for analyst reports containing consistent signals (O_TO_B and PP_B reports).

$$\begin{aligned} CAR_{ijt} &= \beta_0 + \beta_1 mix + \beta_2 accuracy_{ijt} + \beta_3 CAR\_prior_{ijt} + \beta_4 ef\_rev_{ijt} + \beta_5 \log MV_{jt} \\ &+ \beta_6 \log BTM_{jt} + \beta_7 std\_consensus_{jt} + \beta_8 \log Follow_{jt} + \beta_9 Gen\_Exp_{it} + \beta_{10} Firm\_Exp_{ijt} \\ &+ \beta_{11} Num\_Ana_{ijt} + \beta_{12} dayElap_{ijt} + \beta_{13} Num\_Ind_{it} + \beta_{14} Num\_Co_{it} + \beta_{15} fh_{ijt} + \beta_{16} fr_{ijt} \\ &+ \beta_{17} Year\_F.E + \beta_{18} Industry\_F.E + \varepsilon_{ijt} \end{aligned} \tag{2.1}$$

[18] Cumulative abnormal return over the period one day before the forecast date and ending one day after the forecast date yields the same result.

In order to examine the intensity of the market reaction to the reports, I also rerun model (2.1) using the absolute value of the cumulative abnormal returns ($absoluteCAR_{ijt}$) instead of the signed cumulative abnormal returns (CAR_{ijt}).

Next, to clearly investigate the market reaction to each type of analyst reports, I replace *mix* with individual dummy variables for each type of report (i.e. O_TO_B, O_TP_B, P_TO_B and PP_B). I rerun this regression four times, each time dropping one of the four dummies.

To eliminate the possibility that the reports overlap with the firm's annual earnings announcement date, forecast dates must be seven days before the current earnings announcement date and seven days after the previous annual's earnings release date (Koh, Matsumoto, and Rajgopal (2008)). I also drop observations when different analysts' reports occur on the same day for the same firm because it is not clear which analyst's report the market is reacting (or not) to.

3.4.5.2 The Control Variables

Consistent with Huang, Zang, and Zheng (2014), and other literature investigating the market reaction to analyst forecasts, the following control variables are included in the models:

Proxy for firm characteristics and market conditions

Firm Size ($logmarkv_{jt}$)

$logmarkv_{jt}$ is the natural log of the firm *j*'s market value at the end of year *t*. Investors may react differently from larger and small companies (Li et al. (2013)).

Book-to-Market Ratio ($logBTM_{jt}$)

$logBTM_{jt}$ is the natural log of the ratio of the book value of equity to the market value of firm *j* at the end of year *t*. Investors may react differently to companies with different risks or growth potentials (Neuhierl, Scherbina, and Schlusche (2013)).

Standard Deviation of prior earnings ($std\_consensus_{jt}$)

$std\_consensus_{jt}$ is the standard deviation of firm *j*'s prior 5 years earnings in year *t*. It is a proxy for the earnings volatility of company *j (*Gu and Wu (2003)).

Prior CAR (CAR_prior_{jt})

CAR_prior_{jt} is the cumulative market-adjusted ten-day abnormal returns for firm *j* ending three days before the current report date in year *t*. It is included to control for any short-term momentum or mean revision in the stock price (Huang et al. (2014)).

Earnings Revisions (ef_rev_{ijt})

ef_rev_{ijt} is calculated as the current report's earnings forecast made by analyst *i* for firm *j* in year *t* minus the last earnings forecast issued by the same analyst for the same firm's same fiscal year (Huang et al. (2014)).

Number of Analysts Following (*logFollow*$_{jt}$)

logFollow$_{jt}$ is measured as the natural log of analysts following firm *j* in year *t*. Investors reaction to each analyst's forecast may be less if firm *j* is followed by a large number of analysts.

Analyst Characteristics Proxies

Because I am interested in investor reactions to individual analysts, the analyst charascteristics could also be influencial. Following Clement and Tse (2005), these analyst features are also controlled for:

Proportional Forecast Horizon (fh_{ijt})

Proportionnal Forecast Horizon measures the amount of information analyst *i* could have at the time they published their forecast report. It is a proxy for forecast timeliness. It is the number of days between analyst *i*'s estimation and firm *j*'s earning announcement in year *t*.

$$FH_{ijt} = \left| ForecastDate_{ijt} - EarningsAnnouncementDate_{ijt} \right|$$

Days Elapsed (*dayElap*$_{ijt}$)

Days Elapsed is the number of days since a prior forecast from an analyst forecasting the same firm. The measure *dayElap*$_{ijt}$ is calculated as the days

between analyst *i*'s forecast of firm *j*'s earnings in year *t* and the most recent preceding forecast of firm *j*'s earnings by any analyst.

Forecast Revisions (fr_{ijt})

fr_{ijt} is the number of firm *j* forecasts made by analyst *i* following firm *j* in year *t*.

Number of firms followed (Num_Co_{ijt})

Num_Co_{ijt} is the number of firms analyst *i* follows in year *t*, calculated as the number of companies followed by analyst *i* following firm *j* in year *t*.

Number of Industries followed (Num_Ind_{ijt})

The measure of the number of industries analyst *i* follows in year *t* is calculated as the number of two-digit SICs followed by analyst *i* following firm *j* in year *t*.

Number of Analysts Working in a Brokerage House (Num_Ana_{t})

Num_Ana_{ijt} is a proxy for brokerage house size. It is calculated as the number of analysts in the brokerage house in year *t*.

Firm-specific Experience ($Firm\_Exp_{ijt}$)

The measure of analyst *i*'s firm-specific experience, calculated as the number of years of firm-specific experience for analyst *i* following firm *j* in year *t*.

General Experience (Gen_Exp_{it})

The measure of analyst *i*'s general experience, calculated as the number of years of working experience for analyst *i* until year *t*.

3.4.5.3 Accuracy of different combinations of analyst forecasts

To test which type of analyst report is associated with the highest forecast accuracy, I estimate the following model (2.2), where the forecasting performance increases with $accuracy_{ijt}$.

Firm characteristics and analyst characteristics used in the prior analyst literature (Clement and Tse (2003)) are also included.

$$\begin{aligned} accuracy_{ijt} &= \beta_0 + \beta_1 OP_{ijt} + \beta_2 PP_{ijt} + \beta_3 PO_{ijt} + \beta_4 OO + \beta_5 roa_{jt} + \beta_6 LogMV_{it} + \beta_7 LogBTM_{it} \\ &+ \beta_8 loss + \beta_9 std\_consensus_{it} + \beta_{10} \log Follow_{it} + \beta_{11} Gen\_Exp_{ijt} + \beta_{12} Firm\_Exp_{ijt} \\ &+ \beta_{13} Num\_Ana_{ijt} + \beta_{14} dayElap_{ijt} + \beta_{15} Num\_Ind_{it} + \beta_{15} Num\_Co + \beta_{17} fh + \beta_{18} fr \\ &+ \beta_{19} Year\_F.E + \varepsilon_{ijt} \end{aligned} \tag{2.2}$$

3.5 Results

3.5.1 Descriptive statistics

Panel A of Table 2.2 reports the descriptive statistics. The distributions of all variables are similar to prior studies (Clement and Tse (2003) and Huang, Zang, and Zheng (2014)). For example, the mean value of the cumulative abnormal return around the analyst report issue date is 0, with a relative symmetric

distribution. On average, analysts have 6 years of firm-specific experience, and follow three industries.

Panel B of Table 2.2 presents a correlations matrix. *CAR* around the analyst report date is negatively correlated with P_TP_B and positively correlated with O_TO_B, which indicates that investors react strongest when both quantitative and qualitative measures are consistent with each other. In line with prior findings, and the multivariate tests below, *CAR* is negatively correlated with book-to-market ratio (*logBTM*) and standard deviation of consensus forecast (*std_consensus*) while positively correlated with revision of earnings forecasts (*ef_rev*), brokerage house size (*Num_Ana*), number of days elapsed (*dayElap*) and forecast horizon (*fh*).

3.5.2 Market reaction to different signals from analyst reports

Table 2.3 presents investor reaction to the combination of quantitative and qualitative measures in analyst reports using different benchmarks. In column 1, panel A of Table 2.3, the dependent variable is the absolute value of the cumulative abnormal return. The coefficient of *mix* here is negative and significant, which indicates that the market reacts more intensively to consistent signals P_TP_B and O_TO_B reports relative to mixed signal reports (O_TP_B and P_TO_B). In column 2 of panel A, the dependent variable is the signed cumulative abnormal return. The coefficient of *mix* here is positive and significant, thus indicating that despite the conflicting signals, these reports (O_TP_B or P_TO_B) on average are responded to more positively compared to the consistent signal reports (P_TP_B and O_TO_B). Further

analysis in columns 3 to 6 reveal why this is the case. I use O_TP_B, P_TO_B, P_TP_B and O_TO_B, instead of *mix*. Specifically, reports with consistent pessimistic signals (P_TP_B) cause the market to react significantly negatively relative to any other type of reports. However, with consistent optimistic signals (O_TO_B), the market reacts more positively than any report that contains a pessimistic text (whether consistent with the bias signal or not) but not significantly different from a report with an optimistic text which is combined with a pessimistic forecast bias. It appears that the market reacts negatively to a pessimistic text but this reaction is moderated slightly if the report also contains an optimistic forecast bias. However, the market does not react significantly differently to an optimistic text, irrespective of the forecast bias.

Panel B of Table 2.3 re-estimates the market reaction to four types of analyst reports by separating the sample into positive CARs and negative CARs. Columns 1 and 2 use P_TO_B reports as the benchmark. In column 1, the dependent variable is positive CAR (*pos_CAR*). The coefficients of O_TP_B and O_TO_B are both positive and significant at the one percent level. This suggests that the market reacts more favourably when observing optimistic sentiment (O_TP_B and O_TO_B) in the analyst reports, regardless of earnings forecast bias, and the conflicting signals do not appeal to moderate investors' reactions. When the dependent variable is negative CAR (*neg_CAR*) in column 2, the coefficient of P_TP_B is negative and significant at the one percent level, indicating the market reacts significantly negatively to P_TO_B reports. This suggests that investors react more negatively when the analyst reports show consistent signals of pessimism. The coefficients of O_TP_B and O_TO_B

are both insignificant. This suggests that, for the negative market reaction, there is no significant difference between O_TP_B and P_TO_B reports. Taken together with the findings in column 1, these results are consistent with Harbaugh et al. (2016) that bad news is less damaging when it is combined with mixed signals. Further analysis reveals that O_TO_B is not significant because there are very few observations of negative reactions and their magnitude are therefore small. Using different benchmarks, in columns 3 to 8, I find the similar patterns to columns 1 and 2.

Overall, these findings support H1 and show that when the signals are consistent, whether optimism or pessimism (i.e. P_TP_B and O_TO_B), the market reacts more strongly than to reports with conflicting signals (i.e. O_TP_B and P_TO_B).

Among the control variables, forecast accuracy is positively associated with market reaction. Consistent with Huang, Zang, and Zheng (2014), abnormal returns during the ten trading days prior to the report date (*CAR_prior*) are negative and significant, showing a mean reverse effect. Earnings revisions from prior forecasts (*ef_rev*) are positive and significant, suggesting incremental information provided by revisions. The negative coefficients of book-to-market ratio (*logBTM*) and the number of analysts following a firm (*logfollow*) is also consistent with Huang, Zang, and Zheng (2014). Investors have more resources to gain information on large firms, and therefore react less strongly to each of the individual analysts, compared with small firms which have fewer analysts following them. Industry and year fixed

effect are also included. Robust standard error is clustered on firm and analyst level. The results however are not sensitive to a different cluster specification.

Table 2.3 also provides the results of H2, which predicts that when quantitative and qualitative attributes are not consistent with each other, investors place a greater weight on the textual analyses, as opposed to the earnings forecasts bias. Table 2.3 shows a positive and significant coefficient of $O_T P_B$ in column 3 and the negative and significant coefficient of $P_T O_B$ in column 4. These results therefore support H2, that the directions of these two coefficients are in line with sentiment of the textual discussion, not the earnings forecasts bias. In other words, despite a report containing a pessimistic forecast bias the market still responds positively due to the optimistic or pessimistic tone of the text contained in the report.

To examine which attribute has the most influence on investors under the different scenarios, in panel A, columns 1 and 2 of Table 2.4 compare the market reaction to analyst reports holding constant the optimistic sentiment, but allowing for different earnings forecast bias, while in columns 3 and 4, I hold constant the forecast bias and allow the sentiment of the text to differ. CAR could be either positive or negative, therefore, in columns 1 and 3 the dependant variable is the cumulative abnormal return (CAR), and in columns 2 and 4 the dependent variable is the absolute CAR, which allows me to examine the intensity of market reaction. I drop all analyst reports with pessimistic sentiment.

Holding constant the textual sentiment, I compare O_TO_B and O_TP_B reports. The coefficients on O_TP_B are insignificant in both columns 1 and 2 of Table 2.4. This indicates that when the textual sentiment is optimistic, investors do not react significantly differently to the earnings forecast bias. However, holding constant the bias, columns 3 and 4 indicate that when the earnings bias is optimistic, investors react more favourably to reports with optimistic sentiment and more unfavourably to reports with pessimistic sentiment. This can be seen from the significant and positive coefficients of P_TO_B in column 3 and the insignificant coefficient of P_TO_B in column 4.

Panel B of Table 2.4 re-estimates the tests from panel A of Table 2.4 by splitting CARs into positive CARs and negative CARs. Columns 1 and 2 hold constant the optimistic sentiment and allow for different earnings forecast bias. Consistent with the results in panel A of Table 2.4, the coefficients of O_TO_B in both columns are positive but insignificant. This suggests that investors react to the optimistic sentiment in the reports and not to the forecast bias associated to these reports. In columns 3 and 4, I hold constant the optimistic earnings forecast bias and allow for different report sentiments. The coefficient of O_TO_B in column 3 is positive and significant at the one percent level, indicating that conditional on the same earnings forecast bias, the market reaction also depends on the sentiment of analyst reports. In column 4, the coefficient of O_TO_B is insignificant due to the small magnitude of negative market reaction on O_TO_B reports.

Table 2.5 compares the reports with pessimistic sentiment or pessimistic earnings forecast. Analyst reports with optimistic sentiment are dropped. Holding constant the pessimistic sentiment, in panel A, the coefficients on P_TP_B are significantly negative in column 1 and significantly positive in column 2. This indicates that P_TP_B reports have significantly more negative and intensive market reaction than P_TO_B reports. This result suggests that when the report contains a pessimistic text, the optimistic bias moderates the impact. In Columns 3 and 4 of panel A, I hold constant the pessimistic earnings forecast. The coefficient on P_TP_B is significantly negative in column 3 and insignificant in column 4. O_TP_B reports have a positive reaction on average (with mean CAR=0.006) while P_TP_B reports have a negative reaction (with mean CAR=-0.003). These indicate that when earnings biases are the same, the direction of market reaction depends on the sentiment. Reports with optimistic sentiment (O_TP_B) have more positive reactions on average while reports with pessimistic sentiment (P_TO_B) have more negative reactions. Industry and year fixed effect are also included. Robust standard errors are clustered on the firm and analyst levels. The results are not sensitive to a different cluster specification.

Panel B of Table 2.5 re-estimates the tests from panel A of Table 2.5 by splitting CARs into positive CARs and negative CARs. Columns 1 and 2 hold constant pessimistic sentiment and allow for different earnings forecast bias. The coefficient of P_TP_B is insignificant in column 1. This suggests that when investors react positively, their reactions are not discernibly different from P_TP_{B} and P_TO_B reports. Column 2 uses negative market reaction as the dependent variable. The coefficient

of P_TP_B is negative and significant at the one percent level, which is consistent with the findings when using CAR in column 1, panel A of Table 2.5. This suggests that when reports have a pessimistic sentiment, investors moderate their reaction when the earnings forecast bias is inconsistent with the sentiment. Columns 3 and 4 hold constant pessimistic earnings forecast bias and allow for different sentiment. The coefficients of P_TP_B in columns 3 and 4 are both negative and significant at the one percent level. This suggests that, conditional on the same earnings forecast bias, investors also rely on the textual discussions in the reports to make their investment decisions. Taking all the results from Table 2.4 and Table 2.5 together, I find that the sentiment of analyst reports is more impactful than the earnings forecasts bias.

Taking all the results from Table 2.4 and Table 2.5 together, I find that the sentiment of analyst reports is more impactful than earnings forecasts bias. This result also suggests that, despite processing costs, the information and discussions in the analyst reports appear to be more informative than the forecast bias. This result is consistent with survey evidence from the Institutional Investor magazine and archive findings from Brown et al. (2015) that textual information could be more credible than final qualitative outputs.

3.5.3 Forecast accuracy and different combinations of forecasts

Table 2.6 reports the results of the association between the different types of analyst reports and forecast accuracy. In column 1, the coefficients of P_TO_B and

P_TP_B is positive and significant at 1% and 5% respectively, showing that they have higher forecast accuracy than those of the O_TP_B and O_TO_B reports. This result demonstrates that forecasts with relatively pessimistic sentiment (P_TO_B and P_TP_B) enjoy a higher forecast accuracy than that those with relatively optimistic sentiment (O_TP_B and O_TO_B). This is consistent with my earlier findings that investors react more intensely to reports containing pessimistic report.

In columns 3 and 4, the coefficients of O_TO_B are both negative and significant at 5% level, with the benchmark of P_TP_B and at 1% level with the benchmark of P_TO_B. This indicates that reports with relatively optimistic sentiment and earnings forecasts tend to have a low level of accuracy. The insignificant coefficient of O_TP_B in column 2 shows that O_TP_B reports are also low in accuracy. In summary, relative sentiment is a good indicator of forecast accuracy and reports with unfavourable sentiment tend to be more accurate.

In addition, the coefficient of P_TO_B in column 1 is larger and more significant than that of P_TP_B. This indicates that P_TO_B reports tend to have higher accuracy relative to P_TP_B reports. From an investor perspective, my results suggest that it is on average better to assess analyst reports using both attributes because reports with relatively pessimistic sentiment and optimistic earnings forecast bias (i.e. P_TO_B reports) are associated with the highest accuracy. The findings also suggest that analysts issuing P_TP_B or O_TO_B reports may be overly obsessed with one side of the firm, while analysts with two-sided arguments take both positive and negative

factors into consideration. Overall, the result suggests that an analyst report with a two-sided argument providing pessimistic information in the text tends to be more credible.

Among the control variables, market value (*logmarkv*) is positive and significant, which is consistent with the finding of Garciá-Meca and Sánchez-Ballesta (2006) that big firms have more information available and are more transparent. Book-to-market ratio (*logBTM),* loss (*loss*) and number of days elapsed (*dayElap*) are negatively related to forecast accuracy because risky firms and firms who make a loss are more difficult to predict, and it is easier to predict performance the closer it gets to the earnings announcement date. These findings are consistent with those of Brown (1997) and Clement and Tse (2003). To eliminate reports with extremely high or low accuracy that drives the results, I drop reports with top and bottom 1% of accuracy. Results still hold if using the whole sample. Robust standard errors are clustered on the firm and analyst levels. Industry and year fixed effect are also included.

3.6 Conclusion

This study examines the market reaction to the different signals contained in analyst reports and investigates which reports are associated with higher forecast accuracy. I am the first to examine the different combinations of forecast reports in terms of their quantitative and qualitative attributes, and highlight the different investor responses when these two signals do not coincide. First, I provided evidence that investors react more strongly to reports with consistent signals (O_TO_B and P_TP_B reports) than conflicting signals (O_TP_B and P_TO_B reports). Second, when these two attributes do not coincide, investors appear to place greater weight on the textual discussions rather than earnings forecast bias. This is consistent with Brown et al. (2015) that opinions provided in analyst reports could be more valuable than their final outputs. Finally, I examined the forecast accuracy of these reports. I find sentiment is a good indicator for report quality. Forecasts with relatively pessimistic sentiment have better accuracy than those with optimistic sentiment, especially those forecasts with relatively pessimistic sentiment and optimistic earnings forecast.

My study shows the importance of the textual discussion in analyst reports and examines the information collaboration between the different signals when investors make investment decisions. My findings have implications for investors who use analyst reports to help them make investment decisions. The textual discussions are a better indicator than earnings forecasts, and therefore investors

should not rely too heavily on reports with both optimistic sentiment and earnings forecasts.

I intend to conduct future research in this area by examining the possible reasons as to why reports with pessimistic sentiment and optimistic EPS bias are the most accurate. There are two potential explanations. The first comes from the argument of Bradshaw, Lee, and Peterson (2016) that optimism indicates the difficulty of the task. Hence, pessimistic sentiment represents analysts' confidence in the credibility of their forecasts. Alternatively, it might be explained by conflicts of interest. O'Brien, McNichols, and Lin (2005) and Kadan et al. (2009) show that affiliated analysts are reluctant to reveal negative news or downgrade those firms with whom they have investment banking ties. This is also consistent with Huang et al. (2014), who suggest that investors view reports containing a pessimistic text as more credible.

Chapter 4

Does Management Use the Tone of 10-Q Filings to Respond to Investor Sentiment?

4.1 Introduction

Managers want to build and preserve an enduring reputation for trustworthiness while influencing sentiment-driven investors (Merkl-Davies and Brennan (2007)). Investor sentiment is investors' expectations or emotional biases towards a firm, which could be rational or irrational (Nofsinger (2005) and Baker and Wurgler (2006)). Corporate disclosures are known to reflect corporate managers' common optimism or pessimism (Feldman et al. (2010) and Huang, Teoh, and Zhang (2014)). I therefore investigate whether firm-specific investor sentiment influences the tone of the 10-Q filings[19]. Specifically I examine whether firm-specific investor sentiment influences: (1) the tone managers use, (2) the readability, and (3) the level of uncertainty of the 10-Q fillings.

Managers face a cost-benefit trade-off when preparing their filings with the intention to present their firm in the best possible light. Huang, Teoh, and Zhang (2014) find that managers use an abnormal positive tone when they have strong incentives to bias investor perception upwards. As a result, investors follow managers' guidance in the short term. Similarly, Schleicher and Walker (2010) find

[19] I include only 10-Qs, but not 10-Ks because managers' preparation times are different between 10-Qs and 10-Ks.

that loss firms report a more positive tone than profit firms. On the other hand, Rogers, Buskirk, and Zechman (2011) and Li (2011) find that litigation risk increases for firms with more optimistic SEC filings. Reputational cost is also a reason not to inflate their firms too much (Rogers and Stocken (2005), Demers and Vega (2010) and Davis et al. (2014)). Hence, Baker and Wurgler (2007) call for more research on how managers respond strategically to investor sentiment via corporate reporting decisions. I examine whether firms with an optimistic or pessimistic investor sentiment respond with a specific tone strategy.

Due to the unavailability of *firm-specific* investor sentiment, the existing literature has tended to use *market-level* investor sentiment to examine how investor sentiment affects the decision-making at the firm level. Bergman and Roychowdhury (2008) find that managers increase earnings estimates, via their disclosures, during low market-level sentiment periods as a way of attempting to adjust market expectations of their firm. However, *market-level* investor sentiment is a confidence index for the whole market and hence does not distinguish sentiment across different industries or firms. To the best of my knowledge, I am the first to investigate the relationship between firm-specific investor sentiment and the tone of the managers' subsequent disclosures. I employ the methodology of Aboody et al. (2016) to calculate firm-specific investor sentiment, which is based on each firm's overnight return. Aboody et al. (2016) argue that retail investors tend to place orders outside of normal working hours, to be executed at the start of the

next trading day and these retail investors are the most likely investors to be influenced by sentiment.

First, I examine the association between firm-specific investor sentiment and the subsequent tone of the firm 10-Q fillings for all S&P 500 firms from 1995 to 2014. Second, I also separate firms into pessimistic and optimistic investor sentiment groups given the findings of Bergman and Roychowdhury (2008) and Hribar and McInnis (2012), who document that managers' strategies differ between high and low investor sentiment periods. I find that overall managers use an optimistic (pessimistic) tone when investor sentiment is optimistic (pessimistic) during the period the filings are prepared, which is consistent with signalling theory. In contrast, for firms with extremely optimistic investor sentiment, managers appear to respond differently. I observe a negative association between investor sentiment and the tone of 10-Qs. It suggests that to avoid future earnings disappointment, managers choose a less optimistic tone when investors sentiment is extremely optimistic. Turning to firms with extremely pessimistic investor sentiment, managers use a more optimistic tone. This indicates that managers are perhaps trying to persuade investors to change their sentiment by emphasizing optimistic prospects when the market has poor confidence in them, which is consistent with impression management theory. Next, I investigate the change of tone and investor sentiment, thereby enabling me to take into account the issue of boilerplate disclosure employed by firms (Feldman et al. (2010)). Overall, the change specification is consistent with the prior results, although this specification provides

higher levels of significance. Specifically, investigating the change in investor sentiment and the change in tone in 10-Qs, I find that when a firm's investor sentiment increases from a below average group in the prior quarter to an above average group in the current quarter, the manager also increases the optimistic tone in the current 10-Q filings. However, when a firm's investor sentiment decreases from an above average group in the prior quarter to a below average group in the current quarter, the manager uses more optimistic words in the current 10-Q filings. Managers for firms with extremely low investor sentiment have a greater incentive to regain market confidence. This is consistent with Merkl-Davies and Brennan (2007), who find that impression management exists for firms with poor performance.

Prior studies show that managers may manipulate the readability of their disclosures to influence investors (Merkl-Davies and Brennan (2007)). For example, Li (2008) finds that managers have the motivation to deliberately obfuscate readers. Therefore, I examine the relationship between readability of the 10-Q filings and investor sentiment. I adopt the most commonly used Fog Index to measure readability. Specifically, I first examine the association between readability of 10-Qs and investor sentiment using the whole sample. Then I focus on firms with extremely optimistic and pessimistic investor sentiment. Lastly, by using the change in readability of investor sentiment, I compare firm investor sentiment between high and low investor sentiment groups.

Overall, I find that when investor sentiment is pessimistic (optimistic), the firms subsequent 10-Q filings are difficult (easy) to understand. This is consistent with the obfuscation hypothesis from Courtis (1998), which argues that some managers could obfuscate failures by increasing the complexity of the text. Li (2008) finds that managers strategically use the opaqueness of filings to hide negative information in corporate annual reports. However, when their investor sentiment is extremely pessimistic, I find that managers use easy-to-understand sentences to communicate with investors. Consistent with Rennekamp (2012), this result suggests that when investor sentiment is extremely poor, managers try not to give investors the impression that they are obfuscating information, but they try to explain the situation in clearer language and convince investors that they have a more optimistic outlook. Similar results are found by using the change of tone and investor sentiment.

Lastly, I investigate whether there is an association between the proportion of uncertain words used in 10-Qs and investor sentiment, again with the same research design as in the previous two questions. Uncertainty sentiment is measured using a wordlist of uncertainty from Loughran and McDonald (2011). I find that, in general, the proportion of uncertain words is low when investor sentiment is high. However, for firms with extremely pessimistic investor sentiment, I find that they tend to disclose less uncertainty when their investor sentiment is pessimistic. Consistent with Kimbrough and Wang (2014), they are eager to assure investors that their firms are less exposed to risks to boost investors' confidence.

Next, using the change in uncertain wording and investor sentiment, I compare firms from an above average investor sentiment group to those below average. Firms from the pessimistic investor sentiment group disclose more (less) uncertain words when investor sentiment decreases (increases). This is consistent with Simpson (2013), who argues that during a pessimistic period firms are more likely to be under greater scrutiny, and hence, their litigation risks and reputation costs increase, which reduces their likelihood of hiding any potential risks. It is the same negative relationship between the change of investor sentiment and uncertainty when investor sentiment deteriorates (improves) from an above (below) average group in the prior quarter to a below (above) average group in the current quarter. Taking the results for tone, readability and uncertainty together, it appears that managers' disclosure incentives vary according to different firm-specific investor sentiment levels.

The study makes several contributions. First, to the best of my knowledge, I am the first to apply firm-specific investor sentiment empirically. Prior studies could only assume the same investor sentiment for all firms in a time period while I adopt a finer proxy by using firm-specific investor sentiment. Secondly, to the best of my knowledge, none of the existing literature has yet examined the impact of investor sentiment on the tone of 10-Q filings. I therefore contribute to the literature by examining whether managers strategically adjust the tone of their quarterly reports in response to their investor sentiment. Lastly, my study complements the literature by investigating the association between firm-specific investor sentiment and the

proportion of uncertainty as well as readability in 10-Q filings. Managers appear to use the combination of these three factors to influence investor belief in a subtle way, rather than through earnings management or forecast guidance (Cheng, Warfield, and Ye (2011) and Simpson (2013).

Section 4.2 presents the prior literature and hypotheses development; Section 4.3 shows sample selection and methodology; Section 4.4 presents the results and discussions and Section 4.5 concludes.

4.2 Literature Review and Hypothesis Development

4.2.1 Importance of SEC filing

Corporate filings reduce information asymmetry and subsequently reduce the cost of capital (Diamond (1985), Diamond and Verrecchia (1991) and Muslu et al. (2015)). In addition, they increase price efficiency and thus the manager's investment incentives (Fishman and Hagerty (1989)). They are the most widely used information source by investors. Hence, market reacts to corporate 10-Q and 10-K filings (Feldman et al. (2010) and Henry and Leone (2016)). Regulators also focus their efforts on improving the efficiency of these filings. Under the FASB's Statement of Financial Accounting Concepts (SFAC) No. 8 (Financial Accounting Standards Board (FASB), 2010) and IASB's Framework for the Preparation and Presentation of Financial Statements (International Accounting Standards Committee (IASC), 1989), a primary objective of financial reporting is to provide

useful and understandable information that will aid investors and other financial statement users to evaluate a firm. The SEC announced the formation of the Investor Advisory Committee (IAC) in 2007 to improve the financial reporting environment for the benefit of individual investors.

4.2.2 Textual analysis of 10-Q reports

Corporate disclosures reflect managers' subjective opinions, beliefs, and projections (Bochkay and Dimitrov (2014) and Jiang, Lee, and Martin (2016)). Textual information contains valuable data which may not be fully captured in the quantitative data. Since the increase in computing power over the past half century, researchers have attempted to analyse the textual information content embedded in financial disclosures (Feldman, Livnat, and Segal (2008), Feldman et al. (2010), Li (2008), Li (2010), Loughran and McDonald (2011), Loughran and Mcdonald (2014), Kravet and Muslu (2013) and Muslu et al. (2015)).

A number of disclosure characteristics have been investigated: first, the disclosure level (i.e. the quality and the amount of disclosure) and its association with a firm's costs of equity (Botosan and Plumlee (2002) and Botosan (1997)) and analyst forecast accuracy (Barron, Kile, and O'Keefe (1999) and Lang and Lundholm (1996)); second, the sentiment of financial disclosures in terms of tone. The tone of financial disclosures has been found to have predictive power of market returns, trading volume, financial distress, financial statement irregularities and corporate environmental performance (Kerl, Schürg, and Walter (2014),

Sprenger et al. (2014), De Franco et al. (2015) and Loughran and McDonald (2016)).

The earlier studies investigating textual disclosures such as those of Bryan (1997), Core (2001), and Callahan and Smith (2004) manually code each disclosure and consequently their sample size is relatively small and due to manual coding, the results lack generalizability.

Recent literature, harnessing computing power and linguistics software, has investigated the textual content of firms 10-K or 10-Q filings (Brown and Tucker (2011), Jegadeesh and Wu (2013), Campbell et al. (2014) and Merkley (2014)). Schleicher and Walker (2010) focus on firms with large impending year-on-year changes in sales and operating profit margins and test their frequency of favourable and unfavourable statements in the outlook section of UK annual reports. They find that these firms bias the tone upwards. Davis and Tama-Sweet (2012) argue that managers will be strategic in their choice of language used in earnings press releases and MD&A from 10-K filings while Muslu et al. (2015) find that firms make more forward-looking MD&A disclosures when their stock prices have lower informational efficiency[20]. Numerous contextual analysis studies have found that the sentiment of financial articles such as earning releases (Davis et al. (2014), Davis, Piger, and Sedor (2011), Davis, Piger, and Sedor (2012), Henry and Leone (2009), Rogers, Van Buskirk, and Zechman (2011), accounting policy

[20] Informational efficiency is measured by the strength of the association between current stock returns and future earnings.

disclosures (Levine and Smith (2011)), audit opinions (Butler, Leone, and Willenborg (2004)), financial news (Tetlock, Saar-tsechansky, and Macskassy (2008) and Core, Guay, and Larcker (2008)), internet stock message board (Antweiler and Frank (2004), Sprenger et al. (2014) and Chen et al. (2014)) have incremental predictive ability. However, none of the existing literature has yet linked the tone of financial disclosure with investor firm sentiment. Kearney and Liu (2014) argue that the relationship between textual sentiment and investor behaviour is an important area to investigate.

4.2.3 Different proxies for market-Level Investor sentiment

Prior studies use different proxies for capturing investor sentiment. The Investors' Intelligence sentiment index is widely publicized by Investors' Intelligence. The editors of Investors' Intelligence read reports from over 135 independent advisory services and rate the current economic situation to produce the investor sentiment score. Markets can be labelled as either 'bullish', 'bearish' or 'correction'. Lee, Jiang, and Indro (2002) use this sentiment index as a direct measure of investor sentiment and find that bullish (bearish) shifts in sentiment lead to downward (upward) revisions in the volatility of returns and are associated with higher (lower) future excess returns. Brown and Cliff (2004) and Brown et al. (2005) use survey data on investor sentiment, providing evidence that sentiment affects asset valuation.

Lemmon and Portniaguina (2006) and Schmeling (2009) apply consumer confidence as a proxy for individual investor sentiment, and find that optimistic investor sentiment is often followed by low market returns and vice versa. Consumer confidence is collected via telephone interviews or surveys each month, asking citizens about (1) their own financial situation; (2) their view about the US economic situation; and (3) their expectation of the long-term economic environment.

Stambaugh, Yu, and Yuan (2012), Yu and Yuan (2011), Brown et al. (2012) and Livnat and Petrovits (2009) all use Baker and Wurgler (2006) market-wide investor sentiment (BW index) to investigate firm performance such as the sensitivity of stock prices to earnings surprises. The BW index takes the first principal component of six measures of investor sentiment. The six measures are the closed-end fund discount, the number and the first-day returns of IPOs, NYSE turnover, the equity share in total new issues, and the dividend premium. Arif and Lee (2014) use aggregate corporate investment as an alternative measure of market-wide investor sentiment. Based on the BW index, Bochkay and Dimitrov (2014) and Huang et al. (2015) proposed a new investor index that is aligned with the purpose of predicting the aggregate stock market. Using internet search volume from Google Trend, Da, Engelberg, and Gao (2015) construct investor sentiment from Financial and Economic Attitudes Revealed by Search (FEARS).

Prior literature has examined investor reactions to stocks when market-level investor sentiment is high and low. Mujtaba Mian and Sankaraguruswamy (2012) use market-wide investor sentiment and find that the stock price sensitivity to good earnings news is higher during high BW index periods than during periods of low BW index, whereas the stock price sensitivity to bad earnings news is higher during periods of low sentiment than during periods of high sentiment. Hribar and McInnis (2012) and Walther and Willis (2013) focus on analysts' forecast errors and find high market-wide sentiment affects forecast accuracy for those hard-to-value firms[21]. The limitation of these studies, however, is that they use one investor sentiment to proxy investors' confidence level for different firms in different industries.

4.2.4 Firm-Specific investor sentiment

Baker and Wurgler (2006) and Brown et al. (2012) acknowledge the limitation of using a market-level index to detect firm-specific strategies. Aboody et al. (2016) therefore propose a measure of firm-specific investor sentiment by using the stock's overnight return. Berkman et al. (2009) find that individual investors tend to place orders outside of the normal working hours, which creates temporary price pressure when the market opens to trades and then reverses during the trading day. In theory, individual investors demand for a firm's share is a natural measure of firm-specific investor sentiment, because they are most likely to be influenced by

[21] Hard-to-value firms refer to those which are small, young and unprofitable, and whose stocks have high volatility or pay no dividends.

sentiment. Aboody et al. (2016) argue that overnight returns therefore better reflect individual investor demands for stock that are not justified by the available information. The reason is that retail investors tend to place orders outside of normal working hours, to be executed at the start of the next trading day. Using this model, Aboody et al. (2016) find short-term stickiness using this overnight return model and present a stronger positive autocorrelation for hard-to-value firms. Hence Aboody et al. (2016) model provides strong evidence that average overnight returns are a good proxy for investor sentiment at firm level. I employ their method of measuring firm-specific investor sentiment.

4.2.5 Strategic reporting: tone

Managers decide whether or not to disclose value-relevant information only after they have learned the value of the signal and in making their disclosure decision they consider the effect of the disclosure on the wealth of current shareholders (Walker (1997)). Early studies by Milgrom (1981) and Grossman (1981) argue that managerial interests are aligned with current owners so they disclose all information except when they receive negative signals. Miller (2002) predicts a separating equilibrium: firms with relatively good news disclose while all other firms remain silent. However, litigation cost and managers' reputation also incentivise managers to disclose more negative news and not to remain silent (Trueman (1997) and Graham, Harvey, and Rajgopal (2005)).

Recent literature employs impression management theory, which argues that managers use their discretion over corporate disclosures opportunistically to manipulate the perceptions and decisions of stakeholders (Clatworthy and Jones (2003), Yuthas, Rogers, and Dillard (2002) and Clatworthy and Jones (2001)). Impression management is also investigated empirically. Rogers and Stocken (2005) find that managers not only bias earnings forecasts in a self-serving way, but also that they are more likely to bias their forecasts when it is more difficult for investors to detect, while Mcnichols (1989) finds only weak evidence of bias in management earnings forecasts. With textual analysis of earnings press releases, Huang, Teoh, and Zhang (2014) find that managers use strategic tone management to mislead investors about firm fundamentals.

While agency theory focuses on poorly performing firms, signalling theory (Smith and Taffler (2000) and Rutherford (2003)) focuses on the behaviour of managers in well-performing firms who signal this superiority by greater transparency in their disclosure and presentation of information. Bowen, Davis, and Matsumoto (2005) and Merkl-Davies and Brennan (2007) believe that most corporate filings are produced with both motivations of managerial opportunism and also the desire to provide value-relevant information. Managers may put more weight on one incentive over others under different situations. Investor sentiment could be one of the factors that drive managers' reporting strategy.

For firms with optimistic investor sentiment, managers want to maintain the momentum. Due the their good performance, managers have little incentive to withhold positive statements and therefore have a more optimistic tone of 10-Qs when investor sentiment is high (Feldman et al. (2010)). For firms with pessimistic investor sentiment, the 'asymmetric loss function' argument predicts a tendency to disclose bad news due to the litigation risks and reputational risks (Verrecchia (1983), Jung and Kwon (1988), Rogers and Stocken (2005) and Schleicher and Walker (2010)) and thereby a less optimistic tone. This leads to my first hypothesis:

> ***Hypothesis 1a****: Firm-specific investor sentiment is positively associated with the tone of 10-Q filings.*

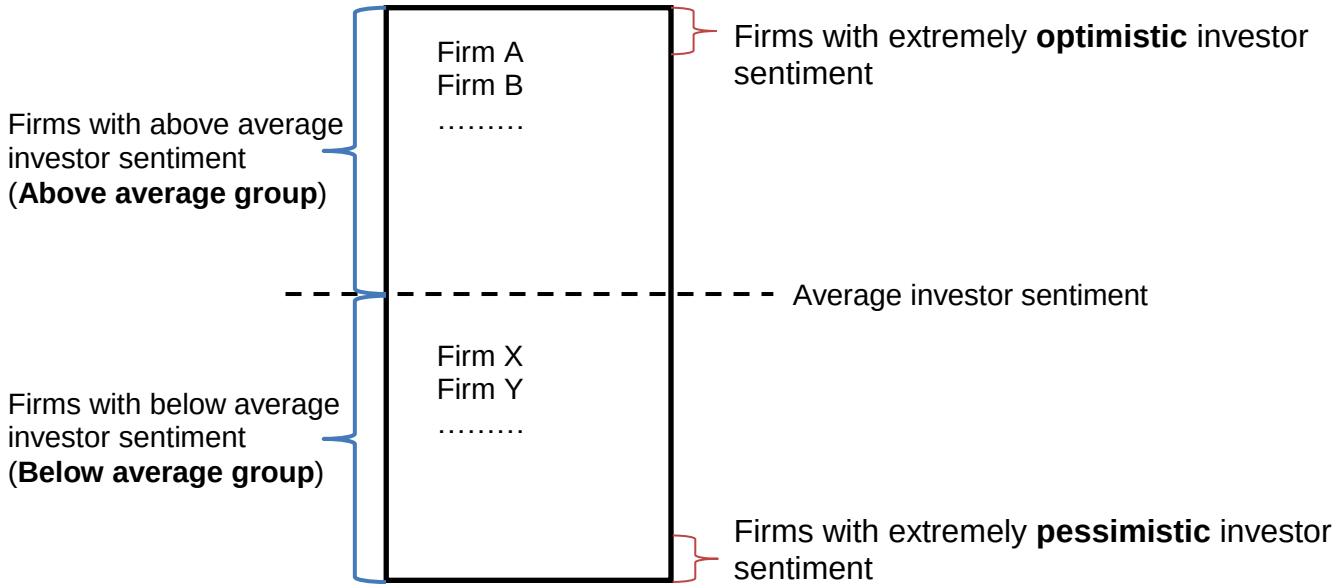
H1a is based on signalling theory, which assumes that managers align with the interests of current owners in general. Managers' main incentive may however shift in high and low investor sentiment environments, supported by social cognition research (Taylor (1991) and Bless et al. (1996)). Bergman and Roychowdhury (2008) demonstrates that during low-sentiment periods, managers increase forecasts to "walk up" current estimates of future earnings over long horizons and during periods of high sentiment, managers reduce their long-horizon forecasting activity. This sentiment-induced shift in disclosure costs leads to different communication strategies. Seybert and Yang (2012) find that management guidance partially corrects the prices for firms which are overvalued. In contrast, Hoberg and Lewis (2015) show that fraudulent managers grandstand good

performance. Brown et al. (2012) find a positive relationship between the pro forma earnings metric and investor sentiment due to the shift in disclosure costs induced by investor sentiment and the pro forma disclosure decisions partly reflecting managers' opportunistic motives. Hribar and Quinn (2013) find a negative association between insider trading and investor sentiment, especially in difficult-to-value firms. Simpson (2013) focuses on earnings management via accruals and argues that firm' incentives to manage earnings upwards or downwards vary strategically with market sentiment. These studies implicitly or explicitly show that managers recognize the different impacts of high and low investor sentiment on firms and respond to it differently. Thus, firms' incentive to manage their tone of words in 10-Q fillings could differ, depending on the level of investor sentiment.

As presented in Figure 2 below, by separating firms into either firms with above average (i.e. optimistic) investor sentiment per quarter per industry ("above average group" for short) and firms with below average (i.e. pessimistic) investor sentiment per quarter per industry ("below average group" for short), I can examine whether firms with extremely optimistic or pessimistic investor sentiment have different disclosure choices. I hypothesize the following:

> ***Hypothesis 1b****: For firms with extremely optimistic or pessimistic investor sentiment, the association between investor sentiment and the tone of 10-Q filings will be different, relative to those firms with an average optimistic or pessimistic investor sentiment.*

Figure 2: Categories of firms with different investor sentiment



4.2.6 Readability

Impression management could also be applied by the readability of 10-Q filings. Clearly written disclosures reduce miscommunication between investors and managers by using shorter sentences with less complex words. Moreover, both the SEC and popular press have criticized firms for the complexity of their language in these filings. In 2012, the Financial Accounting Standards Board (FASB) claimed that clear communication in the information is most important for users of each entity's financial statements (Financial Accounting Standards Board (FASB) (2012)). Miller (2010) and Lehavy, Li, and Merkley (2011) find that more complex

filings are more costly to process for both sophisticated and unsophisticated investors.

Early studies based on obfuscation hypothesis show mixed results. Subramanian, Insley, and Blackwell (1993) and Courtis (2004) find a negative relationship between the reading difficulty of annual reports and company financial performance. Yet Clatworthy and Jones (2001) and Rutherford (2003) find readability is not associated with company performance. Document length and Gunning (1952) Fog Index are extensively used as proxies for readability (Lehavy, Li, and Merkley (2011), Li (2010), Twedt and Rees (2012) and Miller (2010)). You and Zhang (2009) use word counts as a proxy for complexity and find that investors' underreaction tends to be stronger for firms with more complex 10-K reports. Li (2008) finds that 10-Ks with higher Fog Index values (less readable text) and longer document length have lower subsequent earnings. Miller (2010) and Lawrence (2013) use the Fog Index to examine the impact of the readability of 10-Ks on retail investors while De Franco et al. (2015) are interested in the readability of analyst reports. They all find a lower Fog Index (i.e. easier to read) leads to higher trading activity. Similarly, You and Zhang (2009) document a delayed market reaction for complex 10-Ks, using the number of words in 10-Ks. Lehavy, Li, and Merkley (2011) find that 10-Ks with higher Fog Index values are associated with larger levels of analyst dispersion.

Opaque filings may also arise unwittingly or simply be caused by the complexity of companies' business models or products. Or it may be presented because of deliberate intent. Cazier and Pfeiffer (2016) find that disclosure redundancy accounts for as much variation in 10-K length as does operating complexity. Bloomfield (2002) finds that managers have incentives to obfuscate information when firm performance is poor because the market may react with a delayed incorporation of the information contained in complicated disclosures. Based on management obfuscation hypothesis from Courtis (1998) and Courtis (2004), managers may strategically increase the complexity of their filings when they perform poorly and make their filings easier to read when they perform well. This leads to my following hypothesis:

> ***Hypothesis 2a****: Firm-specific investor sentiment is positively associated with the readability of 10-Q filings.*

Baginski et al. (2011) examine corporate fraud issues and find a positive association between the complexity of the Management Discussion and Analysis (MD&A) of 10-Ks and the probability of conducting fraud. In contrast, investors may make more extreme pessimistic predictions when they find filings are more difficult to read. Rennekamp (2012) argue that investors who receive more readable disclosures revise their valuation judgments to be less extreme. Hence, when firms suffer from extremely pessimistic investor sentiment, managers may not risk

having a more extreme valuation from investors by producing more obfuscate quarterly reports. Hence, I hypothesize the following:

> ***Hypothesis 2b****: For firms with an extremely pessimistic investor sentiment, the association between investor sentiment and the readability of 10-Q filings will be different, relative to those firms with an average pessimistic investor sentiment.*

4.2.7 Uncertainty

SEC requires public traded companies to disclose all possible risks. Li (2008) captures uncertain sentiment by the count of words ‘risk’ and ‘uncertainty’ in annual reports and finds an increase in risk sentiment is associated with lower future earnings. Loughran and McDonald (2011) create the financial-specific uncertainty list with an emphasis on the general notion of imprecision rather than exclusively focusing on risk. Loughran and McDonald (2013) argue that S-1 filings with higher proportions of uncertain words make it more difficult for investors to precisely assimilate the value-relevant information. Kravet and Muslu (2013) claim that textual risk disclosures increase investors’ risk perceptions at the industry level. Demers and Vega (2014) find that during the earnings announcement period, abnormal returns are negatively related to the textual uncertainty in managerial earnings press releases. Campbell et al. (2014) find that risk disclosure in 10-K filings increases investors’ assessment of systematic risk. Schleicher and Walker (2010) argue that when expected litigation costs are large managers have an

incentive to err on the side of caution. Therefore, for firms with pessimistic investor sentiment, they are expected to have a high proportion of uncertainty in the 10-Qs in general. For firms with optimistic investor sentiment, they are expected to have a low amount of uncertainty disclosed. Hence, I hypothesize the following:

> ***Hypothesis 3a****: Firm-specific investor sentiment is negatively associated with the proportion of uncertain words in 10-Q filings.*

However, for firms with extremely pessimistic investor sentiment, managers may have the incentive to resist such disclosure. Less uncertainty might weaken the adverse sentiment or a small chance of turning things around. Hence, I hypothesize the following:

> ***Hypothesis 3b****: For firms with extremely pessimistic investor sentiment, the association between investor sentiment and the proportion of uncertain words in 10-Q filings will be different, relative to those firms with an average pessimistic investor sentiment.*

4.3 Data and Methodology

4.3.1 Data sources

The data generated is based on all S&P500 firms from 1994 to 2014. The tone of 10-Q filings is obtained from WRDS SEC Analytics Suite, which contains more than 11 million records of electronic filings with the SEC since 1994. I include only

10-Qs but not 10-Ks because the filings preparation time is different between 10-Qs and 10-Ks and the accounting information behaves differently between 10-Qs and 10-Ks (Das and Shroff (2002) and Li (2010)).

All scores of sentiment and readability measures are derived from the WRDS SEC Analytics Suite. It adopts Loughran and McDonald (2011) wordlist, providing Loughran and McDonald (2011) positive, negative and uncertainty word proportion. It also includes Gunning Fog Readability Index. It provides cleaned filings, with graphics, unwanted XML, tables, exhibits and page numbers are removed.

Data for firm-specific investor sentiment and other control variables are obtained from the quarterly COMPUSTAT files and daily files from CRSP, because investor sentiment is calculated with daily open and close share prices.

Firm-specific investor sentiment is measured by a stock overnight return. This may lead to potential bias if there is a sudden stock price change in one day. Therefore, following Hansen (2000), I use the ‘fixed regressor bootstrap' to calculate the structural break of abnormal returns during -60 and 0 days before the 10-Q filing date. This detects a sudden jump or fall of stock price on a particular day and resulted in approximately 5% of the observations being dropped. Following Simpson (2013) and Luo, Jiang, and Cai (2014), I exclude financial and utility firms with SIC codes 6000-6999 and 4900-4999 due to regulation differences and I retain observations with a stock price greater than $3 per share and positive book-

to-market ratio. Industry is defined using a two-digit SIC code. This data selection results in a total sample of 13,791.

4.4 Methodology

4.4.1 Measure of firm-specific investor sentiment

I adopt Aboody et al. (2016) design of firm-specific investor sentiment, which uses a stock's overnight (close-to-open) return in the measurement. The overnight return on the shares of firm i for day d, CTO_{id} is calculated as below:

$$CTO_{id} = \frac{Openprice_{id} - Closeprice_{id-1}}{Closeprice_{id-1}}$$

where $Openprice_{id}$ is the opening price for the shares of firm i on day d and $Closeprice_{id-1}$ is the closing price for the shares on day $d-1$. The overnight return for week w, CTO_{iw} is the average daily return for that week. Then, they rank all stocks each week in ascending order according to their average overnight return that week and partition the stocks into deciles. Finally, firm-specific investor sentiment is calculated as follows[22]:

$$InvestorSentiment_{iw} = \frac{1}{1 + rankCTO_{iw}}$$

[22] See Aboody et al. (2016) for the details of the derivation of this formula.

$InvestorSentiment$ is bounded from 0.09 to 0.5, and higher values represent lower or more pessimistic investor sentiment. I multiply $InvestorSentiment$ by -1 so that higher $investor\_sent$ represents high or more optimistic investor sentiment.

$$investor\_sent_{iw} = -InvestorSentiment_{iw}$$

I calculate $investor\_sent_{i-50}$ and $investor\_sent_{i-40}$, which are investor sentiment 50 to 57 calendar days before a firm's filing date and investor sentiment 40 to 47 calendar days before a firm's filing date. These are the days I assume managers are writing the 10-Q filings. In the main tests, I use $investor\_sent_{i-50}$ and $investor\_sent_{i-40}$ is used as a sensitivity test. Following consultation with industry practitioners, I am confident that these days seemed appropriate.

Firms with low investor sentiment may communicate differently with investors compared with those with high investor sentiment. Prior literature (Simpson (2013), Mujtaba Mian and Sankaraguruswamy (2012), Bergman and Roychowdhury (2008) and Baker and Wurgler (2006)) compare market or firms' different behaviours for high and low investor sentiment. Similarly, I construct a dummy variable below_average$_{ij}$ that equals to 1 if firm *i* has below average firm-specific investor sentiment (relative to firms from the same industry) for a quarter *j* (i.e. pessimistic firm-specific investor sentiment)[23], otherwise 0.

[23] Alternatively, I construct *below_average$_{ij}$* which is equal to 1 if firm *i* has below average firm-specific investor sentiment for quarter *j*, compared with other S&P500 firms. Results still hold.

4.4.2 Measure of tone and uncertainty score

Tone captures the optimism or relative pessimism of the sentiment in the 10-Q filings. Loughran and McDonald (2011) wordlist is used to calculate the tone of 10-Qs' since the prior literature shows that it enjoys the highest accuracy for business text (García (2013), Kearney and Liu (2014) and Loughran and McDonald (2015)). Tone is the difference between the number of positive words minus the number of negative words from Loughran and McDonald (2011), scaled by the total number of words. Hence, the higher the tone, the more optimistic the tone managers disseminate through filings.

$$tone_{jt} = \frac{Number\_PositiveWords_{jt} - Number\_NegativeWords_{jt}}{Number\_TotalWords_{jt}}$$

Similarly, the uncertainty score contains the proportion of uncertainty managers discussed in 10-Qs. Since the number is relatively small, it is multiplied by 100. Loughran and McDonald (2011) uncertain wordlist is adopted, which captures the context of imprecision. It contains 285 words, such as *approximate*, *depend*, *fluctuate*, *uncertain*, and *variability*. It is defined as the number of uncertain words divided by the total number of words.

$$uncertain_{jt} = \frac{Number\_UncetainWords_{jt}}{Number\_TotalWords_{jt}} \times 100$$

4.4.3 Measure of readability

Readability is measured using Gunning (1952) Fog Index. The index indicates the number of years of formal education a reader of average intelligence would need to read the text once and understand that piece of writing with its word-sentence workload.

$$Fog=(words\_per\_sentence+ percent\_of\_complex\_words)\times 0.4$$

The complex words are defined as words with three syllables or more. Texts for a wide audience generally need a Fog Index less than 12. Hence, a higher Fog Index score represents higher complexity.

4.4.4 Empirical model for hypothesis 1

I employ an OLS regression to examine the association between firm-specific investor sentiment and the subsequent tone of 10-Q filings in model (3.1). I exclude quarter four[24] and use quarter fixed effects to control for the possibility the managers' strategies differ depending on the timing of the quarterly report. I also include others' control variables, which I explain in section 4.5.1. For all models, robust standard errors are clustered at the firm level. Firm fixed effects are also included for all models as some firms may have higher or lower investor sentiment that is time invariant due to firm characteristics. The expected coefficient β_1 is positive and significant.

[24] As a result, change from quarter three to quarter four (annual report) and change from quarter four (annual report) to quarter one in the following year are not included.

$$Tone_{it} = \alpha_0 + \beta_1 investor\_sent_{it-50} + \beta_2 roa_{it} + \beta_3 sue_{it} + \beta_4 accruals_{it} + \beta_5 earn_{it} + \beta_6 sd\_earn_{it} + \beta_7 ret_{it} + \beta_8 sd\_ret_{it} + \beta_9 \log estimates_{it} + \beta_{10} btm_{it} + \beta_{11} tover_{it} + \beta_{12} \log markv_{it} + \beta_{13} \log Geo_{it} + \beta_{14} \log Biz_{it} + \beta_{15} MA_{it} + \beta_{16} crisis + \beta_{17} si_{it} + \beta_{18} age_{it} + \beta_{19} leverage_{it} + quarterF.E + YearF.E + FirmF.E + \varepsilon_{it} \quad (3.1)$$

To test H1b, whether managers have different tone strategies depending on whether the firms' investor sentiment is extremely optimistic or pessimistic investor sentiment, I create a sub-sample which only contains those firms with above average sentiment per industry per quarter (e.g. optimistic -"above average group" for short). Within this above average sub-sample, I construct a dummy variable $high$, which equals 1 if investor sentiment is in the top 10% of the above average group per industry per quarter ("extremely high group" for short), otherwise 0. Using this sub-sample enables me to hold constant the optimism and therefore focus on the relative sentiment. I expect the coefficient β_3 on the $high \times investor\_sent$ in model (3.2) to be positive.

$$Tone_{it} = \alpha_0 + \beta_1 investor\_sent + \beta_2 high + \beta_3 high \times investor\_sent + \beta_4 roa_{it} + \beta_5 sue_{it} + \beta_6 accruals_{it} + \beta_7 earn_{it} + \beta_8 sd\_earn_{it} + \beta_9 ret_{it} + \beta_8 sd\_ret_{it} + \beta_{10} \log estimates_{it} + \beta_{11} btm_{it} + \beta_{12} tover_{it} + \beta_{13} \log markv_{it} + \beta_{14} \log Geo_{it} + \beta_{15} \log Biz_{it} + \beta_{16} MA_{it} + \beta_{17} crisis + \beta_{18} si_{it} + \beta_{19} age_{it} + \beta_{120} leverage_{it} + quarterF.E + YearF.E + FirmF.E + \varepsilon_{it} \quad (3.2)$$

In a similar manner, I also examine whether managers respond differently when faced with extremely pessimistic investor sentiment relative to other firms with pessimistic investors. Again, I create a sub-sample but this time only use

observations where the investor sentiment is below average per quarter per industry ("below average group" for short). The dummy variable low equals 1 if investor sentiment is in the bottom ten percent of the sub-sample per quarter per industry, otherwise 0.

4.4.4.1 Control Variables

I control for firm fundamentals and the business environment that could affect the tone of 10-Qs identified in the prior textual analysis literature (Bergman and Roychowdhury (2008), Li (2008), Li (2010), Feldman et al. (2010), Davis and Tama-Sweet (2012), Jegadeesh and Wu (2013) Huang, Teoh, and Zhang (2014) and Muslu et al. (2015)).

Current Performance

Current earnings, contemporaneous stock return and return on assets are proxies for current performance. Current earnings ($earn_{it}$) are the quarterly earnings scaled by the book value of assets. The contemporaneous stock returns (ret_{it}) in the fiscal quarter are calculated using CRSP monthly return data. Return on assets for the current quarter (roa_{it}) is calculated as COMPUSTAT earnings before extraordinary items scaled by total assets as of the beginning of the quarter.

If a firm has high performance this quarter, managers are likely to use a more optimistic tone. However, due to litigation concerns, a company may also be

cautious and hence may moderate such optimism. Therefore, the relationship between tone of 10-Qs and current performance is unclear.

Size

Firm size captures the operational and business environment. I use the natural logarithm of the market capitalization of equity at the end of the quarter before the 10-Q filing date as a proxy for firm size.

Firms with a high market value may be more cautious in their tone due to the higher political and legal costs and hence, I predict a negative correlation for market value.

Book-to-market ratio

btm_{it} is the book value of total assets divided by the market value of equity plus the book value of total liabilities. It represents different investment opportunity sets and growth potential.

Growing firms tend to have an optimistic tone in corporate filings (Huang, Teoh, and Zhang (2014)) and hence, I predict a negative correlation for book-to-market ratio.

Accruals

Accruals allow a company to show assets that do not have a cash value. Consistent with Jegadeesh and Wu (2013), they are measured as the earnings subtracting cash flow from operations, scaled by the book value of assets.

Higher accruals do not necessarily mean poor performance and hence, the relationship between the tone of 10-Qs and accruals is unclear

Volatility of operations

Firms with volatile performance tend to have more uncertainty in their business environment. I employ the standard deviation of earnings and standard deviation of stock return as proxies for volatility. sd_earn_{it} is the standard deviation of earnings scaled by the book value of assets calculated using data from the last four quarters. sd_ret_{it} is the stock return volatility calculated using 12 months of monthly return data before the fiscal quarter ending date.

Operational volatility is expected to be negatively correlated with the tone of 10-Q filings since high volatility is viewed as a negative signal.

Complexity of operations

Firm complexity could also influence the tone of 10-Qs. I use the number of business segments and number of geographic segments as proxies for operational

complexity. $\log Biz_{it}$ is the logarithm of 1 plus the number of business segments. $\log Geo_{it}$ is the logarithm of 1 plus the number of geographic segments.

Complexity may lead to more volatile performance, but more business segments with international trading may also diversify the risk. Therefore, the sign for complexity in the regression of the tone of 10-Qs is unclear.

Firm age

I define age as the number of years since a firm appears in CRSP. This captures the life cycle stage of the company. Due to high growth or uncertainty, younger firms may experience a higher tone change in their 10-Qs. Older firms may exhibit different quarterly report readability because there is less information asymmetry and less information uncertainty for these firms.

M&A activity

Companies with current merger and acquisition activities may have incentives to disseminate a more positive outlook. Therefore, MA is a dummy variable that equals 1 if a company has a M&A this quarter and 0 otherwise.

Special items

Special items are associated with firm-specific uncertainty when the amount is large or they are reported year after year.

Leverage

Leverage controls for increased informational demand when firms are experiencing financial distress. $leverage_{it}$ is expressed as the ratio of total liabilities to total assets.

Turnover

Jegadeesh and Wu (2013) find that high turnover firms are the ones that attract more investor interest, and the management would be likely to be more cautious in setting investor expectations. $tover_{it}$ is the natural logarithm of the number of shares traded divided by the number of shares outstanding on the filing date.

Lnestimates

Chen, Harford, and Lin (2015) find that analysts play an important governance role in controlling management behaviour. Hence, the natural logarithm of the number of analysts following the company per quarter is included.

The Crisis dummy

The financial crisis from 2007 to 2010 could have influenced investor sentiment as well as the firm's tone strategy. Therefore, crisis equals 1 if it is during the crisis period, otherwise 0.

Consistent with the prior literature (Matsumoto, Pronk, and Roelofsen (2011) and Huang, Zang, and Zheng (2014)), the models are robust clustered at the firm level

and all variables are winsorized at the one percent level, top and bottom, to avoid the influences of outliers.

4.4.5 Empirical model for hypothesis 2

Filing readability also influences the way investors interpret firm performance. To test how managers respond to investor sentiment in terms of the readability of 10-Qs I run a similar OLS regressions to model (3.1). Model (3.3) tests H2a, which explores the association between investor sentiment ($investor\_sent$) and the Fog Index (Fog) using the whole sample. A higher Fog Index reflects a greater difficulty in reading the report. The expected coefficient β_1 is negative and significant.

$$\begin{aligned} Fog_{it} &= \alpha_0 + \beta_1 investor\_sent_{it-50} + \beta_2 roa_{it} + \beta_3 sue_{it} + \beta_4 accruals_{it} + \beta_5 earn_{it} + \beta_6 sd\_earn_{it} \\ &+ \beta_7 ret_{it} + \beta_8 sd\_ret_{it} + \beta_9 \log estimates_{it} + \beta_{10} btm_{it} + \beta_{11} tover_{it} + \beta_{12} \log markv_{it} + \beta_{13} \log Geo_{it} \\ &+ \beta_{14} \log Biz_{it} + \beta_{15} MA_{it} + \beta_{16} crisis + \beta_{17} si_{it} + \beta_{18} age_{it} + \beta_{19} leverage_{it} + quarterF.E + YearF.E \\ &+ FirmF.E + \varepsilon_{it} \end{aligned} \tag{3.3}$$

Model (3.4) tests H2b, which compares firms with extremely pessimistic investor sentiment (low) to firms with below average investor sentiment in terms of their readability in 10-Qs using a sub-sample with the same research design as H1b. I expect coefficient β_3 on the $low \times investor\_sent$ to be positive.

$$Fog_{it} = \alpha_0 + \beta_1 investor\_sent_{it-50} + \beta_2 low + \beta_3 low \times investor\_sent + \beta_4 roa_{it} + \beta_5 sue_{it}$$
$$+ \beta_6 accruals_{it} + \beta_7 earn_{it} + \beta_8 sd\_earn_{it} + \beta_9 ret_{it} + \beta_8 sd\_ret_{it} + \beta_{10} \log estimates_{it} + \beta_{11} btm_{it}$$
$$+ \beta_{12} tover_{it} + \beta_{13} \log markv_{it} + \beta_{14} \log Geo_{it} + \beta_{15} \log Biz_{it} + \beta_{16} MA_{it} + \beta_{17} crisis + \beta_{18} si_{it}$$
$$+ \beta_{19} age_{it} + \beta_{120} leverage_{it} + quarterF.E + YearF.E + FirmF.E + \varepsilon_{it} \quad (3.4)$$

I also rerun model (3.4) to examine firms with extremely optimistic investor sentiment ($high$) to firms with below average investor sentiment in terms of their readability in 10-Qs using a sub-sample above average group.

4.4.6 Empirical model for hypothesis 3

The proportion of uncertainty managers disclosed in the 10-Qs also reflects the way they communicate with investors. H3a is tested using model (3.5) which examines the association between investor sentiment ($investor\_sent$) and the proportion of uncertain words ($Uncertain$) managers use in the 10-Q filings.

$$Uncertain_{it} = \alpha_0 + \beta_1 investor\_sent_{it-50} + \beta_2 roa_{it} + \beta_3 sue_{it} + \beta_4 accruals_{it} + \beta_5 earn_{it} + \beta_6 sd\_earn_{it}$$
$$+ \beta_7 ret_{it} + \beta_8 sd\_ret_{it} + \beta_9 \log estimates_{it} + \beta_{10} btm_{it} + \beta_{11} tover_{it} + \beta_{12} \log markv_{it} + \beta_{13} \log Geo_{it}$$
$$+ \beta_{14} \log Biz_{it} + \beta_{15} MA_{it} + \beta_{16} crisis + \beta_{17} si_{it} + \beta_{18} age_{it} + \beta_{19} leverage_{it} + quarterF.E + YearF.E$$
$$+ FirmF.E + \varepsilon_{it} \quad (3.5)$$

H3b is tested by model (3.6), which compares firms with extremely pessimistic investor sentiment (low) to firms with below average investor sentiment in terms of the uncertainty proportion disclosed in the 10-Qs. I also rerun model (3.6) to examine firms with extremely optimistic investor sentiment ($high$) to firms with

below average investor sentiment in terms of their uncertainty in 10-Qs using a sub-sample above average group.

$$Uncertain_{it} = \alpha_0 + \beta_1 investor\_sent_{it-50} + \beta_2 low + \beta_3 low \times investor\_sent_{it-50} + \beta_4 roa_{it} + \beta_5 sue_{it} + \beta_6 accruals_{it} + \beta_7 earn_{it} + \beta_8 sd\_earn_{it} + \beta_9 ret_{it} + \beta_8 sd\_ret_{it} + \beta_{10} \log estimates_{it} + \beta_{11} btm_{it} + \beta_{12} tover_{it} + \beta_{13} \log markv_{it} + \beta_{14} \log Geo_{it} + \beta_{15} \log Biz_{it} + \beta_{16} MA_{it} + \beta_{17} crisis + \beta_{18} si_{it} + \beta_{19} age_{it} + \beta_{120} leverage_{it} + quarterF.E + YearF.E + FirmF.E + \varepsilon_{it} \quad (3.6)$$

4.5 Results

4.5.1 Descriptive statistics

Table 3.1 shows the descriptive statistics for the 10-Q filings. The number of observations is 13,791. The mean and median value of $Tone_{it}$ is slightly negative (-0.01) and it is close to a normal distribution. Consistent with Li (2008), the mean value for Fog_{it} is 19.37. The guidance Fog Index is 12 for easy understanding and hence, the 10-Q filings on average represent complex text. Uncertainty is measured as a percentage. On average, the proportion of uncertain words in 10-Q filings is 1.34% with a relatively small standard deviation of 0.005. $\Delta Tone_{it}$ is the change in the tone of 10-Qs from past filings, scaled for the variability. $\Delta Tone_{it}$ has a mean of -0.08, which is consistent with Brown and Tucker (2011), who report a mean of 0.00 and median of -0.041. This indicates that the overall 10-Q modification is slightly negative, but that the 10-Q varies substantially across quarters and across firms. $\Delta Tone_{it}$ has a large standard deviation of 1.76, which is

consistent with Feldman et al. (2010). ΔFog_{it} measures the modification of 10-Q readability, with a mean of 0.27 and standard deviation of 2.05. This highlights a large variation in report readability for different firms and years. A similar pattern is observed for $\Delta Uncertain_{it}$. Uncertain tone change has a small mean, which is -0.16 and a standard deviation of 1.29. Firm-specific investor sentiment change also follows a similar pattern with a mean of 0 and a standard deviation of 0.17. The standard deviation is high because firm-specific investor sentiment is bounded from 0.09 to 0.5 due to its design. To the best of my knowledge, no prior literature examines ΔFog_{it} and $\Delta Uncertain_{it}$, but the level of the Fog Index and ucertain score is consistent with existing studies (Li (2008), Lehavy, Li, and Merkley (2011) and Merkley (2014)). The mean and median of firm-specific investor sentiment is the same, indicating an equal amount of negative change and positive change of investor sentiment. The statistics of other accounting variables, such a negative mean of *accruals* and a zero median of *sue*, are consistent with the prior literature (Feldman et al. (2010), Li (2010), Brown and Tucker (2011) and Davis and Tama-Sweet (2012)).

Panel B of Table 3.1 reports the Pearson correlations. It indicates a significant negative correlation between the optimistic tone of 10-Qs and uncertainty tone of 10-Qs, which highlights that when firms are in a less uncertain situation, they tend to report more optimistically. Similarly, I observe a significant negative correlation between the optimistic tone of 10-Qs and the Fog index of 10-Qs. This indicates

that managers write 10-Qs in a more complex way when they report more pessimistically. Firm-specific investor sentiment is positively correlated with the optimistic tone of 10-Qs, which indicates that when investor sentiment changes to be more optimistic, 10-Q sentiment also becomes more optimistic. Other correlations with respect to the accounting variables are consistent with the existing literature. For example, there is a positive and significant correlation between current earnings ($earn_{it}$) and tone, which indicates an improving performance is positively correlated with the optimistic tone in 10-Q filings.

4.5.2 Tone optimism

Table 3.2 presents the result of model (3.1), which examines the association between investor sentiment ($investor\_sent_{it-50}$) and the tone of 10-Qs ($Tone_{it}$). In Column 1, the $investor\_sent$ coefficient is positive and significant (0.001), at the ten percent level. This suggests that when investor sentiment is optimistic (pessimistic) during the period managers prepare their 10-Qs, managers use an optimistic (pessimistic) tone in their 10-Qs. This supports H1a and is consistent with signalling theory. This neutral rhetoric is also supported by Rogers, Buskirk, and Zechman (2011) argument that overly optimistic or pessimistic language that does not truthfully reflect a firm's performance will increase litigation costs and reputational costs.

Following the findings of Bergman and Roychowdhury (2008) and Hribar and McInnis (2012), who document that managers' strategies differ between high and low investor sentiment periods, I separate the sample into two sub-samples: investor sentiment above average group and investor sentiment below average group. Column 2 of Table 3.2 focuses on above average group which represents 58% of the overall sample. I examine whether managers respond differently in terms of tone strategy if their firms have extremely optimistic investor sentiment. $high$ is a dummy variable which equals 1 if the investor sentiment of a firm is in the top 10% of this group, otherwise 0. The coefficient on investor sentiment ($investor\_sent$) in column 2 is positive and a significant coefficient at the ten percent level, which indicates a positive association between investor sentiment and the tone of 10-Qs. This is supported by Merkl-Davies and Brennan (2007) argument that signalling theory focuses on the behaviour of managers in well-performing firms. Interestingly, $high \times investor\_sent$ has a negative and significant correlation at the ten percent level. This shows that managers from extremely optimistic investor sentiment firms present a less (more) optimistic tone when they observe optimistic (pessimistic) investor sentiment, relative to general optimistic investor sentiment firms. This suggests managers' intention is to walk-down investor sentiment when the market is extremely optimistic about them. This supports H1b and is consistent with Cheng and Warfield (2005) that some managers choose to be conservative to avoid future disappointment.

Column 3 turns to the below average group and compares firms with extremely pessimistic investor sentiment to other firms in this group. low is a dummy variable equal to 1 if investor sentiment of a firm is in the bottom ten percent of this group, otherwise 0. $investor\_sent$ in column 3 is not statistically significant, indicating the result from column 1 is mainly driven by the above average group. Importantly, $low \times investor\_sent$ has a negative and significant coefficient of 0.004 at the ten percent level. This negative association suggests that when investor sentiment is low, for firms with extremely pessimistic investor sentiment, managers choose a more optimistic tone to persuade investors to believe in their firms. The results from columns 2 and 3 support H1b and are consistent with Cheng, Warfield, and Ye (2011), who find that some banking managers are more conservative in accounting estimates when capital ratios are high, but they are more likely to manage earnings upward in bad times. For all tests in this Chapter, firm and year fixed effects are included. Robust standard errors are clustered at the firm level for all tests.

Among the control variables, consistent with Simpson (2013), the coefficient on return on assets (roa) is positive and significant at the 5% level in most cases, indicating a positive association between current performance and optimistic tone in 10-Q filings. The coefficient on book-to-market ratio (btm) and special items (si) is negative and significantly different from zero, which is consistent with Huang, Teoh, and Zhang (2014). Li (2010) and Christensen et al. (2011) view special items as a negative indicator for firm performance. Hence, the tone is higher for growing

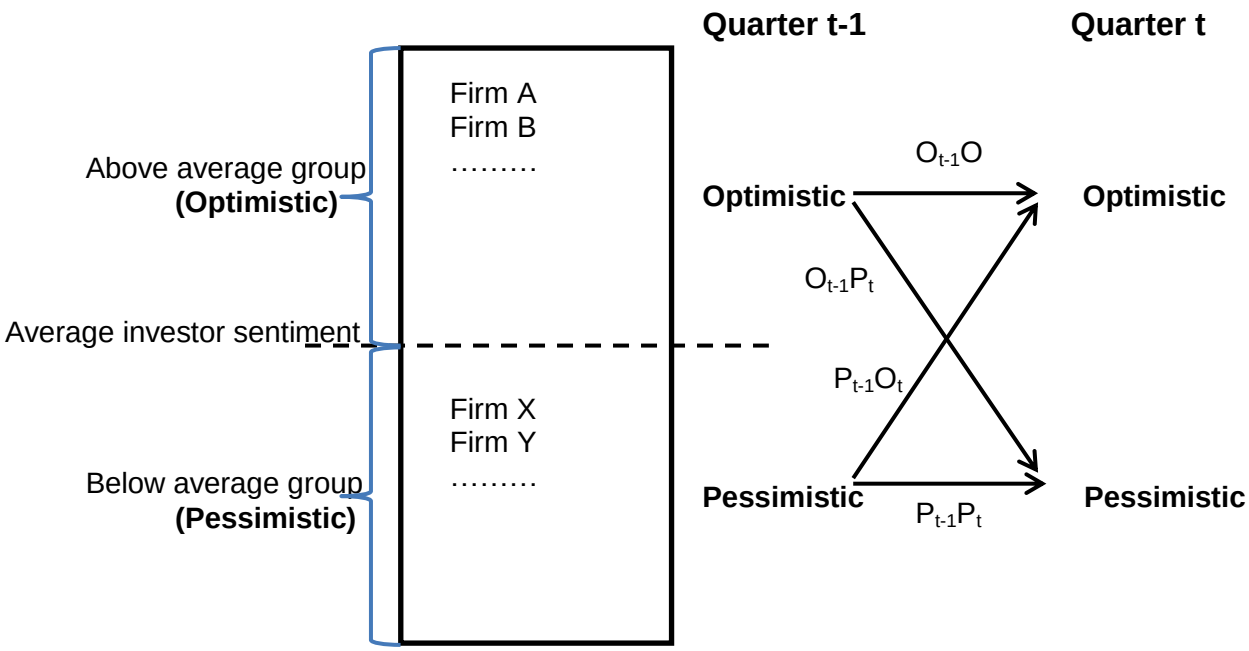
firms and firms with a low amount of special items. Lastly, older firms and firms with low leverage have a more optimistic tone.

I also examine whether the change in investor sentiment from the prior quarter to the current quarter is associated with a change in the tone of the quarterly reports. Using change of investor sentiment and change of tone could mitigate the boilerplate associated with corporation disclosure (Feldman et al. (2010)). Table 3.3 uses the change of tone ($\Delta investor\_sent$) and investor sentiment ($\Delta Tone_{it}$) from the prior quarter instead of the levels. Column 1 compares the tone change between the above average group and the below average group. $below\_average$ equals 1 if a firm's investor sentiment is below average, compared with other firms in the same industry and same year-quarter. The coefficient on $\Delta investor\_sent$ in column 1 is 0.503 and it is significant at the one percent level. In addition, $\Delta investor\_sent \times below\_average$ has a negative and significant coefficient of -0.571, at the five percent level. This indicates that, relative to the above average group, firms with poor investor sentiment tend to increase (decrease) their optimistic tone when their investor sentiment decreases (increases). This confirms the finding from $low \times investor\_sent$ in column 3 of Table 3.2. This is also consistent with Schleicher and Walker (2010), who find firms with large decreases in performances use more positive statements than negative statements in their annual reports.

In columns 2 and 3 of Table 3.3, I examine managers' responses, considering their firms' prior investor sentiment. Investor sentiment in the prior quarter could

influence managers tone strategy, conditional on investor sentiment in the current quarter. Specifically, I focus on those firms where investor sentiment has changed from the above (below) average group in quarter t-1 to the below (above) average group in quarter t. i.e. $O_{t-1}P_t$ and $P_{t-1}O_t$ firms in Figure 3.

Figure 3: Different combinations of firm investor sentiment change between current and prior quarters



Column 2 of Table 3.3 shows how managers change the tone of 10-Qs when their firms' investor sentiment decreases from the above average group in the prior quarter to the below average group in the current quarter. $O_{t-1}P_t$ is a dummy variable which captures these firms. $\Delta investor\_sent$ is the difference between investor sentiment in the current quarter and the prior quarter. The interaction term $\Delta investor\_sent \times O_{t-1}P_t$ is negative and significant at the one percent level. It shows

that when a firm's investor sentiment decreases from the above average group in quarter t-1 to the below average group in quarter t, the manager uses more optimistic words in the current 10-Q filings. Here, the managers' main concern could be to convince the market with more positive prospects, preventing investors from extrapolating the current low investor sentiment into the future, consistent with impression management.

In column 3 of Table 3.3, $P_{t-1}O_t$ is a dummy variable which equals 1 when the firms' investor sentiment increases from the below average group in the prior quarter to the above average group in the current quarter. The interaction term $\Delta investor\_sent \times P_{t-1}O_t$ is positive and significant at the ten percent level. It shows that when a firm's investor sentiment increases from the below average group in quarter t-1 to the above average group in quarter t, the manager also increases the optimistic tone in the current 10-Q filings. This result suggests that when the firms' investor sentiment increases from the below average group to the above average group, impression management makes the same prediction as signalling theory. Firms benefit from truthfully revealing their positive aspects. These findings of column 2 and 3 in Table 3.3 are consistent with the findings of Clatworthy and Jones (2003), who find firms with both improving and declining performance emphasize their positive statements in the Chairman's Statement while distancing themselves from negative aspects.

4.5.3 Readability

Table 3.4 presents the results examining the association between investor sentiment ($investor\_sent$) and readability of 10-Qs (Fog_{it}), where a high value of the Fog Index (Fog_{it}) indicates low readability. Column 1 uses the whole sample. The coefficient on $investor\_sent$ is -0.230 and it is significant at the five percent level. This shows that when investor sentiment is optimistic, managers prefer to report their performance with easy to read filings. When investor sentiment is pessimistic, managers use a more complex context in the 10-Q filings. This may suggest that managers tend to make their filings easy to understand when having a more optimistic tone, but try to leave readers confused and to put them off probing further when their disclosure has a more pessimistic tone. This result supports H2a and is consistent with Li (2008) that managers may be opportunistically choosing the readability of annual reports to hide adverse information from investors.

Column 2 focuses on the above average group. In terms of the ease of reading, there is no association between investor sentiment and readability. This suggests that, for firms with optimistic investor sentiment, managers do not have the incentive to manipulate 10-Qs readability. Column 3 refers to the below average group. The coefficient on $investor\_sent$ is -0.627 and it is significant at the one percent level. This shows that managers increase (decrease) the readability of 10-Qs when investor sentiment is optimistic (pessimistic), which may suggest that the result in the overall sample is mainly driven by the below average group. The

coefficient on $low \times investor\_sent$ is 0.520, statistically significant at the ten percent level, which suggests a difference of 82.9% (0.52/0.627) for firms with extremely pessimistic investor sentiment in the below average groups. These results show that, when firms have extremely low market confidence, managers make their filings easier to read. This is consistent with Rutherford (2003), who finds that poorly performing firms do not obfuscate investors by the use of textual complexity. When investors find filings difficult to understand, they can make more extreme predictions (Rennekamp (2012)). Managers in this below average group maybe choose not to risk themselves by having more extreme valuation from investors by producing more obfuscate quarterly reports.

Among the control variables, return on assets (roa), return (ret), and firm age (age) are negatively significant. This indicates firms with a high performance and older firms use easier to read 10-Q filings on average, which is consistent with Li (2008). For older firms, investors are more familiar with and have more precise information about the business models of older firms. There is a positive and significant coefficient on book-to-market ratio (btm) and special items (si). Growth firms may have more complex and uncertain business models and therefore a higher Fog Index. Firms with a high number of special items are more likely to experience unusual events and therefore use more complex rhetoric.

Table 3.5 uses the change of readability and investor sentiment instead of the levels. Although complex language in filings can be explained by managers

deliberately increasing the level of opacity, with the intention to enhance 'the story' and calm or reduce investor uncertainty, it may also be introduced by different people writing different sections of the report, or even different sections of one part of the report (Merkl-Davies and Brennan (2007)). I try to mitigate the second effect by subtracting readability the current quarter from the prior quarter. The coefficient on the interaction term $\Delta investor\_sent \times below\_average$ in column 1 is positively significant at the ten percent level. This shows that, compared with the above average group, managers from the below average group tend to increase (decrease) 10-Qs readability when firms' investor sentiment deteriorates (improves). This is consistent with the result in column 3 of Table 3.4, which examines manager response in the below average group.

Columns 2 and 3 of Table 3.5 focuses on firms with an investor sentiment change from the above (below) average group in quarter t-1 to the below (above) average group in quarter t, using the dummy variable $O_{t-1}P_t$ and $P_{t-1}O_t$. I do not find a significant coefficient on the interaction terms $\Delta investor\_sent*O_{t-1}P_t$ and $\Delta investor\_sent*P_{t-1}O_t$, which suggests that extreme investor sentiment does not affect the readability of 10-Qs, compared with other firms in the same group. The coefficient on $\Delta investor\_sent$ is negative and significant at the five percent level in both columns. This result suggests that firms make their 10-Qs easier to read (more complex to read) when investor sentiment improves (deteriorates), independent of which investor sentiment group they belong to.

4.5.4 Proportion of uncertainty

Table 3.6 presents the results of examining the association between investor sentiment ($investor\_sent$) and the proportion of uncertainty in 10-Qs ($Uncertain$). Column 1 uses the whole sample and the coefficient on $investor\_sent$ is negative and significant at the ten percent level. It shows that when investor sentiment is optimistic (pessimistic), the proportion of uncertain words in the 10-Qs is low (high). This suggests that firms disclose more risky statements when having a pessimistic investor sentiment. This supports H3a and is consistent with signalling theory. When expected litigation risks and reputational risks are large, managers have an incentive to err on the side of caution. Therefore, for firms with pessimistic investor sentiment, they have a high proportion of uncertainty in the 10-Qs in general. Column 2 uses the above average sub-sample and it presents a negative and significant coefficient on $high \times investor\_sent$, which is the same as the result for the whole sample. In column 3, the dummy variable low is negative and significant at the one percent level, which suggests that firms with extremely pessimistic investor sentiment have a more uncertain situation to disclose on average. However, the coefficient on $low \times investor\_sent$ is positive and significant at the one percent level, which suggests that for firms with extremely poor investor sentiment, firms with pessimistic investor sentiment disclose less uncertain information. This result may highlight that managers' main concern here is to regain market confidence for firms with extremely pessimistic investor sentiment. Taking the results of tone and readability together, for firms with extremely poor

investor sentiment, I find that their managers respond to investors by using a more optimistic tone, less uncertain information and easy to understand language. Managers may be responding in this way with the hope of boosting investor confidence and turning things around.

In Table 3.7, column 1 reports the change in uncertain sentiment ($\Delta Uncertain$) and the change in investor sentiment ($\Delta investor\_sent$). The interaction term $\Delta investor\_sent \times below\_average$ is statistically significant with a coefficient of -0.345. This indicates that in the below average group, when managers observe the deterioration (improvement) of investor sentiment, they increase (decrease) the amount of uncertainty being disclosed in the 10-Q filings. More pessimistic investor sentiment firms may tend to have more scrutiny, relative to firms from the above average group. Their litigation costs would be high if they did not disclose their risks. Therefore, managers from the below average group tend to be more cautious and disclose more risks to avoid any litigation costs (Trueman (1997) and Baginski, Hassell, and Kimbrough (2002)).

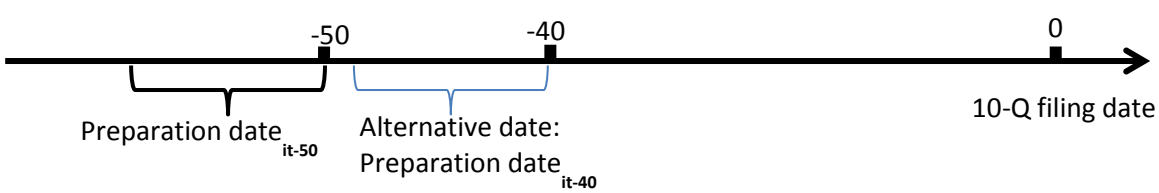
Column 2 of Table 3.7 reports on firms whose investor sentiment deteriorated from the above average group in quarter t-1 to the below average group in quarter t. The negative and significant coefficient on $\Delta investor\_sent \times O_{t-1}P_t$ suggests that more risks are disclosed in 10-Qs when investor sentiment decreases. For firms with below average investor sentiment, especially those who were in the above average group, they may be under greater investor attention in the risk disclosure part.

Investors may increase their intensity of scrutinizing their risk disclosure to understand the future prospects and associated risks of firms. The coefficient on $\Delta investor\_sent \times P_{t-1}O_t$ is negative and significant in column 3. This indicates that fewer risks are shown when investor sentiment increases. In summary, there is a negative association between investor sentiment and the proportion of uncertainty in 10-Q filings for most firms, except for firms with extremely pessimistic investor sentiment.

4.5.5 Robustness check for different preparation date

Although the time period in which managers prepare their 10-Q reports varies from firm to firm, most of them prepare their quarter filings 40 days to 60 days in advance, as I mentioned in Section 4.4.1. In the main tests, I use 57 to 50 calendar days before the filing date to calculate average firm-specific investor sentiment. In the robustness check, I use alternative 47 to 40 calendar days before the filing date to calculate average firm-specific investor sentiment ($investor\_sent2$) (see Figure 4 below). ΔY_{it} represents $Tone_{it}$, Fog_{it} and $Uncertain_{it}$ in model (3.7), respectively.

Figure 4: Alternative preparation date of 10-Q filings



$$Y_{it} = \alpha_0 + \beta_1 investor\_sent2 + \beta_2 roa_{it} + \beta_3 sue_{it} + \beta_4 accruals_{it} + \beta_5 earn_{it} + \beta_6 sd\_earn_{it}$$
$$+ \beta_7 ret_{it} + \beta_8 sd\_ret_{it} + \beta_9 \log estimates_{it} + \beta_{10} btm_{it} + \beta_{11} tover_{it} + \beta_{12} \log markv_{it} + \beta_{13} \log Geo_{it}$$
$$+ \beta_{14} \log Biz_{it} + \beta_{15} MA_{it} + \beta_{16} crisis + \beta_{17} si_{it} + \beta_{18} age_{it} + \beta_{19} leverage_{it} + quarterF.E + YearF.E$$
$$+ FirmF.E + \varepsilon_{it} \qquad (3.7)$$

Table 3.8 presents the relationship of the three hypotheses by using 47 to 40 days before filing dates to calculate firm-specific investor sentiment. In column 1, investor sentiment is still positively associated with the tone of 10-Qs, with a higher significance level (1 percent), compared with using investor sentiment 57 to 50 days before the 10-Q announcement date. In column 2 of Table 3.8, investor sentiment is still negatively associated with the tone of 10-Qs, which is consistent with using investor sentiment 57 to 50 days before the 10-Q announcement date. In column 3 of Table 3.8, I do not observe a significant association between investor sentiment and uncertainty. A possible explanation is that firms in the optimistic and pessimistic investor sentiment groups behave differently in terms of uncertainty. Perhaps their effects moderate each other, resulting in the insignificance here.

Next, I rerun model (3.7), regressing the change in investor sentiment ($\Delta investor\_sent2_{it-40}$) on the change tone ($\Delta Tone_{it}$), fog index ($\Delta Fog_{it}$) and uncertainty ($\Delta Uncertain_{it}$), instead of the levels. The results are shown in Table 3.9 and all results hold as in the main test. This shows that the results are not sensitive to the alternative investor sentiment date.

Last, the robustness check is related to the standardisation of the control variables. The prior literature uses a mix of changes of control variables (Brown and Tucker (2011)) and levels of control variables (Demers and Vega (2010)). I use changes in control variables as a robustness check in model (3.8).

$$\begin{aligned}\Delta Y_{it} &= \alpha_0 + \beta_1 \Delta investor\_sent_{it-50} + \beta_2 below\_average + \beta_3 \Delta investor\_sent_{it-50} \times below\_average \\ &+ \beta_4 \Delta roa_{it} + \beta_5 \Delta sue_{it} + \beta_6 \Delta accruals_{it} + \beta_7 \Delta earn_{it} + \beta_8 \Delta sd\_earn_{it} f + \beta_9 \Delta ret_{it} + \beta_{10} \Delta sd\_ret_{it} \\ &+ \beta_{11} \Delta \log estimates_{it} + \beta_{12} \Delta btm_{it} + \beta_{13} \Delta tover_{it} + \beta_{14} \Delta \log markv_{it} + \beta_{15} \Delta \log Geo_{it} + \beta_{16} \Delta \log Biz_{it} \\ &+ \beta_{17} MA_{it} + \beta_{18} \Delta si_{it} + \beta_{19} age_{it} + \beta_{20} \Delta leverage_{it} + quarterF.E + YearF.E + FirmF.E + \varepsilon_{it}\end{aligned} \tag{3.8}$$

Table 3.10 presents the results. Again, all results are consistent with the main test. In column 1 of testing hypothesis one, $\Delta investor\_sent$ is still positive and statistically significant while interaction term $\Delta investor\_sent \times below\_average$ is still negative and significant. For control variables, the change of current performance (*Δearn*) is positively significant and so is the change of market value (*Δlogmarkv*). The change of volatility of return (*Δsd_ret)* is negatively related to optimistic tone. Adjusted R^2 increases from 4.5% to 4.8%. Columns 2 and 3 follow the same pattern. Therefore, my results are not affected by different standardisations of control variables. Although I have consulted industry practitioners about the preparation time, the caveat here is that I cannot rule out that some managers prepared the 10-Qs outside my test period. However, I have tried to mitigate this issue with alternative windows.

4.6 Conclusion

This study examines how managers respond to investor sentiment by using (1) the optimism of the tone, (2) the readability of the 10-Q filings and (3) the level of inclusion of uncertain words, segregated by the level and its change in the firm-specific investor sentiment.

In general, I find that firm-specific investor sentiment is positively associated with the tone and readability of 10-Q filings while negatively associated with the proportion of uncertain words of the 10-Q filings. Managers use different strategies to communicate with investors through their 10-Q filings for different firm-specific investor sentiment levels and directions. Especially, for firms with extremely high investor sentiment, managers tend to walk-down the tone to avoid future disappointment. I do not find a significant difference in terms of readability for firms with extremely optimistic investor sentiment but these firms have a low proportion of uncertain words in their 10-Qs. For firms with extremely pessimistic investor sentiment, I find that managers tend to use more optimistic and easy to understand language, and minimize their proportion of uncertainty in their 10-Q filings. This suggests that managers may try to boost investor confidence by using less uncertain words when the firms have extremely low investor sentiment.

The caveat in this chapter is the time period when managers prepare their 10-Q filings. Although I have consulted industry practitioners and used alternative

preparation time, I cannot rule out some managers preparing the 10-Qs outside my test period.

Investor sentiment reflects investors' expectations or emotional biases towards a firm, which could either be rational or irrational. Classical financial theory believes that investor sentiment has no influence on stock prices. However, there is an extensive behaviour finance literature which examines the impact of investor sentiment on stock prices and how it influences both firms and investors' decisions. Recent work by Baker and Wurgler (2007) call for more research on how managers respond strategically to investor sentiment via corporate reporting decisions. To the best of my knowledge, my study is the first to investigate how investor sentiment potentially influences the way managers prepare their 10-Q filings.

SEC regulations postulating that the quarterly reports need to be truthful and they need to contain all the material information about the firm. However, the SEC cannot postulate what the tone and readability of the quarterly reports need to be or how certain or uncertain the wording of the reports needs to be. So the mangers can and do use the tone, readability and/or uncertainty of the reports to potentially influence their investors. Anecdotal evidence suggests that after the Sarbanes-Oxley Act of 2002, managers began to shift from traditional earnings management or forecast guidance to subtler ways to affect investors' impressions of firm performance and outlook. Consequently, my study produces the first evidence for

market participants who need to understand the factors that influence managers' narrative disclosures and thereby debiasing corporate disclosures. Second, this shift of reporting strategy could be viewed as a function of regulatory responses. Therefore, my study should be of interest to standard setters and regulators. Is it possible to regulate textual disclosures? Some statements may induce a wrong impression or distorted perceptions of firm prospects (Huang (2005)). Given it has the potential to impair the quality of financial reporting and to result in capital misallocations, do regulators pay enough attention to the more subtle aspects of financial reporting? Lastly, auditor could also extend their work to the narrative disclosures instead of just scrutinizing the quantitative characteristics.

Chapter 5

Conclusion

5.1 General

Broadly speaking, this thesis expands the literature in three main areas. First, it extends the literature related to the conflicts of interest faced by sell-side analysts, highlighting that job concerns appear to influence the way banking analysts provide forecasts. Secondly, it examines analyst reports when the quantitative and qualitative signals are conflicting, and shows market participants that textual analysis of analyst reports could be more credible than a quantitative measure. Lastly, it complements the research on investor sentiment in relation to the disclosure decisions of individual firms by highlighting that managers' different strategies of communicating with investors through 10-Qs is dependent on firm-specific investor sentiment.

Chapter 2 investigates the source of forecast distortion of sell-side analysts from a new angle. Unlike non-banking analysts, banking analysts have more incentive to curry favour with the management team they cover for due to their career concerns. I find that banking analysts exhibit a walk-down forecast bias pattern to other investment banks, compared with forecasting non-banks. This pattern of earnings bias enables banking analysts to move up to better ranked brokerage houses. Moreover, the Global Settlement is used as an exogenous shock and I show that

banking analysts have stronger incentives to walk down their forecasts after the Settlement due to their career concerns.

Chapter 3 examines the power of consistent and conflicting signals in analyst reports. I find that the market reacts strongly when the tone of analyst reports is consistent with earnings forecasts bias. Interestingly, when the tone of reports does not coincide with earnings forecasts, investors place greater weight on the textual information rather than on their final output figures. Although forecasts with consistent signals (O_TO_B and P_TP_B) have a stronger market reaction, they are not necessarily the most credible forecasts. I find that sentiment is priced and it is a good indicator of the quality of analyst reports. Reports with relatively pessimistic sentiment enjoy higher report quality than those which are relatively more optimistic.

Chapter 4 examines the influence of firm-specific investor sentiment on managers when they prepare their 10-Q filings. Instead of using earnings management or even fraud, firms could use more subtle forms to influence investors' impressions of firm performance and prospects, namely the tone in corporate disclosures. In general, investor sentiment is positively associated with the tone of optimism and readability in 10-Qs, but negatively associated with the proportion of uncertain words in 10-Qs. However, managers' priorities appear to vary when they experience extremely high or low firm-specific investor sentiment. For firms with extremely high investor sentiment, managers choose to use a less optimistic tone

when investor sentiment increases. This helps firms to smooth investor expectation, thereby avoiding any future disappointment. However, for firms with extremely low investor sentiment, managers tend to use more optimistic and easy to understand language, and minimize their proportion of uncertainty in their 10-Q filings when investor sentiment is low. This is different from firms with high investor sentiment because their priority is to convey a more positive impression to stakeholders. Therefore, the tone strategy used by managers is associated with different levels of firm-specific investor sentiment.

5.2 Implications

My study has implications for regulators related to the findings that banking analysts appear to bias their forecasts for career concerns. Hence, this conflicts of interest faced by banking analysts could contribute to the poor information environment but prior regulations such as the Global Settlement do not take these into consideration. Second, my study has implications for investors who use analyst reports in their investing decisions. Investors should be aware of these conflicts of interest in the research coverage for banking stocks. Third, by measuring the tone of analyst reports or corporate disclosures, my study could also be of interest to retail investors as well as institutional investors such as fund managers for trading strategy design. Lastly, my study has implications both for investors and regulators in assessing different signalling strategies used in corporate disclosure and improving the quality of corporate filings.

5.3 Limitations

For the career concerns analysis in Chapter 2, I assume that analysts experience favourable job separation when they move to better-ranked brokerage houses and vice versa. Due to data availability, however, I do not know the actual positon they hold in the new brokerage houses. Although this is consistent with Hong and Kubik (2003), it limits my analysis.

Second, for any dictionary-based content analysis, it is always difficult to ascertain whether the tone is appropriately captured. Although Loughran and McDonald (2011) is the most popular dictionary in accounting and finance studies, it may still be argued as lack of authority.

Lastly, due to the lack of firm-specific investor sentiment, prior literature uses *market-wide* investor sentiment for the empirical tests of sentiment on decisions and prices at the individual firm level. I adopt the *firm-specific* investor sentiment from Aboody et al. (2016), which is a novel measurement but to-date lacks sufficient empirical tests.

5.4 Future Research

The findings of Chapter 2 show that analysts covering the banking industry have different incentives compared with other analysts. That is to say, the incentives of analysts' behaviour may shift according to different situations. Apart from industry difference, reputational cost may also influence analysts' behaviour. In future research, I therefore intend to examine whether the increase in reputation is

associated with a positive or negative influence on their performance. In addition, future research questions could include: Do investors recognize this source of bias when incorporate analyst earnings forecasts in the market prices? Do bias incentives from revolving doors generalize to investment recommendations?

Chapter 3 focuses on the textual discussions and earnings forecast bias of analyst reports. If the data is available, I intend to examine why reports with pessimistic sentiment tend to be more accurate. This could be associated with analyst affiliation (O'Brien, McNichols, and Lin (2005) and Kadan et al. (2009)). In addition, a trading strategy could also be designed since the four combinations of reports have different accuracy and predictive power. In addition, other quantitative outputs such as target price and recommendation level could be included.

Chapter 4 focuses on the content analysis of corporate disclosures. I therefore intend to examine whether the tone of the 10-Qs influences investor sentiment ex-post. I could therefore examine whether the response firm managers wanted have been achieved, via event study focusing on investor reactions shortly after the release of 10-Q filings. With the development of computer power, it is also possible to analyse sentiment automatically. Then the relationship between price movement or volatility and sentiment of all related disclosures could be examined. Trading strategy based on real time sentiment could also be designed. It would be also desirable to conduct a textual analysis of non-English narratives. A proper

dictionary needs to be compiled so that similar tests could be conducted. Investor reactions of sentiment from different cultural backgrounds could also be compared.

References

Aboody, David, Omri Even-Tov, Reuven Lehavy, and Brett Trueman, 2016, Overnight Returns and Firm-Specific Investor Sentiment, *Working Paper*.

Aboody, David, Omri Even-Tov, Reuven Lehavy, and Brett Trueman, 2016, Overnight Returns and Firm-Specific Investor Sentiment, *SSRN Electronic Journal*.

Affleck-Graves, John, Larry R Davis, and Richard R Mendenhall, 1990, 23 Forecasts of earnings per share: Possible sources of analyst superiority and bias, *Contemporary Accounting Research* 6, 501–517.

Agrawal, Anup, and Mark A Chen, 2005, Analyst Conflicts and Research Quality Analyst Conflicts and Research Quality, *American Law & Economics Association Papers*, 1–43.

Ai, Chunrong, and Edward C. Norton, 2003, Interaction terms in logit and probit models, *Economics Letters* 80, 123–129.

Altınkılıç, Oya, Vadim S. Balashov, and Robert S. Hansen, 2013, Are Analysts' Forecasts Informative to the General Public?, *Management Science* 59, 2550–2565.

Anolli, Mario, Elena Beccalli, and Philip Molyneux, 2014, Bank earnings forecasts, risk and the crisis, *Journal of International Financial Markets, Institutions and Money* 29, 309–335.

Antweiler, Werner, and Murray Z. Frank, 2004, Is All That Talk Just Noise? The Information Content of Internet Stock Message Boards, *The Journal of Finance* 59, 1259–1294.

Arand, Daniel, and Alexander G. Kerl, 2015, Sell-Side Analyst Research and Reported Conflicts of Interest, *European Financial Management* 21, 20–51.

Arif, Salman, and Charles M. C. Lee, 2014, Aggregate Investment and Investor Sentiment, *Review of Financial Studies* 27, 3241–3279.

Asquith, Paul, Michael B. Mikhail, and Andrea S. Au, 2005, Information content of equity analyst reports, *Journal of Financial Economics* 75, 245–282.

Baginski, SP, S McGuire, N Sharp, and B Twedt, 2011, To Tell the Truth: Management Forecasts in Periods of Accounting Fraud, *Working paper*.

Baginski, Stephen P., John M. Hassell, and Michael D. Kimbrough, 2002, The Effect of Legal Environment on Voluntary Disclosure: Evidence from Management Earnings Forecasts Issued in U.S. and Canadian Markets, *The Accounting Review*

77, 25–50.

Baik, Bok, and Guohua Jiang, 2006, The use of management forecasts to dampen analysts' expectations, *Journal of Accounting and Public Policy* 25, 531–553.

Bailey, Warren, Haitao Li, Connie X. Mao, and Rui Zhong, 2003, Regulation Fair Disclosure and Earnings Information: Market, Analyst, and Corporate Responses, *Journal of Finance*.

Baker, Malcolm, 2011, Behavioral Corporate Finance: An Update Survey, *National Bureau Of Economic Research*.

Baker, Malcolm, and Jeffrey Wurgler, 2006, Investor Sentiment and the Cross-Section of Stock Returns, *The Journal of Finance* 61, 1645–1680.

Baker, Malcolm, and Jeffrey Wurgler, 2007, Investor Sentiment in the Stock Market, *Journal of Economic Perspectives* 21, pp. 129–51.

Balboa, Marina, J. Carlos Gómez-Sala, and Germán López-Espinosa, 2009, The Value of Adjusting the Bias in Recommendations: International Evidence, *European Financial Management* 15, 208–230.

Barber, Brad M., Reuven Lehavy, and Brett Trueman, 2007, Comparing the stock recommendation performance of investment banks and independent research firms, *Journal of Financial Economics* 85, 490–517.

Barron, Orie E., Charles O Kile, and Terrence B O'Keefe, 1999, MD&A quality as measured by the SEC and analysts' earning forecasts, *Contemporary Accounting Research* 16, p75–109.

Bartholdy, Jan, and Tiyi Feng, 2013, The quality of securities firms' earnings forecasts and stock recommendations: Do informational advantages, reputation and experience matter in China?, *Pacific-Basin Finance Journal* 24, 66–88.

Bartov, Eli, Dan Givoly, and Carla Hayn, 2002, The rewards to meeting or beating earnings expectations, *Journal of Accounting and Economics* 33, 173–204.

Bergman, Nittai K., and Sugata Roychowdhury, 2008, Investor Sentiment and Corporate Disclosure, *Journal of Accounting Research* 46, 1057–1083.

Bergstresser, Daniel, and Thomas Philippon, 2006, CEO incentives and earnings management, *Journal of Financial Economics* 80, 511–529.

Berkman, Henk, Valentin Dimitrov, Prem C. Jain, Paul D. Koch, and Sheri Tice, 2009, Sell on the news: Differences of opinion, short-sales constraints, and returns around earnings announcements, *Journal of Financial Economics* 92, 376–399.

Beyer, Anne, and Ilan Guttman, 2011, The effect of trading volume on analysts' forecast bias, *Accounting Review* 86, 451–481.

Bilinski, Pawel, Douglas Cumming, Lars Hass, Konstantinos Stathopoulos, and Martin Walker, 2016, Strategic distortions in analyst target prices in the presence of short-term institutional investors., *Working paper*, 1–52.

Blau, Benjamin M., Jared R. DeLisle, and S. McKay Price, 2015, Do sophisticated investors interpret earnings conference call tone differently than investors at large? Evidence from short sales, *Journal of Corporate Finance* 31, 203–219.

Bless, Herbert, Norbert Schwarz, Gerald L. Clore, Verena Golisano, Christina Rabe, and Marcus Wölk, 1996, Mood and the use of scripts: Does a happy mood really lead to mindlessness?, *Journal of Personality & Social Psychology* 71, p665–679.

Bligh, Michelle C, Jeffrey C Kohles, and James R Meindl, 2004, Charisma under crisis: Presidential leadership, rhetoric, and media responses before and after the September 11th terrorist attacks, *The Leadership Quarterly* 15, 211–239.

Bligh, Michelle C., and Gregory D. Hess, 2007, The power of leading subtly: Alan Greenspan, rhetorical leadership, and monetary policy, *The Leadership Quarterly* 18, 87–104.

Bloomfield, Robert J, 2002, The "incomplete revelation hypothesis" and financial reporting, *Accounting Horizons* 16, p233–243.

Bochkay, Khrystyna, and Valentin Dimitrov, 2014, Qualitative Management Disclosures and Market Sentiment, *Working Paper*, 1–45.

Boni, Leslie, and K. Womack, 2002, Solving the sell-side research problem: Insights from buy-side professionals, *Working Paper*.

Bonner, Sarah E., Artur Hugon, and Beverly R. Walther, 2007, Investor Reaction to Celebrity Analysts: The Case of Earnings Forecast Revisions, *Journal of Accounting Research* 45, 481–513.

Botosan, CA, and MA Plumlee, 2002, A re-examination of disclosure level and the expected cost of equity capital, *Journal of accounting research* 40, p21–40.

Botosan, Christine A., 1997, Disclosure level and the cost of equity capital, *Accounting review* 72, 323–349.

Bowen, Robert M., Angela K. Davis, and Dawn A. Matsumoto, 2005, Emphasis on Pro Forma versus GAAP Earnings in Quarterly Press Releases: Determinants, SEC Intervention, and Market Reactions, *The Accounting Review* 80, 1011–1038.

Bradley, Daniel J., Sinan Gokkaya, and Xi Liu, 2015, Before an Analyst Becomes an Analyst: Does Industry Experience Matter?, *Journal of Finance (Forthcoming)*.

Bradshaw, Mark T., Lian Fen Lee, and Kyle Peterson, 2016, The Interactive Role of Difficulty and Incentives in Explaining the Annual Earnings Forecast Walkdown, *The Accounting Review*.

Bradshaw, Mark Thomas, 2011, Analysts' Forecasts: What Do We Know after Decades of Work?, *SSRN Electronic Journal*, 1–55.

Brown, Stephen V., and Jennifer Wu Tucker, 2011, Large-Sample Evidence on Firms' Year-over-Year MD&A Modifications, *Journal of Accounting Research* 49, 309–346.

Brown, Stephen V., and Jennifer Wu Tucker, 2011, Large-Sample Evidence on Firms' Year-over-Year MD&A Modifications, *Journal of Accounting Research* 49, 309–346.

Brown, Gregory W, Michael T Cliff, Mike Cooper, Kent Daniel, Greg Kadlec, Adam Reed, Meir Statman, and Kent Womack, 2005, Investor Sentiment and Asset Valuation, *The Journal of Business* 78, 405–440.

Brown, Gregory W., and Michael T. Cliff, 2004, Investor sentiment and the near-term stock market, *Journal of Empirical Finance* 11, 1–27.

Brown, Lawrence D., 1997, Analyst forecasting errors: Additional evidence, *Financial Analysts Journal* 53, 81–88.

Brown, Lawrence D., Andrew C. Call, Michael B. Clement, and Nathan Y. Sharp, 2015, Inside the "Black Box" of Sell-Side Financial Analysts, *Journal of Accounting Research* 53, 1–47.

Brown, Lawrence D., Robert L. Hagerman, Paul A. Griffin, and Mark E. Zmijewski, 1987, Security analyst superiority relative to univariate time-series models in forecasting quarterly earnings, *Journal of Accounting and Economics* 9, 61–87.

Brown, Nerissa C., Theodore E. Christensen, W. Brooke Elliott, and Richard D. Mergenthaler, 2012, Investor sentiment and pro forma earnings disclosures, *Journal of Accounting Research* 50, 1–40.

Brown, Nerissa C., Theodore E. Christensen, W. Brooke Elliott, and Richard D. Mergenthaler, 2012, Investor Sentiment and Pro Forma Earnings Disclosures, *Journal of Accounting Research* 50, 1–40.

Bryan, SH, 1997, Incremental information content of required disclosures contained in management discussion and analysis, *Accounting Review* 72, 285–

301.

Bryan, Stephen H, 1997, Incremental Information Content of Required Disclosures Contained in Management Discussion and Analysis, *The Accounting Review* 72, 285–301.

Buehlmaier, Matthias M. M., 2013, The role of the media in takeovers: Theory and evidence, *Working Paper*.

Butler, Marty, Andrew J. Leone, and Michael Willenborg, 2004, An empirical analysis of auditor reporting and its association with abnormal accruals, *Journal of Accounting and Economics* 37, 139–165.

Callahan, Carolyn M, Doris M Cook, and Rodney E Smith, 2004, Firm Performance and Management's Discussion and Analysis Disclosures: An Industry Approach, *Working Paper*.

Callahan, CM, and R Smith, 2004, Firm performance and management's discussion and analysis disclosures: An industry approach, *Available at SSRN 588062*.

Campbell, John L., Hsinchun Chen, Dan S. Dhaliwal, Hsin-min Lu, and Logan B. Steele, 2014, The information content of mandatory risk factor disclosures in corporate filings, *Review of Accounting Studies* 19, 396–455.

Carter, Richard, and Steven Manaster, 1990, Initial Public Offerings and Underwriter Reputation, *Journal of finance* XLV, 1045–1068.

Cazier, Richard A., and Ray J. Pfeiffer, 2016, Why are 10-K filings so long?, *Accounting Horizons* 30, 1–21.

Chan, Louis K. C., Jason Karceski, and Josef Lakonishok, 2007, Analysts' Conflicts of Interest and Biases in Earnings Forecasts, *Journal of Financial and Quantitative Analysis* 42, 893.

Chen, H, P De, YJ Hu, and BH Hwang, 2013, Customers as advisors: the role of social media in financial markets, *Working Paper*.

Chen, Hailiang, Prabuddha De, Yu (Jeffrey) Hu, and Byoung-Hyoun Hwang, 2014, Wisdom of Crowds: The Value of Stock Opinions Transmitted Through Social Media, *Review of Financial Studies* 27, 1367–1403.

Chen, Shuping, and Dawn A. Matsumoto, 2006, Favorable versus Unfavorable Recommendations: The Impact on Analyst Access to Management-Provided Information, *Journal of Accounting Research* 44, 657–689.

Chen, Tao, Jarrad Harford, and Chen Lin, 2015, Do analysts matter for governance? Evidence from natural experiments, *Journal of Financial Economics* 115, 383–410.

Cheng, Q., T. Warfield, and M. Ye, 2011, Equity Incentives and Earnings Management: Evidence from the Banking Industry, *Journal of Accounting, Auditing & Finance* 26, 317–349.

Cheng, Qiang, and L. O. Kin, 2006, Insider trading and voluntary disclosures, *Journal of Accounting Research* 44, 815–848.

Cheng, Qiang, and Terry D. Warfield, 2005, Equity incentives and earnings management, *Accounting Review* 80, 441–476.

Christensen, Theodore E, Kenneth J Merkley, Jennifer Wu Tucker, and Shankar Venkataraman, 2011, Do managers use earnings guidance to influence street earnings exclusions?, *Review of Accounting Studies* 16, 501–527.

Clatworthy, Mark, and Michael John Jones, 2001, The effect of thematic structure on the variability of annual report readability, *Accounting, Auditing & Accountability Journal* 14, 311–326.

Clatworthy, Mark, and Michael John Jones, 2001, The effect of thematic structure on the variability of annual report readability, *Accounting, Auditing & Accountability Journal* 14, 311–326.

Clatworthy, Mark, and Michael John Jones, 2003, Financial reporting of good news and bad news: evidence from accounting narratives, *Accounting and Business Research* 33, 171–185.

Clement, Michael B, 1999, Analyst forecast accuracy : Do ability , resources , and portfolio complexity matter ?, *Journal of finance* 27.

Clement, Michael B, and Senyo Y. Tse, 2003, Do Investors Respond to Analysts' Forecast Revisions as if Forecast Accuracy Is All That Matters?, *The Accounting Review* 78, 227–249.

Clement, Michael B., and Senyo Y. Tse, 2005, Financial Analyst Characteristics and Herding Behavior in Forecasting, *The Journal of Finance* 60, 307–341.

Core, John E, 2001, A review of the empirical disclosure literature: discussion, *Journal of Accounting and Economics* 31, 441–456.

Core, John E, Wayne Guay, and David F. Larcker, 2008, The power of the pen and executive compensation, *Journal of Financial Economics* 88, 1–25.

Cornaggia, Jess, Kimberly J. Cornaggia, and Han Xia, 2016, Revolving doors on

Wall Street, *Journal of Financial Economics* 120, 400–419.

Cotter, Julie, Irem Tuna, and Peter D. Wysocki, 2006, Expectations Management and Beatable Targets: How Do Analysts React to Explicit Earnings Guidance?, *Contemporary Accounting Research* 23, 593–628.

Courtis, John K, 2004, Corporate report obfuscation: artefact or phenomenon?, *The British Accounting Review* 36, 291–312.

Courtis, John K., 1998, Annual report readability variability: tests of the obfuscation hypothesis, *Accounting, Auditing & Accountability Journal* 11, 459–472.

Courtis, John K., 2004, Corporate report obfuscation: artefact or phenomenon?, *The British Accounting Review* 36, 291–312.

Cowen, Amanda, Boris Groysberg, and Paul Healy, 2006, Which types of analyst firms are more optimistic?, *Journal of Accounting and Economics* 41, 119–146.

Crowley, Ayn E., and Wayne D Hoyer, 1994, An Integrative Framework for Understanding Two-Sided Persuasion, *Journal of Consumer Research* 20, 561.

Da, Zhi, Joseph Engelberg, and Pengjie Gao, 2015, The sum of all FEARS investor sentiment and asset prices, *Review of Financial Studies* 28, 1–32.

Das, Somnath, and Pervin K. Shroff, 2002, Fourth Quarter Reversals in Earnings Changes and Earnings Management, *SSRN Electronic Journal*.

Davis, Angela K., Weili Ge, Dawn Matsumoto, and Jenny Li Zhang, 2014, The effect of manager-specific optimism on the tone of earnings conference calls, *Review of Accounting Studies*, 639–673.

Davis, Angela K., Jeremy M Piger, and Lisa M Sedor, 2011, Beyond the Numbers: An Analysis of Optimistic and Pessimistic Language in Earnings Press Releases, *AAA 2008 Financial Accounting and Reporting Section (FARS) Paper*, 1–31.

Davis, Angela K., Jeremy M. Piger, and Lisa M. Sedor, 2012, Beyond the Numbers: Measuring the Information Content of Earnings Press Release Language, *Contemporary Accounting Research* 29, 845–868.

Davis, Angela K., and Isho Tama-Sweet, 2012, Managers' Use of Language Across Alternative Disclosure Outlets: Earnings Press Releases versus MD&A, *Contemporary Accounting Research* 29, 804–837.

De Franco, Gus, Ole-Kristian Hope, Dushyantkumar Vyas, and Yibin Zhou, 2015, Analyst Report Readability, *Contemporary Accounting Research* 32, 76–104.

Dechow, Patricia M., Amy P. Hutton, and Richard G. Sloan, 2000, The relation between analysts' forecasts of long-term earnings growth and stock price performance following equity offerings, *Contemporary Accounting Research* 17, 1–32.

deHaan, Ed, Simi Kedia, Kevin Koh, and Shivaram Rajgopal, 2015, The revolving door and the SEC's enforcement outcomes: Initial evidence from civil litigation, *Journal of Accounting and Economics* 60, 65–96.

Demers, Elizabeth, and C Vega, 2010, Soft information in earnings announcements: News or noise?, *INSEAD Working Papers Collection*, p1–67.

Demers, Elizabeth, and Clara Vega, 2014, Understanding The Role of Managerial Optimism and Uncertainty in the Price Formation Process : Evidence from the Textual Content of Earnings Announcements, *Working Paper*.

Diamond, Douglas W, and Robert E Verrecchia, 1991, Disclosure , Liquidity , and the Cost of Capital, *The Journal of Finance* 46, 1325–1359.

Diamond, Douglas W., 1985, Optimal Release of Information By Firms, *The Journal of Finance* 40, 1071–1094.

Doran, James S., David R. Peterson, and S. McKay Price, 2012, Earnings Conference Call Content and Stock Price: The Case of REITs, *The Journal of Real Estate Finance and Economics* 45, 402–434.

Dugar, Amitabh, and Siva Nathan, 1995, The Effect of Investment Banking Relationships on Financial Analysts' Earnings Forecasts and Investment Recommendations*, *Contemporary Accounting Research* 12, 131–160.

Elsbach, Kimberly D., and Greg Elofson, 2000, How the packaging of decision explanations affects perceptions of trustworthiness, *Academy of Management Journal* 43, 80–89.

Engelberg, Joseph, 2008, Costly Information Processing : Evidence from Earnings Announcements, *AFA 2009 San Francisco Meetings Paper*.

Engelberg, Joseph E., Adam V. Reed, and Matthew C. Ringgenberg, 2012, How are shorts informed? Short sellers,news,andinformationprocessing, *Journal of Financial Economics* 105, 260–278.

Ertimur, Yonca, Jayanthi Sunder, and Shyam V. Sunder, 2007, Measure for Measure: The Relation between Forecast Accuracy and Recommendation Profitability of Analysts, *Journal of Accounting Research* 45, 567–606.

Feldman, Ronen, Suresh Govindaraj, Joshua Livnat, and Benjamin Segal, 2010,

Management's tone change, post earnings announcement drift and accruals, *Review of Accounting Studies* 15, 915–953.

Feldman, Ronen, Suresh Govindaraj, Joshua Livnat, and Benjamin Segal, 2010, Management's tone change, post earnings announcement drift and accruals, *Review of Accounting Studies* 15, 915–953.

Feldman, Ronen, Joshua Livnat, and Benjamin Segal, 2008, Shorting Companies That Restate Previously Issued Financial Statements, *The Journal of Investing* 17, 6–15.

Ferris, S. P., Q. Hao, and M.-Y. Liao, 2013, The Effect of Issuer Conservatism on IPO Pricing and Performance, *Review of Finance* 17, 993–1027.

Financial Accounting Standards Board (FASB), 2012, Invitation to comment-disclosure framework, .

Fishman, Michael J., and Kathleen M. Hagerty, 1989, Disclosure Decisions by Firms and the Competition for Price Efficiency, *Journal of Finance* 44, 633–646.

Flannery, Mark J., Simon H. Kwan, and M. Nimalendran, 2004, Market evidence on the opaqueness of banking firms' assets, *Journal of Financial Economics* 71, 419–460.

Francis, Jennifer, and Leonard Soffer, 1997, The Relative Informativeness of Analysts' Stock Recommendations and Earnings Forecast Revisions, *Journal of Accounting Research* 35, 193–211.

Francis, Jennifer, and Leonard Sofferf, 1997, The Relative Infonnativeiiess of and Earnings Forecast Revisioiis, *Journal of Accounting Research* 35, 193–211.

Fried, Dov, and Dan Givoly, 1982, Financial analysts' forecasts of earnings. A better surrogate for market expectations, *Journal of Accounting and Economics* 4, 85–107.

García, Diego, 2013, Sentiment during Recessions, *The Journal of Finance* 68, 1267–1300.

Garciá-Meca, Emma, and Juan Pedro Sánchez-Ballesta, 2006, Influences on financial analyst forecast errors: A meta-analysis, *International Business Review* 15, 29–52.

Geiger, Marshall A., Clive S. Lennox, and David S. North, 2008, The hiring of accounting and finance officers from audit firms: How did the market react?, *Review of Accounting Studies* 13, 55–86.

Graham, John R., Campbell R. Harvey, and Shiva Rajgopal, 2005, The economic implications of corporate financial reporting, *Journal of Accounting and Economics*.

Grossman, Sanford J., 1981, The Informational Role of Warranties and Private Disclosure about Product Quality, *The Journal of Law and Economics* 24, 461–483.

Gu, Zhaoyang, and Joanna Shuang Wu, 2003, Earnings skewness and analyst forecast bias, *Journal of Accounting and Economics* 35, 5–29.

Guan, Y., H. Lu, and M. H. F. Wong, 2012, Conflict-of-Interest Reforms and Investment Bank Analysts' Research Biases, *Journal of Accounting, Auditing & Finance* 27, 443–470.

Gunning, R, 1952, *The Technique of Clear Writing* (McGraw-Hill International Book Co, New York, NY).

Hanley, KW, and G Hoberg, 2010, The information content of IPO prospectuses, *Review of Financial Studies* 23, p2821–2864.

Harbaugh, Rick, John Maxwell, Kelly Shue, and Draft Version, 2016, Consistent Good News and Inconsistent Bad News, *Wokring Paper*.

Henry, E, and AJ Leone, 2009, Measuring qualitative information in capital markets research, *Available at SSRN 1470807*.

Henry, E., 2008, Are Investors Influenced By How Earnings Press Releases Are Written?, *Journal of Business Communication* 45, 363–407.

Henry, Elaine, and Andrew J Leone, 2016, Measuring Qualitative Information in Capital Markets Research: Comparison of Alternative Methodologies to Measure Disclosure Tone, *The Accounting Review* 91, 153–178.

Heston, Steven L., and Nitish Ranjan Sinha, 2013, News versus Sentiment: Comparing Textual Processing Approaches for Predicting Stock Returns, *SSRN Electronic Journal*.

Hillert, Alexander, Alexandra Niessen-Ruenzi, and Stefan Ruenzi, 2014, Mutual Fund Shareholder Letter Tone Do Investors Listen?, *SSRN Electronic Journal*.

Hirshleifer, David A., James N. Myers, Linda A. Myers, and Siew Hong Teoh, 2008, Do individual investors cause post-earnings announcement drift? Direct evidence from personal trades, *Accounting Review* 83, 1521–1550.

Hoberg, Gerard, and Craig Lewis, 2015, Do Fraudulent Firms Produce Abnormal Disclosure?, *Vanderbilt Owen Graduate School of Management Research Paper No. 2298302*.

Hong, H, Jd Kubik, and a Solomon, 2000, Security Analysts' Career Concerns and Herding of Earnings Forecasts, *The RAND Journal of Economics* 31, 121.

Hong, Harrison, and Marcin Kacperczyk, 2010, Competition and Bias, *The Quarterly Journal of Economics* 125, 1683–1725.

Hong, Harrison, and Jeffrey D Kubik, 2003, Analyzing the Analysts : Career Concerns and Biased Earnings Forecasts, *Journal of finance* LVIII, 313–350.

Hong, Harrison, and Jeffrey D Kubik, 2003, Analyzing the Analysts : Career Concerns and Biased Earnings Forecasts, *THE JOURNAL OF FINANCE* LVIII.

Hong, Harrison, Terence Lim, and Jeremy C Stein, 2000, Bad News Travels Slowly: Size, Analyst Coverage, and the Profitability of Momentum Strategies, *The Journal of Finance* 55, 265–295.

Horton, Joanne, and George Serafeim, 2009, Security Analyst Networks, Performance and Career Outcomes, *SSRN Electronic Journal*, 1–37.

Hovakimian, Armen, and Ekkachai Saenyasiri, 2014, US Analyst Regulation and the Earnings Forecast Bias around the World, *European Financial Management* 20, 435–461.

Hribar, Paul, and John McInnis, 2012, Investor Sentiment and Analysts' Earnings Forecast Errors, *Management Science* 58, 293–307.

Hribar, Paul, and Phil Quinn, 2013, Managers and Investor Sentiment, *SSRN Electronic Journal*.

Huang, Allen H., Amy Y. Zang, and Rong Zheng, 2014, Evidence on the Information Content of Text in Analyst Reports, *The Accounting Review* 89, 2151–2180.

Huang, Dashan, Fuwei Jiang, Jun Tu, and Guofu Zhou, 2015, Investor Sentiment Aligned: A Powerful Predictor of Stock Returns, *Review of Financial Studies* 28, 791–837.

Huang, Peter H., 2005, Moody Investing and the Supreme Court: Rethinking the Materiality of Information and the Reasonableness of Investors, *Supreme Court Economic Review* 13, 99–131.

Huang, Xuan, Siew Hong Teoh, and Yinglei Zhang, 2014, Tone Management, *The Accounting Review* 89, 1083–1113.

Hugon, Artur, and Volkan Muslu, 2010, Market demand for conservative analysts, *Journal of Accounting and Economics* 50, 42–57.

Hunton, James E., and Ruth Ann McEwen, 1997, An assessment of the relation between analysts' earnings forecast accuracy, motivational incentives and cognitive information search strategy, *Accounting Review* 72, 497–515.

Iannotta, Giuliano, Giacomo Nocera, and Andrea Sironi, 2007, Ownership structure, risk and performance in the European banking industry, *Journal of Banking & Finance* 31, 2127–2149.

Institutional Investor, 2011, The Best Analysts of All Time, *London, U.K.: Euromoney Institutional Investor.*

Iskoz, S, 2002, Relative performance and institutional reaction to underwriter analyst recommendations, *Working Paper, Bracebridge Capital*.

Ivkovic, Zoran, and Narasimhan Jegadeesh, 2004, The timing and value of forecast and recommendation revisions, *Journal of Financial Economics* 73, 433–463.

Jackson, Andrew R., 2005, Trade generation, reputation, and sell-side analysts, *Journal of Finance* 60, 673–717.

Jacob, John, Thomas Z Lys, and Margaret A Neale, 1999, Expertise in forecasting performance of security analysts, *Journal of Accounting and Economics* 28, 51–82.

Jegadeesh, Narasimhan, and Di Wu, 2013, Word power: A new approach for content analysis, *Journal of Financial Economics* 110, 712–729.

Jiang, Fuwei, Joshua Lee, and Xiumin Martin, 2016, Manager Sentiment and Stock Returns Manager Sentiment and Stock Returns, *Working Paper*.

Jung, Wo, and YK Kwon, 1988, Disclosure when the market is unsure of information endowment of managers, *Journal of Accounting Research* 26, 146–153.

Kadan, O., L. Madureira, R. Wang, and T. Zach, 2009, Conflicts of Interest and Stock Recommendations: The Effects of the Global Settlement and Related Regulations, *Review of Financial Studies* 22, 4189–4217.

Ke, Bin, and Yong Yu, 2006, The Effect of Issuing Biased Earnings Forecasts on Analysts' Access to Management and Survival, *Journal of Accounting Research* 44, 965–999.

Ke, Bin, and Yong Yu, 2006, The Effect of Issuing Biased Earnings Forecasts on Analysts' Access to Management and Survival, *Journal of Accounting Research* 44, 965–999.

Kearney, Colm, and Sha Liu, 2014, Textual sentiment in finance: A survey of

methods and models, *International Review of Financial Analysis* 33, 171–185.

Kerl, Alexander, and Martin Ohlert, 2015, Star-analysts' Forecast Accuracy and the Role of Corporate Governance, *Journal of Financial Research* 38, 93–120.

Kerl, Alexander, Carolin Schürg, and Andreas Walter, 2014, The impact of Financial Times Deutschland news on stock prices: post-announcement drifts and inattention of investors, *Financial Markets and Portfolio Management* 28, 409–436.

Kimbrough, Michael D., and Isabel Yanyan Wang, 2014, Are seemingly self-serving attributions in earnings press releases plausible? Empirical evidence, *Accounting Review* 89, 635–667.

Klein, April, 1990, A direct test of the cognitive bias theory of share price reversals, *Journal of Accounting and Economics* 13, 155–166.

Koh, Kevin, Dawn a. Matsumoto, and Shivaram Rajgopal, 2008, Meeting or Beating Analyst Expectations in the Post-Scandals World: Changes in Stock Market Rewards and Managerial Actions, *Contemporary Accounting Research* 25, 1067–1098.

Kothari, S. P., Xu Li, and James E. Short, 2009, The Effect of Disclosures by Management, Analysts, and Business Press on Cost of Capital, Return Volatility, and Analyst Forecasts: A Study Using Content Analysis, *The Accounting Review* 84, 1639–1670.

Kravet, Todd, and Volkan Muslu, 2013, Textual risk disclosures and investors' risk perceptions, *Review of Accounting Studies* 18, 1088–1122.

Kravet, Todd, and Volkan Muslu, 2013, Textual risk disclosures and investors' risk perceptions, *Review of Accounting Studies* 18, 1088–1122.

Kucheev, Yury, and Tomas Sörensson, 2015, Do Stars Shine ? Comparing the Performance Persistence of Star Sell-Side Analysts Listed by Institutional Investor , the Wall Street Journal , and StarMine Comparing the performance persistence of star sell-side analysts, .

Laeven, Luc, and Ross Levine, 2009, Bank governance, regulation and risk taking, *Journal of Financial Economics* 93, 259–275.

Lang, MH, and RJ Lundholm, 1996, Corporate disclosure policy and analyst behavior, *Accounting review* 71, p467–492.

Lawrence, Alastair, 2013, Individual investors and financial disclosure, *Journal of Accounting and Economics* 56, 130–147.

Lee, Wayne Y, Christine X Jiang, and Daniel C Indro, 2002, Stock market volatility, excess returns, and the role of investor sentiment, *Journal of Banking & Finance* 26, 2277–2299.

Lehavy, Reuven, Feng Li, and Kenneth Merkley, 2011, The Effect of Firms' Communication Complexity on Analyst Following and the Properties of their Earnings Forecasts, *The Accounting Review* 86(3), pp.1087–1115.

Lehavy, Reuven, Feng Li, and Kenneth Merkley, 2011, The Effect of Annual Report Readability on Analyst Following and the Properties of Their Earnings Forecasts, *The Accounting Review* 86, 1087–1115.

Lemmon, M., and E. Portniaguina, 2006, Consumer Confidence and Asset Prices: Some Empirical Evidence, *Review of Financial Studies* 19, 1499–1529.

Levine, C. B., and M. J. Smith, 2011, Critical Accounting Policy Disclosures, *Journal of Accounting, Auditing & Finance* 26, 39–76.

Li, Feng, 2008, Annual report readability, current earnings, and earnings persistence, *Journal of Accounting and Economics* 45, 221–247.

Li, Feng, 2010, The Information Content of Forward-Looking Statements in Corporate Filings-A Naïve Bayesian Machine Learning Approach, *Journal of Accounting Research* 48, 1049–1102.

Li, Feng, 2010, The Information Content of Forward-Looking Statements in Corporate Filings-A Naïve Bayesian Machine Learning Approach, *Journal of Accounting Research* 48, 1049–1102.

Li, Feng, 2011, Textual Analysis of Corporate Disclosures: A Survey of the Literature, *Journal of Accounting Literature* 29, 143–165.

Li, Xi, Rodney N. Sullivan, Danielle Xu, and Guodong Gao, 2013, Sell-Side Analysts and Gender: A Comparison of Performance, Behavior, and Career Outcomes, *Financial Analysts Journal* 69.

Lim, Terence, 2001, Rationality and Analysts' Forecast Bias, *The Journal of Finance* 56, 369–385.

Lin, Hsiou-Wei, and Maureen F Mcnichols, 1998, Underwriting relationships, analysts' earnings forecasts and investment recommendations, *Journal of Accounting and Economics* 25, 101–127.

Liu, Baixiao, and John J. McConnell, 2013, The role of the media in corporate governance: Do the media influence managers' capital allocation decisions?, *Journal of Financial Economics* 110, 1–17.

Livnat, Joshua, and Christine Petrovits, 2009, Investor Sentiment , Post-Earnings Announcement Drift , and Accruals, *AAA 2009 Financial Accounting & Reporting Section*.

Ljungqvist, a., F. Marston, and W. J. Wilhelm, 2009, Scaling the Hierarchy: How and Why Investment Banks Compete for Syndicate Co-management Appointments, *Review of Financial Studies* 22, 3977–4007.

Ljungqvist, Alexander, Felicia Marston, Laura T. Starks, Kelsey D. Wei, and Hong Yan, 2007, Conflicts of interest in sell-side research and the moderating role of institutional investors, *Journal of Financial Economics* 85, 420–456.

Loughran, Tim, and Biill McDonald, 2011, When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks, *The Journal of Finance* 66, 35–65.

Loughran, Tim, and Bill Mcdonald, 2011, Barron ' s Red Flags : Do They Actually Work ?, *Journal of Behavioral Finance* 12, 90–97.

Loughran, Tim, and Bill McDonald, 2013, IPO first-day returns, offer price revisions, volatility, and form S-1 language, *Journal of Financial Economics* 109, 307–326.

Loughran, Tim, and Bill Mcdonald, 2014, Measuring Readability in Financial Disclosures, *The Journal of Finance* 69, 1643–1671.

Loughran, Tim, and Bill McDonald, 2015, The Use of Word Lists in Textual Analysis, *Journal of Behavioral Finance* 16, 1–11.

Loughran, Tim, and Bill McDonald, 2016, Textual Analysis in Accounting and Finance: A Survey, *Journal of Accounting Research*.

Lourie, Ben, 2015, The Revolving-Door of Sell-Side Analysts: A Threat to Analystss Independence?, *SSRN Electronic Journal*.

Luo, Miao, Daniel X Jiang, and Jun Cai, 2014, Investor Sentiment, Product Features, and Advertising Investment Sensitivities, *Asia-Pacific Journal of Financial Studies* 43, 798–837.

Malmendier, Ulrike, and Devin Shanthikumar, 2007, Are small investors naive about incentives?, *Journal of Financial Economics* 85, 457–489.

Malmendier, Ulrike, and Devin Shanthikumar, 2014, Do Security Analysts Speak in Two Tongues ?, *Review of Financial Studies*, 1–36.

Matsumoto, Dawn, Maarten Pronk, and Erik Roelofsen, 2011, What makes conference calls useful? The information content of managers' presentations and analysts' discussion sessions, *Accounting Review* 86, 1383–1414.

Mayew, William J., 2008, Evidence of Management Discrimination Among Analysts during Earnings Conference Calls, *Journal of Accounting Research* 46, 627–659.

Mcnichols, Maureen, 1989, Evidence of Informational Asymmetries from Management Earnings Forecasts and Stock Returns, *Accounting Review* 64, p1–27.

Menon, Krishnagopal, and David D. Williams, 2004, Former audit partners and abnormal accruals, *Accounting Review*.

Merkl-Davies, Doris M, and Niamh M Brennan, 2007, Title Discretionary disclosure strategies in corporate narratives : incremental information or impression management ?, *Journal of Accounting Literature* 26, 116–196.

Merkley, Kenneth J., 2014, Narrative Disclosure and Earnings Performance: Evidence from R&D Disclosures, *The Accounting Review* 89, 725–757.

Michaely, Roni, and Kent L. Womack, 1999, Conflict of Interest and the Credibility of Underwriter Analyst Recommendations, *Review of Financial Studies* 12, 653–686.

Mikhail, Michael B., Beverly R. Walther, and Richard H. Willis, 2007, When Security Talk , Analysts Who Listens ?, *The Accounting Review* 82, 1227–1253.

Mikhail, Michael, Beverl Walther, and Richard Willis, 1999, Does Forecast Accuracy Matter to Security Analysts ?, *The Accounting Review* 74, 185–200.

Milgrom, Paul R, 1981, Good news and Bad News: Representation Theorems and Applications, *Bell Journal of Economics* 12, 380–391.

Milian, Jonathan A., 2015, Unsophisticated Arbitrageurs and Market Efficiency: Overreacting to a History of Underreaction?, *Journal of Accounting Research* 53, 175–220.

Miller, Brian P., 2010, The Effects of Reporting Complexity on Small and Large Investor Trading, *The Accounting Review* 85, 2107–2143.

Miller, Gregory S, 2002, Earnings Performance and Discretionary Disclosure, *Journal of Accounting Research* 40, 173–204.

Minutti-Meza, Miguel, 2013, Does auditor industry specialization improve audit quality?, *Journal of Accounting Research* 51, 779–817.

Morgan, By Donald P, 2002, Rating Banks : Risk and Uncertainty in an Opaque Industry, *The American Economic Review* 92, 874–888.

Mujtaba Mian, G., and Srinivasan Sankaraguruswamy, 2012, Investor sentiment and stock market response to earnings news, *Accounting Review* 87, 1357–1384.

Muslu, Volkan, Suresh Radhakrishnan, K. R. Subramanyam, and Dongkuk Lim, 2015, Forward-Looking MD&A Disclosures and the Information Environment, *Management Science* 61, 931–948.

Neuhierl, Andreas, Anna Scherbina, and Bernd Schlusche, 2013, Market Reaction to Corporate Press Releases, *Journal of Financial and Quantitative Analysis* 48, 1207–1240.

Nofsinger, John R., 2005, Social Mood and Financial Economics, *Journal of Behavioral Finance* 6, 144–160.

O'brien, Patricia C., 1988, Analysts' forecasts as earnings expectations, *Journal of Accounting and Economics*.

O'Brien, Patricia C., Maureen F. Mcnichols, and Lin Hsiou-Wei, 2005, Analyst Impartiality and Investment Banking Relationships, *Journal of Accounting Research* 43, 623–650.

O'Brien, Patricia C., Maureen F. Mcnichols, and Hsiou Wei Lin, 2005, Analyst impartiality and investment banking relationships, *Journal of Accounting Research* 43, 623–650.

O'Brien, Patricia C., Maureen F. McNichols, and Hsiou-wei Lin, 2005, Analyst Impartiality and Investment Banking Relationships, *Journal of Accounting Research* 43, 623–650.

Ober, S, and JJ Zhao, 1999, Telling it like it is: The use of certainty in public business discourse, *Journal of Business Communication* 36, 280–300.

Opdyke, Jeff D., 2002, Stock Advice You Can Trust?, *Wall Street Journal*.

Pinello, Arianna Spina, 2008, Investors' Differential Reaction to Positive versus Negative Earnings Surprises, *Contemporary Accounting Research* 25, 891–920.

Price, S. McKay, James S. Doran, David R. Peterson, and Barbara a. Bliss, 2012, Earnings conference calls and stock returns: The incremental informativeness of textual tone, *Journal of Banking & Finance* 36, 992–1011.

Rees, Lynn, Nathan Sharp, and Brady Twedt, 2015, Who's heard on the Street? Determinants and consequences of financial analyst coverage in the business press, *Review of Accounting Studies* 20, 173–209.

Rennekamp, Kristina, 2012, Processing Fluency and Investors' Reactions to

Disclosure Readability, *Journal of Accounting Research* 50, 1319–1354.

Richardson, Scott, Siew Hong Teoh, and Peter D. Wysocki, 2004, The Walk-down to Beatable Analyst Forecasts: The Role of Equity Issuance and Insider Trading Incentives, *Contemporary Accounting Research* 21, 885–924.

Rogers, Jonathan L., Andrew Buskirk, and Sarah L. C. Zechman, 2011, Disclosure Tone and Shareholder Litigation, *The Accounting Review* 86, 2155–2183.

Rogers, Jonathan L., and Phillip C. Stocken, 2005, Credibility of management forecasts, *Accounting Review* 80, 1233–1260.

Rogers, Jonathan L., Andrew Van Buskirk, and Sarah L. C. Zechman, 2011, Disclosure Tone and Shareholder Litigation, *The Accounting Review* 86, 2155–2183.

Rutherford, Brian a., 2003, Obfuscation, textual complexity and the role of regulated narrative accounting disclosure in corporate governance, *Journal of Management and Governance* 7, 187–210.

Schipper, Katherine, 1991, Analysts ' Forecasts, *Ah* 5, 105–121.

Schleicher, Thomas, and Martin Walker, 2010, Bias in the tone of forward-looking narratives, *Accounting and Business Research* 40, 371–390.

Schmeling, Maik, 2009, Investor sentiment and stock returns: Some international evidence, *Journal of Empirical Finance* 16, 394–408.

Schumaker, Robert P., Yulei Zhang, Chun-Neng Huang, and Hsinchun Chen, 2012, Evaluating sentiment in financial news articles, *Decision Support Systems* 53, 458–464.

Securities and Exchange Commission, 2010, Analyzing analyst recommendations., *Available online at http://www.sec.gov/investor/pubs/analysts.htm*.

Seybert, Nicholas, and Holly I Yang, 2012, The Party's Over: The Role of Earnings Guidance in Resolving Sentiment-Driven Overvaluation, *Management Science* 58, 308–319.

Sidhu, Baljit, and Hwee Cheng Tan, 2011, The Performance of Equity Analysts During the Global Financial Crisis, *Australian Accounting Review* 21, 32–43.

Simpson, Ana, 2013, Does Investor Sentiment Affect Earnings Management?, *Journal of Business Finance & Accounting* 40, 869–900.

Smith, Malcolm, and Richard J. Taffler, 2000, The chairman's statement - A

content analysis of discretionary narrative disclosures, *Accounting, Auditing & Accountability Journal* 13, 624–647.

Solomon, David H., Eugene Soltes, and Denis Sosyura, 2014, Winners in the spotlight: Media coverage of fund holdings as a driver of flows, *Journal of Financial Economics* 113, 53–72.

Soltes, Eugene, 2014, Private Interaction Between Firm Management and Sell-Side Analysts, *Journal of Accounting Research* 52, 245–272.

Sorenson, Olav, 2013, Status and reputation: Synonyms or separate concepts?, *Strategic Organization* 12, 62–69.

Sprenger, Timm O., Andranik Tumasjan, Philipp G. Sandner, and Isabell M. Welpe, 2014, Tweets and Trades: the Information Content of Stock Microblogs, *European Financial Management* 20, 926–957.

Stambaugh, Robert F., Jianfeng Yu, and Yu Yuan, 2012, The short of it: Investor sentiment and anomalies, *Journal of Financial Economics* 104, 288–302.

Subramanian, R., R. G. Insley, and R. D. Blackwell, 1993, Performance and Readability: A Comparison of Annual Reports of Profitable and Unprofitable Corporations, *Journal of Business Communication* 30, 49–61.

Tama-Sweet, Isho, 2014, Changes in earnings announcement tone and insider sales, *Advances in Accounting* 30, 276–282.

Taylor, SE, 1991, Asymmetrical effects of positive and negative events: the mobilization-minimization hypothesis., *Psychological bulletin* 110, 67–85.

Tetlock, Paul C, 2007, Giving Content to Investor Sentiment : The Role of Media in the Stock Market, *Journal of finance* LXII, 1139–1168.

Tetlock, Paul C, Maytal Saar-tsechansky, and Sofus Macskassy, 2008, More Than Words : Quantifying Language to Measure Firms ' Fundamentals, *Journal of finance* LXIII, 1437–1467.

Trueman, Brett, 1997, Managerial Disclosures and Shareholder Litigation, *Review of Accounting Studies* 2, 181–199.

Twedt, Brady, and Lynn Rees, 2012, Reading between the lines: An empirical examination of qualitative attributes of financial analysts' reports, *Journal of Accounting and Public Policy* 31, 1–21.

Twedt, Brady, and Lynn Rees, 2012, Reading between the lines: An empirical examination of qualitative attributes of financial analysts' reports, *Journal of*

Accounting and Public Policy 31, 1–21.

Verrecchia, RE, 1983, Discretionary disclosure, *Journal of accounting and economics* 5, 179–194.

Walker, M., 1997, The Economics of Corporate Financial Communication, *ACCA Occasional Working Paper No. 19*.

Walther, Beverly R., and Richard H. Willis, 2013, Do investor expectations affect sell-side analysts' forecast bias and forecast accuracy?, *Review of Accounting Studies* 18, 207–227.

Wang, Gang, Tianyi Wang, Bolun Wang, Divya Sambasivan, Zengbin Zhang, Haitao Zheng, and Ben Y Zhao, 2015, Crowds on Wall Street: Extracting Value from Collaborative Investing Platforms, *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing - CSCW '15* (ACM Press, New York, New York, USA).

Winchel, Jennifer, 2015, Investor Reaction to the Ambiguity and Mix of Positive and Negative Argumentation in Favorable Analyst Reports, *Contemporary Accounting Research* 32, 973–999.

You, Haifeng, and Xiao-jun Zhang, 2009, Financial reporting complexity and investor underreaction to 10-K information, *Review of Accounting Studies* 14, 559–586.

Yu, Jianfeng, and Yu Yuan, 2011, Investor sentiment and the mean–variance relation, *Journal of Financial Economics* 100, 367–381.

Yu, Yang, Wenjing Duan, and Qing Cao, 2013, The impact of social and conventional media on firm equity value: A sentiment analysis approach, *Decision Support Systems* 55, 919–926.

Yuthas, K, R Rogers, and JF Dillard, 2002, Communicative action and corporate annual reports, *Journal of Business Ethics* 41, p141–157.

Appendix I: Variable Definitions

Rel_DFB_{ijt}	=	The difference between the forecast error for analyst *i* for firm *j* at time *t* and the average forecast error of analysts from top brokerage houses following firm *j* at time *t*, scaled by the mean absolute forecast error of top analysts for firm j at time *t*. Forecast error is estimated value for analyst *i* minus actual value of firm *j* at time *t*.
Abs_DFB_{ijt}	=	The absolute forecast bias for firm *j* at time *t* is based on the signed forecast error as a percentage of share price
EMPLOYER	=	An indicator variable which takes the value of one if the forecast is for a firm with a sell-side equity department (investment bank) and zero otherwise.
$Earn\_Std_{jt}$	=	Standard deviation of firm *j*'s prior 5 years earning in year *t.*
$Ln(MV_{jt})$	=	Natural log of the firm *j*'s market value at the end of year *t*.
$Ln(BTM_{jt})$	=	Natural log of the ratio of book value of equity to market value of firm *j* at the end of year *t.*
$Ln(Follow_{jt})$	=	Analysts following, measured as the natural log of analysts following firm *j* in year *t*.
$F\_Horizon_{ijt}$	=	The measure of the time from the forecast date to the end of the fiscal period, calculated as the forecast horizon (days from the forecast date to the fiscal year-end) for analyst *i* following firm *j* in year *t.* When scaling I minus the average forecast horizon for analysts from top brokerage houses who follow firm *j* in year *t*, with this difference scaled by the average forecast horizons for analysts from top brokerage houses following firm *j* in year *t*.
$dayElap_{ijt}$	=	The measure of the days elapsed since the last forecast by an analyst following firm *j* in year *t*. When scaling I calculate it as the days between analysts *i*'s forecast of firm *j*'s earnings in year *t* and the most recent preceding forecast of firm *j*'s earnings by analysts from top brokerage houses, minus the average number of days between two adjacent forecasts of firm *j*'s earnings by any two analysts in year *t*, with this difference scaled by the average days between two adjacent forecasts of firm *j*'s earnings in year *t*.
fr_{ijt}	=	The measure of analyst *i*'s forecast frequency for firm *j*, calculated as the number of firm *j* forecasts made by analyst *i* following firm *j* in year *t*. When scaling I minus the average number of firm *j* forecasts for analysts from top brokerage houses following firm *j* in year *t*, with this difference scaled by the average number of firm *j* forecasts issued by analysts from top brokerage houses following firm *j* in year *t*.
$Firm\_Exp_{ijt}$	=	The measure of analyst *i*'s firm-specific experience, calculated as the number of years of firm-specific experience for analyst *i* following firm *j* in year *t*. When scaling I minus the average number of years of firm-specific experience for analysts from top brokerage houses following firm *j* in year *i*, with this difference scaled by the average years of firm experience for analysts from top brokerage houses following firm *j* in year *t*.
Gen_Exp_{ijt}	=	The measure of analyst *i*'s general experience, calculated as the number of years of experience for analyst *i* following firm *j* in year *t*. When scaling I minus the average number of years of experience for analysts from top

brokerage houses following firm *j* in year *t*, with this difference scaled by the range of years of experience for analysts from top brokerage houses following firm *j* in year *t*.

Num_Co_{ijt} = The measure of the number of companies analyst *i* follows in year *t*, calculated as the number of companies followed by analyst *i* following firm *j* in year *t*. When scaling I minus the average number of companies followed by analysts from top brokerage houses who follow firm *j* in year *t*, with this difference scaled by the average number of companies followed by analysts from top brokerage houses following firm *j* in year *t*.

Num_Ind_{ijt} = The measure of number of industries analyst *i* follows in year *t*, calculated as the number of two-digit SICs followed by analyst *i* following firm *j* in year *t*. When scaling I minus the average number of two-digit SICs followed by analysts from top brokerage houses who follow firm *j* in year *t*, with this difference scaled by the average number of two-digit SICs followed by analysts from top brokerage houses following firm *j* in year *t*.

Num_Ana_{ijt} = The measure of the analyst's brokerage size, calculated as the number of analysts employed by the brokerage house employing analyst *i* following firm *j* in year *t.* When scaling I minus the average number of analysts employed by brokerage houses for analysts following firm *j* in year *t*, with this difference scaled by the average brokerage house size for analysts following firm *j* in year *t*.

$Qspread_{jt}$ = The measure of a firms bid-ask spread is the average quoted spread of firm *j* in effect for transactions during the year ending at *t.*

$jspread_{jt}$ = firm j's average percentage spread (i.e. quote spread divided by the mid-point price) calculated from daily values over year t

$Turnover_{jt}$ = The measure of a firm's turnover is the number of shares traded in firm *j*, divided by the number of shares outstanding at the end of the preceding year, time *t–1*.

$Totalrisk_{jt}$ = The measure of total risk is estimated as the standard deviation of firm *j* of monthly returns (computed on a daily basis).

$zscore_{jt}$ = A proxy for insolvency risk of firm *j* at the end of year *t.* A function of net income, total equity and standard deviation of ROA. See Anolli, et al., 2014, Boyd et al., 1993; Laeven and Levine, 2009. By construction higher values of the Z-score imply lower levels of risk.

ROA_{jt} = The measure of return on asset for firm *j* in year *t* is the net accounting income after taxes divided by total assets.

$accuracy_{ijt}$ = Forecast accuracy. Absolute value of $Rel\_DFB_{ijt.}$

Figure 1
Marginal effects of last forecast bias

Figure 1 shows marginal effects of a unit change in bias for movement upwards or downwards in bank reputation calculated from a probit regression. It separates the effect based on whether analysts forecast earnings of employers or non-employers. Employer is any financial institution with a sell-side equity department where non-employer is any financial institution with no sell-side equity department.

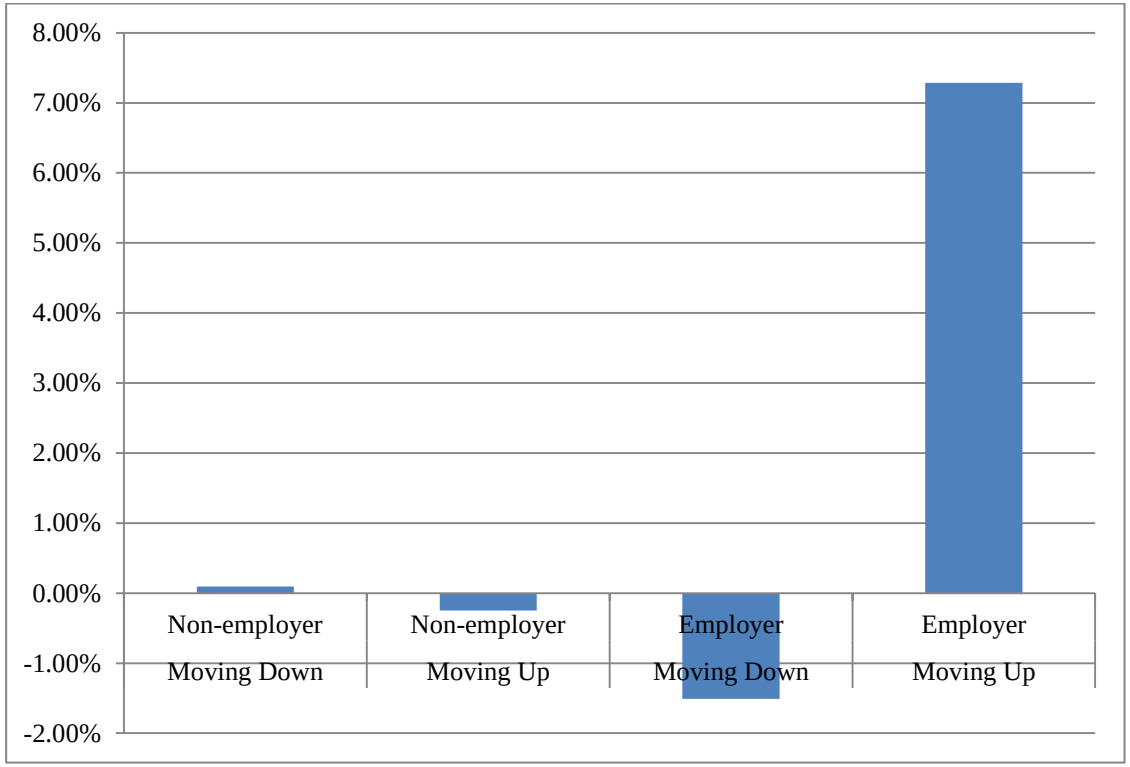


Table 1.1
Descriptive statistics on analyst and firm characteristics

This table reports descriptive statistics for analysts forecast observations from 1999-2006. Analysts and forecast characteristics are derived from detailed I/B/E/S data. My sample is analysts that cover both banks and non-banks. I restrict the sample to forecasts issued no earlier than 1 year and no later than 30 days before the fiscal-year end. And include the last and first forecast issued by the analysts for a particular firm in each sample year. The firm characteristics are *Earn_Std*, earnings dispersion; *MV,* the market capitalization; *BTM*, the book to market and *Follow*, the number of analysts covering the firm. The analyst characteristics are *F_Horizon*, the number of days from the forecast date to the fiscal year-end; *dayElap*, the number of days since any analyst's prior forecast; *fr*, forecast frequency; *Firm_Exp*, the analyst's years of experience forecasting a particular firm's earnings; *Gen_Exp*, the analyst's overall years of forecasting experience; *Num_Co*, the number of companies the analyst follows in each year; *Num_Ind*, the number of two-digit SIC industries the analyst follows in each year, and *Num_Ana*, the number of analysts in the analyst's brokerage house each year. Panel A reports the descriptive statistics for raw (unscaled) forecast and analyst characteristics. Panel B reports the descriptive statistic for forecast and analyst characteristics, including relative forecast (*Rel_DFB*), that are scaled to range from 0 to 1 for each firm-year. Panel C reports correlations among scaled characteristics.

Panel A: Distribution of raw unscaled forecast and analyst characteristics

	Full Sample						***Employer***			***Non Employer***		
Variable	*n*	*Mean*	*S.D.*	*25th Q*	*Median*	*75th Q*	*n*	*Mean*	*S.D.*	n	*Mean*	*S.D.*
Abs_DFB(first forecast)	3778	0.23	1.42	-0.23	-0.02	0.29	1956	0.32	1.60	1876	0.16	1.28
Abs_DFB(last forecast)	3832	0.05	0.59	-0.09	-0.01	0.04	1956	0.03	0.34	1876	-0.01	0.4
Earn_Std	3832	0.08	0.04	0.05	0.07	0.1	1956	0.04	0.07	1876	0.08	0.05
MV	3832	29104.77	36537.10	7944.98	16074.45	36017.57	1956	38255.28	43019.42	1876	19859.05	25385.64
BTM	3832	0.45	0.21	0.32	0.44	0.55	1956	0.45	0.18	1876	0.45	0.24
Follow	3832	24.39	6.28	21.00	25.00	28.00	1956	25.12	6.69	1876	23.63	5.73
F_Horizon	3832	288.54	74.75	264.00	300.00	358.00	1956	289.77	75.32	1876	287.26	74.15
dayElap	3832	5.65	11.31	0.00	1.00	6.00	1956	5.63	11.95	1876	5.67	10.6
fr	3832	4.17	2.08	3.00	4.00	5.00	1956	4.28	2.10	1876	4.05	2.05
Firm_Exp	3832	4.50	3.83	2.00	3.00	6.00	1956	4.4	3.75	1876	4.61	3.92
Gen_Exp	3832	8.09	5.10	4.00	7.00	11.00	1956	7.86	4.79	1876	8.33	5.38
Num_Co	3832	21.27	12.84	13.00	18.00	25.00	1956	20.38	11.07	1876	22.19	14.4
Num_Ind	3832	2.29	1.74	1.00	2.00	3.00	1956	2.04	1.45	1876	2.55	1.96
Num_Ana	3832	42.17	28.21	20.00	35.00	57.00	1956	41.63	28.07	1876	42.74	28.36

Panel B: Distribution of scaled forecast and analyst characteristics (n=3652)

Variable	***Mean***	***S.D.***	***25th Q***	***Median***	***75th Q***
Rel_DFB (first forecast)	-0.07	1.99	-0.50	0.00	0.37
Rel_DFB (last forecast)	0.06	4.19	-1.00	-0.20	0.60
Ln(MV)	9.70	1.13	8.95	9.67	10.49
Ln(BTM)	-0.84	0.77	-1.13	-0.80	-0.58
Ln(Follow)	3.15	0.31	3.04	3.22	3.33
F_Horizon	0.02	0.29	-0.13	0.04	0.18
dayElap	1.71	15.89	-1.00	-0.82	0.50
fr	71.22	30.25	50.11	67.10	88.18
Firm_Exp	0.08	0.99	-0.60	-0.20	0.37
Gen_Exp	0.08	0.80	-0.49	-0.13	0.47
Num_Co	0.27	0.83	-0.20	0.08	0.49
Num_Ind	0.44	0.99	-0.14	0.00	0.78
Num_Ana	-0.75	0.16	-0.89	-0.79	-0.64

Panel C: Correlations among scaled forecast, firm characteristics and analysts characteristics

Below the diagonal I present correlations for the last forecast bias (*Rel_DFB*) and above the diagonal I present the correlations for the first forecast bias (*Rel_DFB*) all variables are adjusted for firm-year effects where necessary. The *p*-values are reported below the correlations in parentheses. All variable definitions are as reported in the Appendix I above.

	Rel_DFB	*EMPLOYER*	*Earn_Std*	*Ln(MV)*	*Ln(BTM)*	*Ln(Follow)*	*F_Horizon*	*dayElap*	*fr*	*Firm_Exp*	*Gen_Exp*	*Num_Co*	*Num_Ind*	*Num_Ana*
Rel_DFB		0.004	0.103	-0.020	-0.045	0.038	0.110	0.028	0.062	0.015	0.009	0.010	-0.016	0.005
		(0.007)	(<0.001)	(0.276)	(0.012)	(0.035)	(<0.001)	(0.125)	(<0.001)	(0.392)	(0.631)	(0.569)	(0.377)	(0.785)
EMPLOYER	-0.035		-0.067	0.223	0.060	0.085	0.014	-0.002	-0.065	0.024	-0.046	-0.044	0.041	-0.016
	(0.047)		(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.413)	(0.902)	(<0.001)	(0.142)	(0.005)	(0.007)	(0.020)	(0.324)
Earn_Std	0.081	-0.057		-0.163	-0.244	0.041	0.050	0.000	0.089	-0.001	-0.003	-0.013	-0.011	0.139
	(<0.001)	(0.001)		(<0.001)	(<0.001)	(0.021)	(0.005)	(0.984)	(<0.001)	(0.956)	(0.876)	(0.456)	(0.522)	(<0.001)
Ln(MV)	-0.027	0.285	-0.160		-0.025	0.545	0.067	-0.021	-0.046	-0.100	-0.146	-0.015	0.012	-0.001
	(0.117)	(<0.001)	(<0.001)		(0.155)	(<0.001)	(<0.001)	(0.238)	(0.011)	(<0.001)	(<0.001)	(0.419)	(0.486)	(0.946)
Ln(BTM)	-0.047	0.095	-0.186	-0.034		0.116	-0.026	-0.014	-0.146	-0.001	-0.038	0.020	0.018	-0.126
	(0.006)	(<0.001)	(<0.001)	(0.051)		(<0.001)	(0.145)	(0.428)	(<0.001)	(0.964)	(0.032)	(0.268)	(0.309)	(<0.001)
Ln(Follow)	0.031	0.217	0.030	0.553	0.108		0.012	-0.017	-0.009	-0.084	-0.129	-0.032	-0.020	0.012
	(0.072)	(<0.001)	(0.075)	(<0.001)	(<0.001)		(0.497)	(0.333)	(0.620)	(<0.001)	(<0.001)	(0.072)	(0.271)	(0.495)
F_Horizon	0.086	0.059	0.066	0.084	-0.015	0.018		-0.090	0.583	0.029	0.031	0.011	0.113	-0.025
	(<0.001)	(0.001)	0.0001	(<0.001)	(0.377)	(0.294)		(<0.001)	(<0.001)	(0.106)	(0.085)	(0.530)	(<0.001)	(0.169)
dayElap	0.029	0.023	-0.004	-0.020	-0.012	-0.021	-0.093		-0.078	0.072	0.081	0.028	0.026	-0.034
	(0.099)	(0.192)	(0.808)	(0.248)	(0.494)	(0.232)	(<0.001)		(<0.001)	(<0.001)	(<0.001)	(0.112)	(0.154)	(0.055)
fr	0.067	-0.053	0.078	-0.049	-0.139	0.010	0.559	-0.075		0.065	0.074	0.059	0.029	0.007
	(<0.001)	(0.003)	(<0.001)	(0.005)	(<0.001)	(0.579)	(<0.001)	(<0.001)		(<0.001)	(<0.001)	(0.001)	(0.107)	(0.688)
Firm_Exp	0.016	0.011	-0.012	-0.119	0.000	-0.106	0.011	0.076	0.065		0.606	0.174	0.029	0.002
	(0.354)	(0.537)	(0.490)	(<0.001)	(0.986)	(<0.001)	(0.531)	(<0.001)	(<0.001)		0.000	(<0.001)	(0.104)	(0.904)
Gen_Exp	0.013	-0.054	-0.016	-0.161	-0.036	-0.146	0.024	0.085	0.082	0.603		0.276	0.051	0.069
	(0.453)	(0.002)	(0.341)	(<0.001)	(0.036)	(<0.001)	(0.156)	(<0.001)	(<0.001)	(<0.001)		(<0.001)	(0.004)	0.0001
Num_Co	0.017	-0.031	-0.025	-0.031	0.023	-0.053	0.001	0.035	0.057	0.173	0.293		0.403	-0.026
	(0.315)	(0.074)	(0.152)	(0.076)	(0.187)	(0.002)	(0.942)	(0.043)	(0.001)	(<0.001)	(<0.001)		(<0.001)	(0.149)
Num_Ind	-0.019	0.040	-0.004	0.009	0.014	-0.042	0.106	0.030	0.013	0.031	0.060	0.401		-0.095
	(0.274)	(0.022)	(0.838)	(0.601)	(0.402)	(0.014)	(<0.001)	(0.085)	(0.456)	(0.072)	0.0004	(<0.001)		(<0.001)
Num_Ana	0.002	-0.018	0.150	-0.001	-0.116	0.000	-0.025	-0.034	-0.002	0.000	0.060	-0.018	-0.095	
	(0.932)	(0.294)	(<0.001)	(0.953)	(<0.001)	(0.988)	(0.151)	(0.050)	(0.899)	(0.997)	(<0.001)	(0.281)	(<0.001)	

Table 1.2

Comparing forecast bias of bank-analysts first and last yearly earnings forecast

$$DFB_{ijt}=\alpha+\beta_1 EMPLOYER+\beta_2 Earn\_Std+\beta_3 Ln(MV_{ijt})+\beta_4 Ln(BTM_{ijt})+\beta_5 Ln(Follow_{ijt})+\beta_6 F\_Horizon_{ijt}+\beta_7 dayElap_{ijt}+\beta_8 fr_{ijt}+\beta_9 Firm\_Exp_{it}+\beta_{10} Gen\_Exp_{ijt}+\beta_{11} Num\_Co_{ijt}+\beta_{12} Num\_Ind_{ijt}+\beta_{13} Num\_Ana_{ijt}+\beta_{14} Year\_F.E+\varepsilon_{ijt}$$

Panel A: Full Sample

Dependent Variable	***Rel_DFB***		***Abs_DFB***	
	(1)	(2)	(3)	(4)
	First Forecast	*Last Forecast*	*First Forecast*	*Last Forecast*
Constant	-0.308	-4.321**	-1.879***	0.008
	(-0.61)	(-2.21)	(-5.05)	(0.02)
EMPLOYER	**0.177****	**-0.369***	**0.127*****	**-0.186*****
	(2.57)	**(-1.72)**	**(2.76)**	**(-2.78)**
Earn_Std	-0.005	17.704***	8.698***	2.277***
	(-0.00)	(3.07)	(7.40)	(6.10)
Ln(MV)	-0.011	-0.314**	-0.051	0.300**
	(-0.26)	(-2.41)	(-1.64)	(2.10)
Ln(BTM)	0.050	-0.581**	0.317***	-0.619***
	(0.83)	(-2.03)	(5.41)	(-3.98)
Ln(Follow)	0.182	1.898***	0.182	1.898***
	(1.33)	(3.39)	(1.33)	(3.39)
F_Horizon	0.731***	0.809**	0.000	0.002***
	(4.47)	(2.45)	(1.14)	(2.58)
dayElap	0.000	0.031	-0.002	0.004
	(0.20)	(1.32)	(-0.95)	(1.64)
fr	-0.001	-0.011	0.060***	0.037
	(-0.77)	(-1.00)	(3.97)	(1.18)
Firm_Exp	-0.015	0.158	0.034***	-0.007
	(-0.44)	(0.88)	(3.93)	(-0.58)
Gen_Exp	0.017	-0.106	-0.010*	0.016
	(0.43)	(-0.52)	(-1.90)	(1.25)
Num_Co	0.004	0.385	0.001	-0.017***
	(0.09)	(1.59)	(0.44)	(-3.80)
Num_Ind	0.036	-0.504***	-0.054***	0.139***
	(1.13)	(-2.93)	(-2.79)	(3.19)
Num_Ana	0.055	-1.237	0.055	-1.237
	(0.25)	(-1.59)	(0.25)	(-1.59)
Year_F.E	Yes	Yes	Yes	Yes
Observations	3652	3225	3778	3832
Adjusted R^2	0.90%	1.00%	20.2%	8.9%

This table reports the ordinary least squares estimation results using two alternative measures of forecast bias; relative and absolute, for the period 1999-2006. First forecast is the initial forecast analyst *i* issued for firm *j* in year *t* and last forecast is the last forecast revision analyst *i* issued for firm *j* in year *t*. Heteroskedasticity-robust standard errors are clustered by analyst. *t*-statistics are reported in parentheses. *,**,and***represent significance level of 10%, 5%, and 1%, respectively (two-tailed). All variable definitions are as reported in the Appendix I.

Panel B: Banks Only Sample

Dependent Variable	***Rel_DFB***		***Abs_DFB***	
	(1)	(2)	(3)	(4)
	First Forecast	*Last Forecast*	*First Forecast*	*Last Forecast*
Constant	-0.453	-3.046	-2.235***	-0.104
	(-0.82)	(-1.57)	(-5.54)	(-0.20)
EMPLOYER	**0.182****	**-0.430****	**0.141*****	**-0.272*****
	(2.51)	**(-2.06)**	**(3.03)**	**(-3.32)**
Earn_Std	-0.080	15.009**	9.125***	0.430
	(-0.07)	(2.39)	(7.19)	(0.87)
Ln(MV)	-0.016	-0.402***	-0.041	0.305*
	(-0.34)	(-2.99)	(-1.27)	(1.88)
Ln(BTM)	0.006	-0.758**	0.323***	-0.654***
	(0.08)	(-2.18)	(4.74)	(-3.99)
Ln(Follow)	0.206	2.089***	0.206	2.089***
	(1.36)	(3.24)	(1.36)	(3.24)
F_Horizon	0.788***	0.950***	0.000	0.003**
	(4.41)	(2.70)	(0.87)	(2.56)
dayElap	0.000	0.046*	-0.001	0.005*
	(0.17)	(1.90)	(-0.55)	(1.75)
fr	-0.001	-0.023*	0.059***	0.030
	(-0.59)	(-1.93)	(3.75)	(0.89)
Firm_Exp	-0.035	0.107	0.027***	-0.008
	(-1.04)	(0.57)	(2.98)	(-0.66)
Gen_Exp	-0.000	-0.123	-0.008	0.019
	(-0.01)	(-0.59)	(-1.47)	(1.30)
Num_Co	0.019	0.308	0.001	-0.018***
	(0.43)	(1.29)	(0.62)	(-3.64)
Num_Ind	0.056	-0.601***	-0.083***	0.207***
	(1.54)	(-3.53)	(-3.96)	(3.16)
Num_Ana	0.000	-0.935	0.000	-0.935
	(0.00)	(-1.30)	(0.00)	(-1.30)
Year_F.E	Yes	Yes	Yes	Yes
Observations	3327	2956	3427	3488
Adjusted R^2	1.0%	2.7%	21.8%	9.8%

This table reports the ordinary least squares estimation results using two alternative measures of forecast bias; relative and absolute for the banking only sample 1999-2006. First forecast is the initial forecast analyst *i* issued for firm *j* in year *t* and last forecast is the last forecast revision analyst *i* issued for firm *j* in year *t*. Heteroskedasticity-robust standard errors are clustered by analyst. *t*-statistics are reported in parentheses. *,**,and***represent significance level of 10%, 5%, and 1%, respectively (two-tailed). All variable definitions are as reported in the Appendix I.

Table 1.3:

Propensity Score Matching Results

Panel A: Effects of propensity score matching: Full sample (*Rel_DFB)*

	Unmatched				Matched			
	Employer	Non-Employer	%Bias	t-test	Employer	Non-Employer	%Bias	t-test
Variable	Mean	Mean			Mean	Mean		
First Forecast								
Market								
Value	38657	17919	63.9	20.70***	25182	24876	0.9	0.33
BTM	0.4695	0.4756	-2.6	-0.85	0.4630	0.4489	6.1	1.83*
Follow	25.082	23.091	32.3	10.50***	24.227	24.007	3.6	1.05
Firm_Exp	4.5212	4.5613	-1.1	-0.35	4.4771	4.4211	1.5	0.45
Qspread	0.1523	0.1625	-4.7	-1.52	0.1587	0.1529	2.6	0.77
Turnover	1.3313	1.5254	-18.3	-5.96***	1.3808	1.3774	0.3	0.10
Total Risk	0.0701	0.0780	-20.2	-6.59***	0.0734	0.0695	9.8	3.18***
Zscore	382.89	317.11	12.4	4.02***	358.68	356.05	0.5	0.15
Last Forecast								
Market								
Value	39946	17951	69.1	19.52***	22628	23441	-2.6	-1.02
BTM	0.4472	0.4338	8.0	2.28**	.43958	0.4276	7.1	1.77*
Follow	26.342	23.601	49.8	14.14***	25.142	24.973	3.1	0.83
Firm_Exp	4.5570	4.6996	-3.8	-1.07	4.4663	4.5394	-1.9	-0.48
Qspread	0.1679	0.1715	-1.6	-0.45	.16879	0.1818	-5.6	-1.32
Turnover	1.1692	1.3459	-21.2	-6.03***	1.2762	1.2627	1.6	0.43
Total Risk	0.0706	0.0770	-16.6	-4.71***	.07522	0.0729	5.9	1.53
Zscore	394.35	312.90	18.5	5.26***	359.35	348.91	2.4	0.53

Panel B: Effects of propensity score matching: Bank only sample (*Rel_DFB*)

	Unmatched				Matched			
	Employer	Non-Employer	%Bias	t-test	Employer	Non-Employer	%Bias	t-test
Variable	Mean	Mean			Mean	Mean		
First Forecast								
Market Value	39111	17936	65.8	19.24***	21960	21800	0.5	0.24
BTM	0.4696	0.4700	-0.2	-0.06	0.4574	0.4678	-4.6	-1.30
Follow	25.395	23.672	29.7	8.96***	24.411	23.923	8.4	2.41**
Firm_Exp	4.6106	4.2758	9.2	2.78***	4.4831	4.5482	-1.8	-0.50
Qspread	0.1492	0.1668	-8.0	-2.45**	0.1567	0.1482	3.9	1.15
Turnover	1.2877	1.5092	-21.1	-6.49***	1.3507	1.3681	-1.7	-0.51
Total Risk	0.0685	0.0773	-22.8	-6.99***	0.0725	0.0702	5.9	1.85*
Zscore	394.42	352.5	7.5	2.26**	379.96	347.14	5.9	1.66*
ROA	0.0219	0.0279	-14.1	-4.26***	0.0243	0.0249	-1.3	-0.38
Last Forecast								
Market Value	39952	18244	68.3	17.68***	19987	21241	-3.9	-1.90*
BTM	0.4485	0.4226	16.4	4.38***	0.4397	0.4303	5.9	1.37
Follow	26.496	24.121	45.4	12.10***	25.229	24.893	6.4	1.64
Firm_Exp	4.6331	4.3905	6.6	1.76*	4.5241	4.5751	-1.4	-0.32
Qspread	0.1634	0.1720	-3.7	-1.00	0.1570	0.1764	-8.4	-2.00**
Turnover	1.1309	1.3356	-24.9	-6.74***	1.2285	1.2636	-4.3	-1.06
Total Risk	0.0696	0.0765	-17.6	-4.75***	0.0741	0.0739	0.5	0.12
Zscore	404.85	346.45	12.8	3.41***	369.41	371.78	-0.5	-0.11
ROA	0.0204	0.0270	-17.0	-4.52***	0.0218	0.0239	-5.2	-1.22

Panel C: Full Sample

$$DFB_{ijt}=\alpha+\beta_1 EMPLOYER+\beta_2 Earn\_Std+\beta_3 Ln(MV_{ijt})+\beta_4 Ln(BTM_{ijt})+\beta_5 Ln(Follow_{ijt})+\beta_6 F\_Horizon_{ijt}+\beta_7 dayElap_{ijt}+\beta_8 fr_{ijt}+\beta_9 Firm\_Exp_{it}+\beta_{10} Gen\_Exp_{ijt}+\beta_{11} Num\_Co_{ijt}+\beta_{12} Num\_Ind_{ijt}+\beta_{13} Num\_Ana_{ijt}+\beta_{14} Year\_F.E+\varepsilon_{ijt}$$

Dependent Variable	***Rel_DFB***		***Abs_DFB***	
	(1)	(2)	(3)	(4)
	First Forecast	*Last Forecast*	*First Forecast*	*Last Forecast*
Constant	0.251	-0.963	-2.242***	-0.314
	(0.39)	(-0.31)	(-4.60)	(-0.16)
EMPLOYER	**0.204****	**-0.752****	**0.213*****	**-0.386****
	(2.47)	**(-2.07)**	**(3.68)**	**(-2.04)**
Earn_Std	0.705	16.439*	8.375***	6.439*
	(0.50)	(1.96)	(4.34)	(1.72)
Ln(MV)	0.019	-0.478**	0.004	-0.420**
	(0.30)	(-2.39)	(0.08)	(-2.43)
Ln(BTM)	0.018	-0.457	0.344***	-0.057
	(0.23)	(-0.79)	(4.50)	(-0.21)
Ln(Follow)	-0.060	1.102	0.469***	1.106*
	(-0.32)	(1.14)	(2.87)	(1.96)
F_Horizon	1.071***	0.616**	0.000	0.329*
	(5.50)	(2.28)	(0.83)	(1.77)
dayElap	0.007	0.052**	-0.003	0.019
	(0.90)	(2.16)	(-0.98)	(0.76)
fr	-0.002	0.016	0.064***	0.004
	(-0.75)	(1.44)	(3.40)	(0.52)
Firm_Exp	-0.039	0.267	0.029***	0.124
	(-0.88)	(1.39)	(2.60)	(1.23)
Gen_Exp	0.061	-0.445**	-0.001	-0.256*
	(1.07)	(-2.13)	(-0.13)	(-1.74)
Num_Co	-0.062	-0.244	-0.000	-0.047
	(-0.62)	(-0.97)	(-0.02)	(-0.25)
Num_Ind	0.060	-0.310*	-0.072***	0.032
	(1.10)	(-1.66)	(-2.84)	(0.22)
Num_Ana	0.189	-0.546	-0.001	0.436
	(0.71)	(-0.71)	(-0.61)	(0.78)
Year_F.E	Yes	Yes	Yes	Yes
Observations	2335	1920	2424	1980
Adjusted R^2	1.90%	2.70%	20.3%	1.80%

This table reports the ordinary least squares estimation results using two measure of forecast bias, relative and absolute, for the years 1999-2006. First forecast is the initial forecast analyst *i* issued for firm *j* in year *t* and last forecast is the last forecast revision analyst *i* issued for firm *j* in year *t*. Heteroskedasticity-robust standard errors are clustered by analyst. *t*-statistics are reported in parentheses. *,**,and***represent significance level of 10%, 5%, and 1%, respectively (two-tailed). All variable definitions are as reported in the Appendix I.

Panel D: Banking Only Sample

Dependent Variable	***Rel_DFB***		***Abs_DFB***	
	(1)	(2)	(3)	(4)
	First Forecast	*Last Forecast*	*First Forecast*	*Last Forecast*
Constant	-0.100	0.530	-3.503***	-0.181
	(-0.15)	(0.24)	(-7.00)	(-0.10)
EMPLOYER	**0.209*** **	**-0.760** **	**0.210*** **	**-0.419* **
	(2.60)	**(-2.41)**	**(3.43)**	**(-1.80)**
Earn_Std	-1.278	27.602*	8.778***	12.297***
	(-0.96)	(1.85)	(3.58)	(2.82)
Ln(MV)	-0.036	-0.587**	0.102*	-0.658***
	(-0.64)	(-2.53)	(1.74)	(-3.94)
Ln(BTM)	-0.145*	-1.377**	0.286***	-0.314
	(-1.69)	(-2.17)	(3.38)	(-1.08)
Ln(Follow)	0.274	1.119	0.564***	1.336**
	(1.54)	(1.38)	(4.02)	(2.41)
F_Horizon	1.059***	0.900***	0.000	0.362*
	(5.13)	(3.10)	(0.01)	(1.87)
dayElap	0.010	0.040	-0.000	0.071***
	(1.21)	(1.63)	(-0.04)	(2.64)
fr	-0.003	-0.001	0.064***	-0.003
	(-1.23)	(-0.11)	(2.77)	(-0.36)
Firm_Exp	-0.123***	0.001	0.020	-0.105
	(-2.89)	(0.01)	(1.64)	(-0.71)
Gen_Exp	0.069	-0.679**	-0.017*	-0.084
	(1.21)	(-2.01)	(-1.87)	(-0.52)
Num_Co	-0.040	0.030	0.005*	0.223
	(-0.48)	(0.13)	(1.68)	(0.93)
Num_Ind	0.070	-0.535**	-0.101***	-0.191
	(1.30)	(-2.20)	(-3.27)	(-1.30)
Num_Ana	0.344	-0.944	-0.001	-0.818
	(1.23)	(-1.27)	(-0.55)	(-1.18)
Year_F.E	Yes	Yes	Yes	Yes
Observations	2118	1792	2188	1858
Adjusted R^2	2.1%	5.4%	22.0%	4.4%

This table reports the ordinary least squares estimation results using two forecast bias measures: relative and absolute for a sub-sample of banks for the years 1999-2006. First forecast is the initial forecast analyst *i* issued for firm *j* in year *t* and last forecast is the last forecast revision analyst *i* issued for firm *j* in year *t*. Heteroskedasticity-robust standard errors are clustered by analyst. *t*-statistics are reported in parentheses. *,**,and***represent significance level of 10%, 5%, and 1%, respectively (two-tailed). All variable definitions are as reported in the Appendix I.

Table 1.4:

Non-Linear Variables: Full Sample

	Relative Forecast Bias		*Absolute Forecast Bias*	
	(1)	(2)	(3)	(4)
Dependent Variable	*First Forecast Rel_DFB*	*Last Forecast Rel_DFB*	*First Forecast Abs_DFB*	*Last Forecast Abs_DFB*
Constant	0.278	2.119***	0.139	0.263***
	(1.03)	(3.58)	(0.79)	(3.76)
EMPLOYER	**0.214*** **	**-0.296** **	**0.103** **	**-0.029* **
	(3.04)	**(-2.01)**	**(2.10)**	**(-1.68)**
Earn_Std_Q1	0.058	-0.534**	-0.299***	-0.126***
	(0.50)	(-2.33)	(-3.66)	(-3.07)
Earn_Std_Q2	0.156*	-0.540**	-0.447***	-0.160***
	(1.69)	(-2.46)	(-5.05)	(-4.29)
Earn_Std_Q3	-0.127	-0.278	-0.395***	-0.163***
	(-1.31)	(-1.09)	(-4.43)	(-4.25)
Earn_Std_Q4	-0.200*	-0.384	-0.225**	-0.192***
	(-1.82)	(-1.64)	(-2.19)	(-4.98)
Ln(MV)_Q1	-0.119	0.029	-0.025	-0.023
	(-0.94)	(0.10)	(-0.27)	(-0.58)
Ln(MV)_Q2	0.005	0.551*	-0.085	-0.025
	(0.04)	(1.91)	(-1.01)	(-0.73)
Ln(MV)_Q3	-0.002	0.657**	-0.237***	-0.008
	(-0.02)	(2.43)	(-3.19)	(-0.21)
Ln(MV)_Q4	-0.093	-0.195	-0.087	0.063*
	(-0.73)	(-0.69)	(-1.03)	(1.74)
Ln(BTM)_Q1	0.028	0.073	-0.105	0.046**
	(0.25)	(0.30)	(-1.44)	(2.11)
Ln(BTM)_Q2	0.004	-0.155	-0.087	0.013
	(0.03)	(-0.64)	(-1.10)	(0.54)
Ln(BTM)_Q3	0.163	-0.350	-0.066	0.025
	(1.49)	(-1.51)	(-0.81)	(0.72)
Ln(BTM)_Q4	-0.025	-0.158	0.001	0.056*
	(-0.28)	(-0.54)	(0.01)	(1.88)
Ln(Follow)_Q1	-0.023	-0.468*	-0.124	-0.131***
	(-0.17)	(-1.65)	(-1.35)	(-3.50)
Ln(Follow)_Q2	0.127	-0.584**	-0.005	-0.100***
	(1.03)	(-2.08)	(-0.06)	(-2.82)
Ln(Follow)_Q3	-0.007	-0.058	0.247***	-0.038
	(-0.05)	(-0.22)	(3.21)	(-1.31)
Ln(Follow)_Q4	0.139	-0.229	0.540***	-0.014
	(1.01)	(-0.81)	(6.73)	(-0.42)
F_Horizon_Q1	-0.683***	-0.901***	-0.551***	-0.168***
	(-4.85)	(-2.70)	(-7.31)	(-4.66)
F_Horizon_Q2	-0.329***	-0.786***	-0.183***	-0.157***
	(-3.04)	(-2.68)	(-2.68)	(-4.54)
F_Horizon_Q3	-0.112	-0.483*	-0.052	-0.146***
	(-1.00)	(-1.69)	(-0.84)	(-4.82)
F_Horizon_Q4	-0.148	-0.621**	0.064	-0.108***
	(-1.30)	(-2.25)	(0.91)	(-3.63)
dayElap_Q1	0.039	-0.478**	0.022	-0.004
	(0.39)	(-2.34)	(0.41)	(-0.18)
dayElap_Q2	-0.167	-0.485	0.340	-0.189*
	(-0.73)	(-0.76)	(1.36)	(-1.93)
dayElap_Q3	-0.107	-0.574**	-0.030	-0.014
	(-0.96)	(-2.14)	(-0.45)	(-0.52)

dayElap_Q4	0.060	-0.471**	0.050	-0.032
	(0.52)	(-1.99)	(0.78)	(-1.29)
fr_Q1	0.234*	0.184	0.724***	0.107***
	(1.65)	(0.55)	(7.68)	(2.95)
fr_Q2	0.157	-0.140	0.827***	0.064**
	(1.36)	(-0.57)	(9.95)	(2.15)
fr_Q3	0.209*	0.091	0.204***	0.031
	(1.74)	(0.32)	(3.41)	(1.15)
fr_Q4	0.311**	0.353	0.140***	0.068**
	(2.42)	(1.22)	(2.69)	(2.27)
Firm_Exp_Q1	0.016	-0.049	-0.235***	-0.031
	(0.13)	(-0.17)	(-3.03)	(-1.06)
Firm_Exp_Q2	0.108	-0.357	-0.102	-0.053*
	(0.91)	(-1.48)	(-1.35)	(-1.82)
Firm_Exp_Q3	0.051	0.035	-0.154**	-0.017
	(0.47)	(0.15)	(-1.97)	(-0.59)
Firm_Exp_Q4	-0.139	0.143	-0.175**	-0.074***
	(-1.30)	(0.61)	(-2.42)	(-3.03)
Gen_Exp_Q1	-0.172	0.145	-0.001	-0.006
	(-1.40)	(0.53)	(-0.01)	(-0.20)
Gen_Exp_Q2	-0.092	-0.090	0.117	0.008
	(-0.80)	(-0.37)	(1.59)	(0.29)
Gen_Exp_Q3	0.032	0.004	-0.007	-0.013
	(0.31)	(0.02)	(-0.10)	(-0.51)
Gen_Exp_Q4	-0.058	0.271	-0.009	-0.004
	(-0.64)	(1.26)	(-0.12)	(-0.16)
Num_Co_Q1	0.021	0.150	0.056	-0.022
	(0.18)	(0.57)	(0.72)	(-0.83)
Num_Co_Q2	0.002	-0.421	0.133*	0.026
	(0.02)	(-1.62)	(1.73)	(0.94)
Num_Co_Q3	-0.063	-0.265	0.141*	0.019
	(-0.54)	(-1.12)	(1.87)	(0.71)
Num_Co_Q4	-0.177	-0.041	0.018	-0.016
	(-1.52)	(-0.17)	(0.28)	(-0.69)
Num_Ind_Q1	-0.214*	0.333	-0.121	-0.018
	(-1.92)	(1.34)	(-1.58)	(-0.70)
Num_Ind_Q2	-0.219*	0.307	0.031	-0.051*
	(-1.89)	(1.16)	(0.40)	(-1.91)
Num_Ind_Q3	0.124	0.563*	-0.099	-0.029
	(1.07)	(1.86)	(-1.16)	(-0.96)
Num_Ind_Q4	-0.063	0.289	-0.039	-0.053**
	(-0.58)	(1.15)	(-0.50)	(-1.97)
Num_Ana_Q1	-0.035	0.060	0.141*	0.002
	(-0.34)	(0.27)	(1.82)	(0.10)
Num_Ana_Q2	-0.013	0.106	0.040	0.009
	(-0.13)	(0.46)	(0.58)	(0.33)
Num_Ana_Q3	-0.002	-0.068	0.017	-0.002
	(-0.02)	(-0.32)	(0.25)	(-0.06)
Num_Ana_Q4	-0.075	-0.119	-0.076	-0.009
	(-0.75)	(-0.59)	(-1.15)	(-0.38)
Year_F.E	Yes	Yes	Yes	Yes
Observations	3652	3225	3778	3832
Adjusted R^2	2.0%	1.90%	23.0%	9.4%

This table reports the ordinary least squares estimation results using two forecast bias measures: relative and absolute for a sub-sample of banks for the years 1999-2006. All independent variables (except dummy variable EMPLOYER) are in quintile (i.e. non-linear independent variables). First forecast is the initial forecast analyst *i* issued for firm *j* in year *t* and last forecast is the last forecast revision analyst *i* issued for firm *j* in year *t*. Heteroskedasticity-robust standard errors are clustered by analyst. *t*-statistics are reported in parentheses. *,**,and***represent significance level of 10%, 5%, and 1%, respectively (two-tailed). All variable definitions are as reported in the Appendix I.

Table 1.5

Panel A: Comparing forecast bias of analysts who follow investment banks and non-banks before and after the Global Settlement

$$Rel\_DFB_{ijt} = \alpha + \beta_1 EMPLOYER + \beta_2 Earn\_Std + \beta_3 Ln(MV_{ijt}) + \beta_4 Ln(BTM_{ijt}) + \beta_5 Ln(Follow_{ijt}) + \beta_6 F\_Horizon_{ijt} + \beta_7 dayElap_{ijt} + \beta_8 fr_{ijt} + \beta_9 Firm\_Exp_{it} + \beta_{10} Gen\_Exp_{ijt} + \beta_{11} Num\_Co_{ijt} + \beta_{12} Num\_Ind_{ijt} + \beta_{13} Num\_Ana_{ijt} + \beta_{14} Year\ F.E + \varepsilon_{ijt}$$

	Before Global Settlement		*After Global Settlement*	
	First Forecast	*Last Forecast*	*First Forecast*	*Last Forecast*
	(1)	(2)	(3)	(4)
Constant	-0.063	-1.126	0.122	-1.954
	(-0.08)	(-0.66)	(0.11)	(-0.74)
EMPLOYER	**0.050**	**-0.092**	**0.236***	**-0.554***
	(0.46)	**(-0.40)**	**(1.87)**	**(-1.68)**
Earn_Std	0.094	4.223	-0.219	7.416*
	(0.07)	(0.86)	(-0.07)	(1.70)
Ln(MV)	-0.028	0.051	-0.031	-0.272
	(-0.49)	(0.36)	(-0.43)	(-1.13)
Ln(BTM)	-0.015	-0.177	-0.076	-0.296
	(-0.17)	(-0.51)	(-0.49)	(-0.74)
Ln(Follow)	0.287	0.133	0.002	0.988
	(1.42)	(0.22)	(0.01)	(1.17)
F_Horizon	1.384***	0.041	0.787**	0.376
	(5.76)	(0.14)	(2.39)	(1.23)
dayElap	0.020***	0.046	-0.015	0.062
	(2.85)	(1.51)	(-1.38)	(1.45)
fr	-0.008***	0.011	-0.004	-0.005
	(-2.97)	(1.20)	(-1.02)	(-0.31)
Firm_Exp	-0.086	0.095	0.022	0.168
	(-1.21)	(0.62)	(0.30)	(0.56)
Gen_Exp	0.208**	0.074	0.011	-0.134
	(2.27)	(0.36)	(0.13)	(-0.50)
Num_co	-0.022	-0.120	0.012	0.553
	(-0.27)	(-0.62)	(0.08)	(1.54)
Num_ind	0.018	-0.258	0.004	-0.590**
	(0.28)	(-1.53)	(0.04)	(-2.01)
Num_ana	0.312	-0.353	-0.422	0.634
	(0.95)	(-0.56)	(-0.86)	(0.43)
Year F.E.	YES	YES	YES	YES
N	926	1125	1494	981
Adjusted R^2	3.8%	0.03%	0.01%	0.01%

This table compares analyst bias before and after the Global Settlement in year 2003 using analyst constant sample from year 1999 to 2006. Before the settlement represents years 1999 to 2003 while after the settlement represents years 2004 to 2006. First forecast is the initial forecast analyst *i* issued for firm *j* in year *t* and last forecast is the last forecast revision analyst *i* issued for firm *j* in year *t*. Heteroskedasticity-robust standard errors are clustered by firm and analyst pair. t-statistics are reported in parentheses. *, **, and *** represent significance level of 10%, 5%, and 1%, respectively. All variable definitions are as reported in the Appendix I.

Panel B: Sub-sample of firms that experienced no decrease in analyst coverage following the Global Settlement

	Before Global Settlement		*After Global Settlement*	
	First Forecast	*Last Forecast*	*First Forecast*	*Last Forecast*
	(1)	(2)	(3)	(4)
Constant	0.040	-1.165	-0.004	-2.137
	(0.05)	(-0.66)	(-0.00)	(-0.76)
EMPLOYER	**0.063**	**-0.080**	**0.234***	**-0.560***
	(0.56)	**(-0.34)**	**(1.85)**	**(-1.68)**
Earn_Std	-0.945	4.462	-1.165	17.349*
	(-0.75)	(0.89)	(-0.37)	(1.70)
Ln(MV)	-0.072	0.040	-0.038	-0.274
	(-1.26)	(0.26)	(-0.53)	(-1.11)
Ln(BTM)	-0.069	-0.181	-0.116	-0.305
	(-0.77)	(-0.51)	(-0.75)	(-0.75)
Ln(Follow)	0.429**	0.155	0.082	1.046
	(2.08)	(0.24)	(0.30)	(1.18)
F_Horizon	1.455***	0.025	0.822**	0.386
	(6.01)	(0.08)	(2.51)	(1.19)
dayElap	0.019**	0.046	-0.017	0.062
	(2.29)	(1.51)	(-1.56)	(1.45)
fr	-0.009***	0.011	-0.005	-0.005
	(-3.12)	(1.19)	(-1.26)	(-0.31)
Firm_Exp	-0.084	0.112	0.010	0.167
	(-1.15)	(0.72)	(0.14)	(0.55)
Gen_Exp	0.205**	0.061	0.016	-0.132
	(2.16)	(0.30)	(0.18)	(-0.49)
Num_co	0.003	-0.135	0.013	0.561
	(0.03)	(-0.68)	(0.09)	(1.54)
Num_ind	-0.013	-0.250	0.004	-0.599**
	(-0.19)	(-1.46)	(0.04)	(-2.01)
Num_ana	0.372	-0.371	-0.473	0.604
	(1.12)	(-0.58)	(-0.97)	(0.40)
Year F.E.	YES	YES	YES	YES
N	895	1102	1482	975
Adjusted R^2	0.41%	0.02%	0.00%	0.01%

This table compares analyst bias before and after the Global Settlement in year 2003 using analyst constant sample and excluding any firms that experienced a drop in analysts following after Settlement. Before the settlement represents years 1999 to 2003 while after the settlement represents years 2004 to 2006. First forecast is the initial forecast analyst *i* issued for firm *j* in year *t* and last forecast is the last forecast revision analyst *i* issued for firm *j* in year *t*. Heteroskedasticity-robust standard errors are clustered by firm and analyst pair. t-statistics are reported in parentheses. *, **, and *** represent significance level of 10%, 5%, and 1%, respectively. All variable definitions are as reported in the Appendix I.

Table 1.6
Comparing microstructure properties of investment banks versus non-bank firms

	NYSESample,1999-2006							NASDAQSample,1999-2006						
		Means			Medians				Means			Medians		
Variable	N	Bank	Control	Prop'al difference	Bank	Control	Prop'al difference	N	Bank	Control	Prop'al difference	Bank	Control	Prop'al difference
markv	110	38.00	40.00	0.76%	18.00	20.00	0.09%	32	11.00	10.00	-0.86%	6.40	5.90	-1.19%
price	110	50.508	52.862	4.63%	46.62	49.12	4.04%	32	44.91	44.64	3.86%	45.51	43.61	3.82%
volume	110	829.88	707.82	-10.82%	522.29	341.67	-15.85%	32	1100.00	239.47	-104.25%***	642.96	184.51	-103.76%***
std	110	30.79%	27.31%	-9.01%	26.66%	23.35%	-8.69%	32	60.04%	26.44%	-72.34%***	42.28%	21.65%	-73.4%***
Qspread	110	18.81%	19.69%	27.89%	8.82%	5.33%	-11.46%*	32	4.51%	4.24%	-35.04%	2.06%	2.64%	29.00%
jspread	110	0.47%	0.39%	-20.30%	0.24%	0.11%	-18.55%	32	0.12%	0.13%	51.33%	0.04%	0.07%	47.06%
tover	105	1.37	1.13	-9.58%*	1.07	0.92	-9.56%**	32	7.48	1.27	-110.77%***	4.56	1.11	-123.81%***

This table summarizes and compares the microstructure of investment banks and non-investment banks. ‘‘Prop’al difference’’ is computed as the control firm’s value less the bank’s value, divided by the average of the two firms’ values. Other variables are defined in the Appendix I.*, **, and *** represent significance level of 10%, 5%, and 1%, respectively.

Table 1.7
Comparing analyst forecast accuracy of bank-analysts first and last yearly earnings forecast

Dependent Variable	*Forecast Accuracy*	
	(1)	(2)
	First Forecast	*Last Forecast*
Constant	-0.316	0.061
	(-1.40)	(0.400)
EMPLOYER	**0.232*** **	**-0.038**
	(4.69)	**(-1.18)**
Earn_Std	-0.144***	-0.080*
	(-2.88)	(-1.86)
Ln(MV)	0.027	-0.012
	(1.08)	(-0.88)
Ln(BTM)	0.056	-0.026
	(1.57)	(-0.63)
Ln(Follow)	-0.194**	0.176***
	(-2.07)	(2.68)
F_Horizon	-1.251***	-0.292***
	(-17.21)	(-7.44)
dayElap	-0.026**	-0.049**
	(-2.42)	(-2.00)
fr	0.002***	-0.003***
	(4.73)	(-5.88)
Firm_Exp	-0.013	-0.009
	(-0.39)	(-0.41)
Gen_Exp	0.053	0.047*
	(1.37)	(1.73)
Num_Co	-0.003	0.019
	(-0.09)	(0.75)
Num_Ind	0.024	-0.099***
	(0.67)	(-2.67)
Num_Ana	0.021	0.031
	(0.86)	(1.49)
Year_F.E	Yes	Yes
Observations	3778	3832
Adjusted R^2	10.1%	8.1%

This table reports the ordinary least squares estimation results of regressing forecast accuracy on *EMPLOYER*, for the period 1999-2006. *Accuracy* is the absolute value of forecast bias (*Rel_DFB*). First forecast is the initial forecast analyst *i* issued for firm *j* in year *t* and last forecast is the last forecast revision analyst *i* issued for firm *j* in year *t*. Heteroskedasticity-robust standard errors are clustered by analyst. *t*-statistics are reported in parentheses. *,**,and***represent significance level of 10%, 5%, and 1%, respectively (two-tailed). All variable definitions are as reported in the Appendix I.

Table 1.8
Brokerage House Status and Job Movement

Panel A: Percentage of analysts who in different status brokerage houses each year

The table presents the percentage of all analysts in I/B/E/S who are categorized as working for high-status, median-status and low-status brokerage houses.

Brokerage House Status	High-status Brokerage House	Median-status Brokerage House	Low-status Brokerage House
Year	Analyst%	Analyst%	Analyst%
1999	27.33%	48.17%	24.49%
2000	26.44%	51.57%	21.99%
2001	30.62%	45.26%	24.13%
2002	33.12%	43.88%	23.01%
2003	33.31%	45.12%	21.57%
2004	35.02%	43.28%	21.70%
2005	33.95%	45.15%	20.90%
2006	32.51%	47.58%	19.91%
Overall(1998-2006)	31.53%	46.25%	22.21%

Panel B: Summary statistics of analyst job movement

This table presents the averaged percentage of all analyst and analysts who forecast potential employers in the I/B/E/S database who move between brokerage houses each year during 1999-2006 and the percentage who experience various types of job separations in a year averaged over year 1999-2006.

	All Analysts	Analysts forecasting Employers
% of Analysts Who Change Houses each Year:	6.05%	6.93%
Averaged % of Analysts move up each year	49.39%	51.35%
Averaged % of Analysts move down each year	30.17%	29.73%
Averaged % of Analysts stay high each year	11.32%	12.61%
Averaged % of Analysts stay low each year	9.14%	4.50%
% of Analysts move from High-Status House	16.32%	16.41%
% of Analysts move from Low-Status House	24.61%	15.90%
% of Analysts move from Mid-Status House	59.07%	67.69%

Panel C: The effect of relative forecast bias on job separations of bank analysts and non-bank analysts

$Move\_status_{t+1} = \beta_1\ BIAS_{ijt} + \beta_2 EMPLOYER + \beta_3\ BIAS_{ijt} * EMPLOYER + \beta_4 Gen\_Exp_{ijt} + \beta_5 Num\_Co_{ijt} + \beta_6 Accuracy + \beta_7 Status\ F.E. + \beta_8 Year\ F.E + \varepsilon_{ijt}$

Dependent Variable= *Move_status*	*Relative Forecast Bias*			
Variable	*First Forecast*		*Last Forecast*	
	Coefficient	*Odds Ratio or Ratios of odds ratios*	*Coefficient*	*Odds Ratio or Ratios of odds ratios*
	(1)	(2)	(3)	(4)
Rel_BIAS	0.000	1.000	-0.000	1.000
	(0.26)		(-0.29)	
EMPLOYER	0.915	2.496	1.366**	3.921*
	(1.45)		(2.20)	
Rel_BIAS*EMPLOYER	**-0.003**	**0.997**	**-0.339****	**0.712***
	(-0.05)		**(-2.30)**	
Gen_Exp	-0.029	0.971	-0.043**	0.957*
	(-1.37)		(-1.97)	
Num_Co	0.040**	1.041*	0.033*	1.033
	(2.35)		(1.87)	
Accuracy	-0.024	0.976	-0.127	0.881
	(-0.09)		(-0.49)	
Status F.E.	Yes		Yes	
Year F.E.	Yes		Yes	
N	568		512	
Pesudo-R^2	28.40%		27.60%	

This table present estimations from the ordinal logit regression to examine if past forecast optimism from bank and non-bank analysts have different effect on the likelihood of analyst moves to a higher or lower status brokerage house during 1999 to 2006. The sample contains only those analysts from medium or low status houses. The dependent variable *move-status* equals the value 1 if the analyst in time *t* moves up one hierarchy of brokerage house status and the value of 2 if the move up represents a move of two hierarches. If the analyst moves side-ways then it takes the value of zero. If, however, the analysts moves down one hierarchy then it takes the value of -1. Similar with Hong and Kubik (2003), I measure the forecast bias for each firm the analyst forecasts in year *t* minus the average bias of analysts from the high-status house who follow the firms, which I then average across the stocks that the analysts covers which provides me with a bias measure for analysts *i* in year *t*. The *Rel_BIAS* variable is the average of this relative forecast bias in year *t* and the two previous years. Analysts who have less than three prior years of experience are therefore excluded. *Accuracy* is a dummy variable taking the value of 1 if the analyst is ranked in the top 10% in terms of their average 3 year forecast accuracy and zero otherwise. All other variables are as defined in the Appendix I. Heteroskedasticity-robust standard errors are clustered by firm and analyst pair. *, **, and *** represent significance level of 5%, 1%, and 0.1%, respectively (two-tailed).

Panel D: The effect of absolute forecast bias on job separations of bank analysts and non-bank analysts

Dependent Variable= *Move_status*	*Absolute Forecast Bias*			
Variable	*First Forecast*		*Last Forecast*	
	Coefficient	*Odds Ratio or Ratios of odds ratios*	*Coefficient*	*Odds Ratio or Ratios of odds ratios*
	(1)	(2)	(3)	(4)
Abs_BIAS	-0.094	0.911	0.038	1.039
	(-1.13)		(0.15)	
EMPLOYER	0.810	2.248	1.345**	3.839*
	(1.24)		(2.32)	
***Abs_BIAS*EMPLOYER**	**0.138**	**1.148**	**-2.532***	**0.0795***
	(0.31)		**(-1.89)**	
Gen_Exp	-0.028	0.972	-0.045**	0.956*
	(-1.33)		(-2.02)	
Num_Co	0.040**	1.040*	0.034*	1.034
	(2.35)		(1.95)	
Accuracy	0.112	1.118	0.055	1.057
	(0.49)		(0.26)	
Status F.E.	YES		YES	
Year F.E.	YES		YES	
N	568		516	
Pesudo-R^2	28.2%		27.4%	

This table present estimations from the ordinal logit regression to examine if past forecast optimism from bank and non-bank analysts have different effect on the likelihood of analyst moves to a higher or lower status brokerage house during 1999 to 2006. The sample contains only those analysts from medium or low status houses. The dependent variable *move-status* equals the value 1 if the analyst in time *t* moves up one hierarchy of brokerage house status and the value of 2 if the move up represents a move of two hierarches. If the analyst moves side-ways then it takes the value of zero. If, however, the analysts moves down one hierarchy then it takes the value of -1. Similar with Hong and Kubik (2003), I measure the forecast bias for each firm the analyst forecasts in year *t*, which I then average across the stocks that the analysts covers which provides me with a bias measure for analysts *i* in year *t*. The *Abs_BIAS* variable is the average this forecast bias in year *t* and the two previous years. Analysts who have less than three prior years of experience are therefore excluded. *Accuracy* is a dummy variable taking the value of 1 if the analyst is ranked in the top 10% in terms of their average 3 year forecast accuracy and zero otherwise. All other variables are as defined in the Appendix I. Heteroskedasticity-robust standard errors are clustered by firm and analyst pair. *, **, and *** represent significance level of 5%, 1%, and 0.1%, respectively (two-tailed).

Appendix II: Variable Definitions

Name		Description
CAR_{ijt}	=	Cumulative market-adjusted abnormal return over the five- day window centred on the forecast report date (-2 day to +2 day).
$absoluteCAR_{ijt}$	=	Absolute value of $CAR_{ijt.}$
P_TP_B	=	Analyst *i* provides pessimistic sentiment in the textual discussion and pessimistic earnings forecasts for firm *j* in year *t*.
O_TP_B	=	Analyst *i* provides optimistic sentiment in the textual discussion but pessimistic earnings forecasts for firm *j* in year *t*.
O_TO_B	=	Analyst *i* provides optimistic sentiment in the textual discussion and optimistic earnings forecasts for firm *j* in year *t*.
P_TO_B	=	Analyst *i* provides pessimistic sentiment in the textual discussion and optimistic earnings forecasts for firm *j* in year *t*.
$accuracy_{ijt}$		The maximum absolute forecast errors for analysts following firm *j* in year *t* minus the absolute forecast errors for analyst *i* following firm *j* in year *t*, scaled by the difference between the maximum and minimum absolute forecast errors for analysts following firm *j* in year *t*.
car_prior_{jt}	=	Cumulative market adjusted (value weighted) ten-day abnormal returns ending three days before the current report date.
ef_rev_{ijt}	=	Earnings forecast of current report minus the last earnings forecast issued by the same analyst for firm *j* in year *t*.
$logmarkv_{jt}$	=	Natural log of the firm *j*'s market value at the end of year *t* .
$logBTM_{jt}$	=	Natural log of the ratio of book value of equity to market value of firm *j* at the end of year *t.*
$std\_consensus_{jt}$	=	Standard deviation of firm *j*'s prior 5 years earning in year *t.*
$logFollow_{jt}$	=	Analysts following, measured as the natural log of analysts following firm *j* in year *t*.
Gen_Exp_{ijt}	=	The measure of analyst *i*'s general experience, calculated as the number of years of experience for analyst *i* following firm *j* in year *t*. When scaling we minus the average number of years of experience for analysts from top brokerage houses following firm *j* in year *t*, with this difference scaled by the range of years of experience for analysts from top brokerage houses following firm *j* in year *t*.
$Firm\_Exp_{ijt}$	=	The measure of analyst *i*'s firm-specific experience, calculated as the number of years of firm-specific experience for analyst *i* following firm *j* in year *t*. When scaling we minus the average number of years of firm-specific experience for analysts from top brokerage houses following firm *j* in year *i*, with this difference scaled by the average years of firm-specific experience for

analysts from top brokerage houses following firm *j* in year *t*.

Num_Ana_{ijt}	=	The measure of the analyst's brokerage size, calculated as the number of analysts employed by the brokerage house employing analyst *i* following firm *j* in year *t.* When scaling we minus the average number of analysts employed by brokerage houses for analysts following firm *j* in year *t*, with this difference scaled by the average brokerage house size for analysts following firm *j* in year *t*.
$dayElap_{ijt}$	=	The measure of the days elapsed since the last forecast by an analyst following firm *j* in year *t*. When scaling we calculate it as the days between analysts *i*'s forecast of firm *j*'s earnings in year *t* and the most recent preceding forecast of firm *j*'s earnings by analysts from top brokerage houses, minus the average number of days between two adjacent forecasts of firm *j*'s earnings by any two analysts in year *t*, with this difference scaled by the average days between two adjacent forecasts of firm *j*'s earnings in year *t*.
Num_Ind_{ijt}	=	The measure of number of industries analyst *i* follows in year *t*, calculated as the number of two-digit SICs followed by analyst *i* following firm *j* in year *t*. When scaling we minus the average number of two-digit SICs followed by analysts from top brokerage houses who follow firm *j* in year *t*, with this difference scaled by the average number of two-digit SICs followed by analysts from top brokerage houses following firm *j* in year *t*.
Num_Co_{ijt}	=	The measure of the number of companies analyst *i* follows in year *t*, calculated as the number of companies followed by analyst *i* following firm *j* in year *t*. When scaling we minus the average number of companies followed by analysts from top brokerage houses who follow firm *j* in year *t*, with this difference scaled by the average number of companies followed by analysts from top brokerage houses following firm *j* in year *t*.
fh_{ijt}	=	The measure of the time from the forecast date to the end of the fiscal period, calculated as the forecast horizon (days from the forecast date to the fiscal year-end) for analyst *i* following firm *j* in year *t.* When scaling we minus the average forecast horizon for analysts from top brokerage houses who follow firm *j* in year *t*, with this difference scaled by the average forecast horizons for analysts from top brokerage houses following firm *j* in year *t*.
fr_{ijt}	=	The measure of analyst *i*'s forecast frequency for firm *j*, calculated as the number of firm *j* forecasts made by analyst *i* following firm *j* in year *t*. When scaling we minus the average number of firm *j* forecasts for analysts from top brokerage houses following firm *j* in year *t*, with this difference scaled by the average number of firm *j* forecasts issued by analysts from top brokerage houses following firm *j* in year *t*.

Table 2.1
Sample Selection

	Dropped No. Obs.	Total No. Obs.
Total number of analyst reports analysed		118,527
Less		
Number of analyst following <3	50	118,477
Stock price <3	644	117,833
Equity value<=0	2,643	115,190
Different analysts forecasting the same firm on the same date or cumulative abnormal return around analyst report date missing	22	115,168
Missing values from control variables, especially earnings forecast revisions because first reports have no earnings forecast revisions.	31,386	83,782
Financial crisis period 2007-2011	63,048	20,734

This table describes the sample selection process for the sample used in Chapter 3. 118,527 analyst reports are collected from Investext. After data cleaning and data selection, 20,734 analyst reports are used in the tests.

Table 2.2
Descriptive statistics

This table reports descriptive statistics for all variables from 1999-2014. CAR_{ijt} is cumulative market adjusted (value weighted) abnormal return two days before and two days after analyst report issue date. $absoluteCAR_{ijt}$ is the absolute value of CAR_{ijt}. P_TP_B denotes reports with pessimistic sentiment and pessimistic earnings forecast bias. O_TP_B denotes reports with optimistic sentiment but pessimistic earnings forecast bias. O_TO_B denotes reports with optimistic sentiment and optimistic earnings forecast bias. P_TO_B denotes reports with pessimistic sentiment but optimistic earnings forecast bias. car_prior_{ijt} is cumulative market adjusted (value weighted) ten-day abnormal returns ending three days before the current report date. ef_rev_{ijt} is the current report's earnings forecast minus the last earnings forecast issued by analyst *i* in year *t*. All other variable definitions are as reported in the Appendix II. Panel A reports the descriptive statistics and Panel B reports correlations matrix.

Panel A: Descriptive Statistics (n=20734)

Variable	*Mean*	*S.D.*	*25th Percentile*	*Median*	*75th Percentile*
CAR_{ijt}	0.00	0.06	-0.02	0.00	0.03
$absoluteCAR_{ijt}$	0.04	0.04	0.01	0.03	0.05
P_TP_B	0.36	0.48	0.00	0.00	1.00
O_TP_B	0.24	0.43	0.00	0.00	0.00
O_TO_B	0.19	0.39	0.00	0.00	0.00
P_TO_B	0.22	0.41	0.00	0.00	0.00
car_prior_{ijt}	-0.00	0.06	-0.03	0.00	0.03
ef_rev_{ijt}	-0.01	0.18	-0.03	0.00	0.03
$logmarkv_{jt}$	9.43	1.21	8.60	9.36	10.18
$logBTM_{jt}$	-1.04	0.77	-1.48	-0.99	-0.54
$std\_consensus_{jt}$	0.08	0.07	0.03	0.05	0.12
$logFollow_{jt}$	3.13	0.47	2.89	3.18	3.47
Gen_Exp_{ijt}	9.69	6.11	5.00	9.00	13.00
$Firm\_Exp_{ijt}$	5.82	4.84	2.00	4.00	8.00
Num_Ana_{ijt}	86.94	52.91	43.00	88.00	125.00
$dayElap_{ijt}$	3.32	3.75	0.00	1.00	6.00
Num_Ind_{ijt}	3.26	2.09	2.00	3.00	4.00
Num_Co_{ijt}	17.69	7.97	13.00	16.00	21.00
fh_{ijt}	167.19	87.11	98.00	174.00	234.00
fr_{ijt}	6.72	3.59	4.00	6.00	8.00
$accuracy_{ijt}$	0.65	0.33	0.40	0.74	0.94

Panel B: Correlation Matrix

	CAR	PP	OP	OO	PO	accuracy	car_prior	ef_rev	logmarkv	logBTM	std	logFollow	Gen_Exp	Firm_Exp	Num_Ana	dayElap	Num_Ind	Num_Co	fh
PP	-0.067																		
	(0.000)																		
OP	0.030	-0.418																	
	(0.000)	(0.000)																	
OO	0.047	-0.359	-0.269																
	(0.000)	(0.000)	(0.000)																
PO	0.002	-0.392	-0.293	-0.252															
	(0.818)	(0.000)	(0.000)	(0.000)															
accuracy	0.006	-0.054	-0.038	0.025	0.078														
	(0.432)	(0.000)	(0.000)	(0.000)	(0.000)														
car_prior	-0.010	-0.055	0.021	0.039	0.005	-0.004													
	(0.147)	(0.000)	(0.003)	(0.000)	(0.451)	(0.548)													
ef_rev	0.107	-0.077	-0.034	0.072	0.057	-0.008	0.067												
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.283)	(0.000)												
logmarkv	0.010	-0.060	-0.008	0.042	0.039	-0.012	0.024	0.036											
	(0.152)	(0.000)	(0.226)	(0.000)	(0.000)	(0.074)	(0.001)	(0.000)											
logBTM	-0.060	0.016	0.040	-0.011	-0.050	0.004	-0.063	-0.061	-0.220										
	(0.000)	(0.019)	(0.000)	(0.121)	(0.000)	(0.553)	(0.000)	(0.000)	(0.000)										
std	-0.012	-0.025	0.053	0.001	-0.026	0.010	-0.012	0.003	0.057	0.365									
	(0.077)	(0.000)	(0.000)	(0.935)	(0.000)	(0.163)	(0.075)	(0.677)	(0.000)	(0.000)									
logFollow	-0.022	-0.053	0.017	0.039	0.008	-0.004	-0.025	-0.001	0.496	-0.036	0.197								
	(0.001)	(0.000)	(0.014)	(0.000)	(0.279)	(0.604)	(0.000)	(0.943)	(0.000)	(0.000)	(0.000)								
Gen_Exp	-0.002	-0.005	0.010	0.016	-0.019	0.015	0.003	-0.001	0.067	0.045	0.104	0.030							
	(0.798)	(0.442)	(0.169)	(0.019)	(0.006)	(0.033)	(0.698)	(0.913)	(0.000)	(0.000)	(0.000)	(0.000)							
Firm_Exp	-0.009	-0.011	0.016	0.012	-0.015	0.011	-0.004	-0.013	0.099	0.061	0.107	0.064	0.675						
	(0.181)	(0.118)	(0.021)	(0.082)	(0.027)	(0.125)	(0.601)	(0.059)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)						
Num_Ana	0.006	0.056	-0.027	-0.042	0.002	0.010	-0.005	-0.017	-0.073	0.026	-0.050	-0.133	-0.071	-0.020					
	(0.366)	(0.000)	(0.000)	(0.000)	(0.764)	(0.166)	(0.449)	(0.013)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)					
dayElap	0.014	-0.005	0.006	0.002	-0.003	-0.032	0.035	0.007	-0.064	-0.039	-0.127	-0.178	0.073	0.037	0.040				
	(0.045)	(0.513)	(0.402)	(0.766)	(0.698)	(0.000)	(0.000)	(0.289)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)				
Num_Ind	-0.006	0.013	-0.003	-0.002	-0.009	0.007	-0.009	-0.003	-0.098	-0.081	-0.115	-0.155	0.131	0.072	-0.042	0.032			
	(0.361)	(0.072)	(0.641)	(0.767)	(0.182)	(0.339)	(0.212)	(0.654)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)			
Num_Co	-0.007	-0.010	0.021	0.001	-0.011	0.004	-0.004	0.006	-0.013	0.079	0.121	0.001	0.258	0.182	0.034	-0.007	0.377		
	(0.314)	(0.169)	(0.003)	(0.944)	(0.111)	(0.588)	(0.554)	(0.429)	(0.065)	(0.000)	(0.000)	(0.873)	(0.000)	(0.000)	(0.000)	(0.335)	(0.000)		
fh	0.024	0.011	0.037	0.007	-0.059	-0.443	0.002	0.010	-0.010	0.017	0.017	0.003	0.003	0.002	0.003	-0.049	0.006	0.016	
	(0.001)	(0.112)	(0.000)	(0.299)	(0.000)	(0.000)	(0.731)	(0.144)	(0.147)	(0.013)	(0.014)	(0.711)	(0.703)	(0.779)	(0.671)	(0.000)	(0.414)	(0.019)	
fr	-0.011	-0.056	0.050	0.033	-0.018	-0.045	-0.005	0.000	0.067	0.172	0.367	0.252	0.066	0.086	-0.016	-0.070	-0.098	0.057	0.083
	(0.124)	(0.000)	(0.000)	(0.000)	(0.011)	(0.000)	(0.433)	(0.969)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.023)	(0.000)	(0.000	(0.000)	(0.000)

Table 2.3
Panel A: Market reaction to earnings forecast bias and textual discussions

	(1)	(2)	(3)	(4)	(5)	(6)
	AbsoluteCAR	CAR	CAR	CAR	CAR	CAR
constant	0.124***	-0.001	-0.003	0.002	-0.007	0.003
	(22.86)	(-0.19)	(-0.31)	(0.28)	(-0.84)	(0.42)
mix	**-0.001****	**0.002*****				
	(-1.99)	**(4.18)**				
O_TP_B			**0.005*****		**0.009*****	**-0.001**
			(3.98)		**(8.00)**	**(-0.99)**
P_TO_B				**-0.005*****	**0.004*****	**-0.006*****
				(-3.98)	**(3.82)**	**(-5.06)**
P_TP_B			**-0.004*****	**-0.009*****		**-0.010*****
			(-3.82)	**(-8.00)**		**(-8.94)**
O_TO_B			**0.006*****	**0.001**	**0.010*****	
			(5.06)	**(0.99)**	**(8.94)**	
accuracy	0.001**	0.001***	0.002**	0.002**	0.002**	0.002**
	(2.02)	(2.70)	(2.18)	(2.18)	(2.18)	(2.18)
CAR_prior	-0.033***	-0.012	-0.026**	-0.026**	-0.026**	-0.026**
	(-4.19)	(-1.47)	(-2.39)	(-2.39)	(-2.39)	(-2.39)
ef_rev	-0.001	0.001**	0.034***	0.034***	0.034***	0.034***
	(-1.27)	(2.35)	(7.97)	(7.97)	(7.97)	(7.97)
logmarkv	-0.008***	0.000	0.000	0.000	0.000	0.000
	(-18.50)	(0.54)	(0.98)	(0.98)	(0.98)	(0.98)
logBTM	-0.001	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***
	(-1.39)	(-7.51)	(-6.87)	(-6.87)	(-6.87)	(-6.87)
std_consensus	0.041***	-0.001	0.002	0.002	0.002	0.002
	(7.29)	(-0.22)	(0.22)	(0.22)	(0.22)	(0.22)
logFollow	0.004***	-0.003***	-0.004***	-0.004***	-0.004***	-0.004***
	(4.37)	(-3.76)	(-3.22)	(-3.22)	(-3.22)	(-3.22)
Gen_Exp	0.000	0.000*	0.000	0.000	0.000	0.000
	(0.58)	(1.71)	(0.99)	(0.99)	(0.99)	(0.99)
Firm_Exp	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(-1.45)	(-1.56)	(-1.23)	(-1.23)	(-1.23)	(-1.23)
Num_Ana	0.000	0.000	0.000	0.000	0.000	0.000
	(1.34)	(0.56)	(0.87)	(0.87)	(0.87)	(0.87)
dayElap	-0.001***	0.000	0.000*	0.000*	0.000*	0.000*
	(-16.16)	(1.11)	(1.74)	(1.74)	(1.74)	(1.74)
Num_Ind	0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(1.46)	(-0.61)	(-0.78)	(-0.78)	(-0.78)	(-0.78)
Num_Co	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(-1.54)	(-0.27)	(-0.30)	(-0.30)	(-0.30)	(-0.30)
fh	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(3.29)	(4.99)	(4.24)	(4.24)	(4.24)	(4.24)
fr	-0.000***	-0.000	-0.000	-0.000	-0.000	-0.000
	(-3.32)	(-0.88)	(-0.83)	(-0.83)	(-0.83)	(-0.83)
Year F.E	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E	Yes	Yes	Yes	Yes	Yes	Yes
N	20734	20734	20734	20734	20734	20734
Adjusted R^2	14.90%	0.80%	2.20%	2.20%	2.20%	2.20%

This table reports the ordinary least squares estimation results of the market reaction to different types of analyst reports for the years 1999-2014, excluding financial crisis in 2007-2009. Columns 1 and 2 use *mix* dummy as an independent variable, which equals to 1 if P_TO_B or O_TP_B reports; and equal to 0 if O_TP_B and P_TP_B reports. Columns 3, 4, 5 and 6 use P_TO_B, O_TP_B, P_TP_B and O_TO_B as benchmark respectively. CAR_{ijt} is cumulative market adjusted (value weighted) abnormal return two days before and two days after analyst report issue date. *AbsoluteCAR* is the absolute value of *CAR*. Column 1 use *AbsoluteCAR* as independent variable and all other columns use CAR_{ijt} as independent variable. Heteroskedasticity-robust standard errors are clustered by firm and analyst. t-statistics are reported in parentheses. *, **, and *** represent significance level of 10%, 5%, and 1%, respectively (two-tailed). All variable definitions are as reported in the Appendix II.

Panel B: Positive and Negative market reactions to earnings forecast bias and textual discussions

	Benchmark: P_TO_B		Benchmark: O_TP_B		Benchmark: P_TP_B		Benchmark: O_TO_B	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	pos_CAR	neg_CAR	pos_CAR	neg_CAR	pos_CAR	neg_CAR	pos_CAR	neg_CAR
constant	0.075***	-0.075***	0.077***	-0.075***	0.075***	-0.077***	0.077***	-0.074***
	(16.60)	(-16.70)	(17.10)	(-16.74)	(16.63)	(-17.30)	(17.05)	(-16.50)
O_TP_B	**0.002*** **	**0.000**			**0.002*** **	**0.002*** **	**-0.000**	**-0.001**
	(3.05)	**(0.29)**			**(3.81)**	**(4.28)**	**(-0.29)**	**(-0.91)**
P_TO_B			**-0.002*** **	**-0.000**	**0.000**	**0.002*** **	**-0.002*** **	**-0.001**
			(-3.05)	**(-0.29)**	**(0.44)**	**(3.81)**	**(-3.30)**	**(-1.16)**
P_TP_B	**-0.000**	**-0.002*** **	**-0.002*** **	**-0.002*** **			**-0.003*** **	**-0.003*** **
	(-0.44)	**(-3.81)**	**(-3.81)**	**(-4.28)**			**(-4.06)**	**(-4.84)**
O_TO_B	**0.002*** **	**0.001**	**0.000**	**0.001**	**0.003*** **	**0.003*** **		
	(3.30)	**(1.16)**	**(0.29)**	**(0.91)**	**(4.06)**	**(4.84)**		
accuracy	0.001**	-0.000	0.001**	-0.000	0.001**	-0.000	0.001**	-0.000
	(2.21)	(-0.58)	(2.21)	(-0.58)	(2.21)	(-0.58)	(2.21)	(-0.58)
CAR_prior	-0.029***	-0.001	-0.029***	-0.001	-0.029***	-0.001	-0.029***	-0.001
	(-4.78)	(-0.11)	(-4.78)	(-0.11)	(-4.78)	(-0.11)	(-4.78)	(-0.11)
ef_rev	0.003**	0.007***	0.003**	0.007***	0.003**	0.007***	0.003**	0.007***
	(2.24)	(4.75)	(2.24)	(4.75)	(2.24)	(4.75)	(2.24)	(4.75)
logmarkv	-0.004***	0.004***	-0.004***	0.004***	-0.004***	0.004***	-0.004***	0.004***
	(-12.50)	(13.87)	(-12.50)	(13.87)	(-12.50)	(13.87)	(-12.50)	(13.87)
logBTM	-0.002***	-0.000	-0.002***	-0.000	-0.002***	-0.000	-0.002***	-0.000
	(-3.86)	(-0.03)	(-3.86)	(-0.03)	(-3.86)	(-0.03)	(-3.86)	(-0.03)
std_consensus	0.018***	-0.027***	0.018***	-0.027***	0.018***	-0.027***	0.018***	-0.027***
	(4.24)	(-6.25)	(4.24)	(-6.25)	(4.24)	(-6.25)	(4.24)	(-6.25)
logFollow	0.001	-0.003***	0.001	-0.003***	0.001	-0.003***	0.001	-0.003***
	(1.10)	(-4.35)	(1.10)	(-4.35)	(1.10)	(-4.35)	(1.10)	(-4.35)

Gen_Exp	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(1.04)	(0.01)	(1.04)	(0.01)	(1.04)	(0.01)	(1.04)	(0.01)
Firm_Exp	-0.000*	-0.000	-0.000*	-0.000	-0.000*	-0.000	-0.000*	-0.000
	(-1.71)	(-0.17)	(-1.71)	(-0.17)	(-1.71)	(-0.17)	(-1.71)	(-0.17)
Num_Ana	0.000*	0.000	0.000*	0.000	0.000*	0.000	0.000*	0.000
	(1.77)	(0.08)	(1.77)	(0.08)	(1.77)	(0.08)	(1.77)	(0.08)
dayElap	-0.001***	0.001***	-0.001***	0.001***	-0.001***	0.001***	-0.001***	0.001***
	(-10.42)	(13.42)	(-10.42)	(13.42)	(-10.42)	(13.42)	(-10.42)	(13.42)
Num_Ind	0.000	-0.000*	0.000	-0.000*	0.000	-0.000*	0.000	-0.000*
	(0.35)	(-1.94)	(0.35)	(-1.94)	(0.35)	(-1.94)	(0.35)	(-1.94)
Num_Co	-0.000	0.000	-0.000	0.000	-0.000	0.000	-0.000	0.000
	(-0.31)	(1.14)	(-0.31)	(1.14)	(-0.31)	(1.14)	(-0.31)	(1.14)
fh	0.000***	0.000	0.000***	0.000	0.000***	0.000	0.000***	0.000
	(4.08)	(0.30)	(4.08)	(0.30)	(4.08)	(0.30)	(4.08)	(0.30)
fr	-0.000***	0.000	-0.000***	0.000	-0.000***	0.000	-0.000***	0.000
	(-2.94)	(1.50)	(-2.94)	(1.50)	(-2.94)	(1.50)	(-2.94)	(1.50)
Year F.E	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	10838	9896	10838	9896	10838	9896	10838	9896
Adjusted R^2	13.10%	15.20%	13.10%	15.20%	13.10%	15.20%	13.10%	15.20%

This table reports the ordinary least squares estimation results of the positive and negative market reaction to different types of analyst reports for the years 1999-2014, excluding financial crisis in 2007-2009. Columns 1,3, 5 and 7 use non-negative CAR (*pos_CAR*) as dependent variables while columns 2, 4, 6 and 8 use negative CAR (*neg_CAR*) as dependent variables. Heteroskedasticity-robust standard errors are clustered by firm and analyst. t-statistics are reported in parentheses. *, **, and *** represent significance level of 10%, 5%, and 1%, respectively (two-tailed). All variable definitions are as reported in the Appendix II.

Table 2.4

Panel A: Investor reaction to analyst reports with optimistic earnings forecast bias or optimistic sentiment

	Same Sentiment		Same Bias	
	O_TO_B vs. O_TP_B		O_TO_B vs. P_TO_B	
	(1)	(2)	(3)	(4)
	CAR	AbsoluteCAR	CAR	AbsoluteCAR
constant	0.028***	0.110***	0.007	0.106***
	(2.63)	(13.56)	(0.56)	(13.11)
O_TO_B	**0.002**	**-0.001**	**0.007*** **	**0.001**
	(1.46)	**(-1.33)**	**(5.63)**	**(1.16)**
accuracy	0.003**	0.002**	0.005***	0.001
	(2.42)	(2.15)	(5.15)	(0.95)
CAR_prior	-0.014	-0.028**	-0.043***	-0.055***
	(-0.86)	(-2.37)	(-2.65)	(-4.74)
ef_rev	0.026***	-0.006	0.043***	-0.004
	(4.37)	(-1.37)	(4.90)	(-0.70)
logmarkv	-0.001	-0.007***	0.001	-0.006***
	(-1.33)	(-12.67)	(1.18)	(-11.52)
logBTM	-0.004***	-0.001	-0.003***	-0.001
	(-4.01)	(-1.25)	(-3.25)	(-1.56)
std_consensus	0.022**	0.036***	-0.010	0.022***
	(1.99)	(4.47)	(-1.05)	(3.00)
logFollow	-0.003*	0.008***	-0.007***	0.006***
	(-1.73)	(5.32)	(-3.51)	(3.98)
Gen_Exp	0.000**	-0.000	0.000	-0.000
	(2.06)	(-0.12)	(0.71)	(-0.23)
Firm_Exp	-0.000	-0.000	-0.000	-0.000
	(-0.98)	(-1.22)	(-0.69)	(-0.38)
Num_Ana	0.000	0.000	0.000	0.000
	(1.33)	(0.88)	(1.07)	(0.31)
dayElap	-0.000	-0.001***	-0.000	-0.001***
	(-1.35)	(-10.76)	(-0.58)	(-11.06)
Num_Ind	-0.001	0.000	-0.000	-0.000
	(-1.64)	(1.43)	(-0.26)	(-0.13)
Num_Co	-0.000*	-0.000***	-0.000	-0.000
	(-1.89)	(-2.71)	(-0.61)	(-0.52)
fh	0.000**	0.000***	-0.000	0.000***
	(2.42)	(3.03)	(-0.34)	(2.70)
fr	-0.000*	-0.000***	-0.000	-0.000***
	(-1.75)	(-3.01)	(-0.81)	(-2.93)
Year F.E	Yes	Yes	Yes	Yes
Industry F.E	Yes	Yes	Yes	Yes
N	8843	8843	8386	8386
Adjusted R^2	1.40%	13.90%	2.40%	14.70%

This table reports the ordinary least squares estimation results of regressing cumulative abnormal return on O_TO_B, O_TP_B and P_TO_B reports for the years 1999-2014, excluding financial crisis in 2007-2009. Columns 1 and 2 compare the market reaction to O_TO_B and O_TP_B reports while column 3 and 4 compare the market reaction to O_TO_B and P_TO_B reports. Heteroskedasticity-robust standard errors are clustered by firm and analyst. t-statistics are reported in parentheses. *, **, and *** represent significance level of 10%, 5%, and 1%, respectively (two-tailed). All variable definitions are as reported in the Appendix II.

Panel B: Positive and Negative market reactions to analyst reports with optimistic earnings forecast bias or optimistic sentiment

	Same Sentiment		Same Bias	
	O_TO_B vs. O_TP_B		O_TO_B vs. P_TO_B	
	(1)	(2)	(3)	(4)
	pos_CAR	neg_CAR	pos_CAR	neg_CAR
constant	0.079***	-0.092***	0.113***	-0.096***
	(11.48)	(-8.25)	(11.38)	(-7.82)
O_TO_B	**0.000**	**0.002**	**0.003*** **	**0.002**
	(0.38)	**(1.38)**	**(3.13)**	**(1.39)**
accuracy	0.001**	-0.000	0.003***	0.002
	(2.13)	(-0.29)	(2.85)	(1.42)
CAR_prior	-0.013**	0.012	-0.057***	0.053***
	(-2.19)	(0.75)	(-4.05)	(2.75)
ef_rev	0.003	0.022***	0.015**	0.027***
	(1.32)	(3.07)	(2.04)	(3.26)
logmarkv	-0.004***	0.006***	-0.006***	0.007***
	(-9.65)	(8.03)	(-8.80)	(7.92)
logBTM	-0.001	-0.001	-0.001	0.001
	(-1.36)	(-0.49)	(-0.87)	(1.10)
std_consensus	0.012**	-0.031***	0.012	-0.037***
	(2.02)	(-2.63)	(1.23)	(-3.45)
logFollow	0.002*	-0.010***	0.002	-0.010***
	(1.68)	(-4.69)	(1.28)	(-4.41)
Gen_Exp	0.000	0.000	-0.000	-0.000
	(0.99)	(0.67)	(-0.32)	(-0.07)
Firm_Exp	-0.000	0.000	-0.000	0.000
	(-1.06)	(0.42)	(-0.38)	(0.15)
Num_Ana	0.000	0.000	0.000	0.000
	(1.38)	(0.17)	(0.83)	(0.46)
dayElap	-0.001***	0.001***	-0.001***	0.001***
	(-7.97)	(7.47)	(-8.29)	(7.11)
Num_Ind	0.000	-0.001*	-0.000	0.000
	(0.16)	(-1.93)	(-0.13)	(0.08)
Num_Co	-0.000	0.000**	0.000	0.000
	(-0.66)	(2.04)	(0.09)	(0.56)
fh	0.000***	-0.000	0.000**	-0.000
	(2.94)	(-0.45)	(2.09)	(-1.35)
fr	-0.000***	0.000	-0.000*	0.000**
	(-2.69)	(1.13)	(-1.74)	(2.49)
Year F.E	Yes	Yes	Yes	Yes
Industry F.E	Yes	Yes	Yes	Yes
N	4910	3933	4589	3797
Adjusted R^2	12.40%	14.40%	15.60%	15.10%

This table reports the ordinary least squares estimation results of regressing positive or negative abnormal return on O_TO_B, O_TP_B and P_TO_B reports for the years 1999-2014, excluding financial crisis in 2007-2009. Columns 1 and 3 use non-negative CAR (*pos_CAR*) as dependent variables while columns 2 and 4 use negative CAR (*neg_CAR*) as dependent variables. Columns 1 and 2 hold constant optimistic sentiment while columns 3 and 4 hold constant optimistic earnings forecast bias. Heteroskedasticity-robust standard errors are clustered by firm and analyst. t-statistics are reported in parentheses. *, **, and *** represent significance level of 10%, 5%, and 1%, respectively (two-tailed). All variable definitions are as reported in the Appendix II.

Table 2.5
Investor reaction to analyst reports with pessimistic earnings forecast bias or pessimistic sentiment

	Same Sentiment		Same Bias	
	P_TP_B vs P_TO_B		P_TP_B vs O_TP_B	
	(1)	(2)	(3)	(4)
	CAR	AbsoluteCAR	CAR	AbsoluteCAR
constant	-0.022**	0.135***	-0.000	0.137***
	(-2.04)	(17.14)	(-0.04)	(18.12)
P_TP_B	**-0.004*** **	**0.002*** **	**-0.009*** **	**0.001**
	(-3.31)	**(2.74)**	**(-7.74)**	**(0.87)**
accuracy	0.001	0.000	-0.001	0.001
	(1.04)	(0.35)	(-1.44)	(1.15)
CAR_prior	-0.037**	-0.035***	-0.022	-0.021*
	(-2.47)	(-3.10)	(-1.53)	(-1.92)
ef_rev	0.039***	-0.009**	0.030***	-0.008**
	(7.08)	(-2.16)	(6.49)	(-2.33)
logmarkv	0.002**	-0.008***	0.000	-0.008***
	(2.22)	(-14.99)	(0.16)	(-16.32)
logBTM	-0.006***	-0.000	-0.006***	-0.000
	(-5.49)	(-0.32)	(-5.76)	(-0.34)
std_consensus	-0.015	0.041***	0.009	0.047***
	(-1.40)	(5.36)	(0.86)	(6.06)
logFollow	-0.005***	0.005***	-0.003	0.007***
	(-2.76)	(3.61)	(-1.49)	(4.76)
Gen_Exp	-0.000	0.000	0.000	0.000
	(-0.21)	(0.84)	(0.79)	(0.85)
Firm_Exp	-0.000	-0.000	-0.000	-0.000
	(-0.78)	(-1.02)	(-1.01)	(-1.62)
Num_Ana	0.000	0.000	0.000	0.000
	(0.09)	(0.79)	(0.45)	(0.93)
dayElap	0.000***	-0.001***	0.000**	-0.001***
	(3.15)	(-11.14)	(2.40)	(-11.37)
Num_Ind	0.000	0.000	-0.000	0.000
	(0.07)	(0.09)	(-0.85)	(1.22)
Num_Co	0.000	-0.000	0.000	-0.000*
	(0.88)	(-0.33)	(0.04)	(-1.70)
fh	0.000***	0.000	0.000***	0.000**
	(3.59)	(1.61)	(5.24)	(2.44)
fr	0.000	-0.000*	-0.000	-0.000**
	(0.45)	(-1.95)	(-0.07)	(-2.30)
Year F.E	Yes	Yes	Yes	Yes
Industry F.E	Yes	Yes	Yes	Yes
N	11891	11891	12348	12348
Adjusted R^2	2.50%	15.10%	2.40%	14.40%

This table reports the ordinary least squares estimation results of regressing cumulative abnormal return on P_TP_B, P_TO_B and O_TP_B reports for the years 1999-2014, excluding financial crisis in 2007-2009. Columns 1 and 2 compare the market reaction to P_TP_B and P_TO_B reports while columns 3 and 4 compare the market reaction to P_TP_B and O_TP_B reports. Heteroskedasticity-robust standard errors are clustered by firm and analyst. t-statistics are reported in parentheses. *, **, and *** represent significance level of 10%, 5%, and 1%, respectively (two-tailed). All variable definitions are as reported in the Appendix II.

Panel B: Positive and Negative market reactions to analyst reports with pessimistic earnings forecast bias or pessimistic sentiment

	Same Sentiment P_TP_B vs P_TO_B		Same Bias P_TP_B vs O_TP_B	
	(1)	(2)	(3)	(4)
	pos_CAR	neg_CAR	pos_CAR	neg_CAR
constant	0.070***	-0.082***	0.127***	-0.147***
	(11.48)	(-15.47)	(14.18)	(-12.44)
P_TP_B	**-0.0003**	**-0.002*** **	**-0.003*** **	**-0.004*** **
	(-0.52)	**(-3.67)**	**(-2.89)**	**(-3.73)**
accuracy	0.000	-0.000	0.000	-0.001
	(0.96)	(-0.35)	(0.24)	(-0.97)
CAR_prior	-0.016***	-0.001	-0.038**	0.004
	(-3.31)	(-0.24)	(-2.54)	(0.25)
ef_rev	0.004*	0.006***	0.006	0.020***
	(1.79)	(3.67)	(1.43)	(3.74)
logmarkv	-0.003***	0.004***	-0.008***	0.009***
	(-9.66)	(13.77)	(-12.08)	(11.80)
logBTM	-0.002***	0.000	-0.003***	-0.002**
	(-3.32)	(0.77)	(-3.36)	(-2.33)
std_consensus	0.018***	-0.025***	0.051***	-0.043***
	(3.27)	(-4.84)	(5.28)	(-3.47)
logFollow	0.001	-0.003***	0.006***	-0.007***
	(1.47)	(-3.81)	(3.50)	(-3.34)
Gen_Exp	0.000	-0.000	0.000	-0.000
	(0.66)	(-0.96)	(0.31)	(-0.76)
Firm_Exp	-0.000	0.000	-0.000**	0.000
	(-1.46)	(0.35)	(-2.03)	(0.49)
Num_Ana	0.000	0.000	0.000	0.000
	(1.25)	(0.13)	(1.53)	(0.17)
dayElap	-0.001***	0.001***	-0.001***	0.002***
	(-6.80)	(10.92)	(-6.83)	(9.36)
Num_Ind	0.000	-0.000	0.000	-0.001
	(0.29)	(-0.31)	(0.35)	(-1.44)
Num_Co	0.000	0.000	-0.000	0.000
	(0.19)	(0.36)	(-0.87)	(1.36)
fh	0.000***	0.000	0.000***	0.000
	(2.68)	(0.40)	(3.70)	(0.57)
fr	-0.000*	0.000	-0.000**	0.000
	(-1.68)	(1.49)	(-2.33)	(1.13)
Year F.E	Yes	Yes	Yes	Yes
Industry F.E	Yes	Yes	Yes	Yes
N	5928	5963	6249	6099
Adjusted R^2	14.00%	15.90%	14.50%	15.80%

This table reports the ordinary least squares estimation results of regressing positive or negative abnormal return on P_TP_B, P_TO_B and O_TP_B reports for the years 1999-2014, excluding financial crisis in 2007-2009. Columns 1 and 3 use non-negative CAR (*pos_CAR*) as dependent variables while columns 2 and 4 use negative CAR (*neg_CAR*) as dependent variables. Columns 1 and 2 hold constant pessimistic sentiment while columns 3 and 4 hold constant pessimitic earnings forecast bias. Heteroskedasticity-robust standard errors are clustered by firm and analyst. t-statistics are reported in parentheses. *, **, and *** represent significance level of 10%, 5%, and 1%, respectively (two-tailed). All variable definitions are as reported in the Appendix II.

Table 2.6
Forecast accuracy and four combinations of reports

Accuracy	(1)	(2)	(3)	(4)
constant	0.568***	0.577***	0.583***	0.588***
	(10.63)	(10.80)	(10.91)	(11.02)
OP	**0.009**		**-0.006**	**-0.011***
	(1.45)		**(-1.09)**	**(-1.68)**
PO	**0.020*****	**0.011***	**0.005**	
	(3.08)	**(1.68)**	**(0.71)**	
PP	**0.016****	**0.006**		**-0.005**
	(2.40)	**(1.09)**		**(-0.71)**
OO		**-0.009**	**-0.016****	**-0.020*****
		(-1.45)	**(-2.40)**	**(-3.08)**
roa	-0.011	-0.011	-0.011	-0.011
	(-0.25)	(-0.25)	(-0.25)	(-0.25)
logmarkv	0.007***	0.007***	0.007***	0.007***
	(2.70)	(2.70)	(2.70)	(2.70)
logBTM	-0.009**	-0.009**	-0.009**	-0.009**
	(-2.04)	(-2.04)	(-2.04)	(-2.04)
loss	-0.019*	-0.019*	-0.019*	-0.019*
	(-1.67)	(-1.67)	(-1.67)	(-1.67)
std_consensus	0.078	0.078	0.078	0.078
	(1.64)	(1.64)	(1.64)	(1.64)
logFollow	0.012	0.012	0.012	0.012
	(1.64)	(1.64)	(1.64)	(1.64)
Gen_Exp	-0.000	-0.000	-0.000	-0.000
	(-0.02)	(-0.02)	(-0.02)	(-0.02)
Firm_Exp	-0.000	-0.000	-0.000	-0.000
	(-0.34)	(-0.34)	(-0.34)	(-0.34)
Num_Ana	-0.000	-0.000	-0.000	-0.000
	(-1.50)	(-1.50)	(-1.50)	(-1.50)
dayElap	-0.003***	-0.003***	-0.003***	-0.003***
	(-5.13)	(-5.13)	(-5.13)	(-5.13)
Num_Ind	-0.000	-0.000	-0.000	-0.000
	(-0.31)	(-0.31)	(-0.31)	(-0.31)
Num_Co	-0.000	-0.000	-0.000	-0.000
	(-0.12)	(-0.12)	(-0.12)	(-0.12)
fh	-0.001***	-0.001***	-0.001***	-0.001***
	(-58.56)	(-58.56)	(-58.56)	(-58.56)
fr	-0.002**	-0.002**	-0.002**	-0.002**
	(-2.48)	(-2.48)	(-2.48)	(-2.48)
Year F.E	Yes	Yes	Yes	Yes
Industry F.E	Yes	Yes	Yes	Yes
N	16082	16082	16082	16082
Adjusted R^2	21.30%	21.30%	21.30%	21.30%

This table reports the ordinary least squares estimation results of the above regressions for the years 1999-2014, excluding financial crisis in 2007-2009. Columns 1, 2,3 and 4 use O_TO_B, O_TP_B, P_TP_B *and* P_TO_B as benchmark respectively. $accuracy_{ijt}$ is analyst forecast accuracy. Heteroskedasticity-robust standard errors are clustered by firm and analyst. t-statistics are reported in parentheses. *, **, and *** represent significance level of 10%, 5%, and 1%, respectively (two-tailed). All variable definitions are as reported in the Appendix II.

Table 3.1

This table provides pooled descriptive statistics for the sample of all firm-quarters over the time period 1994 to 2014. *Tone, Fog* and *Uncertain* are the optimism tone, readability and proportion of uncertain words in 10-Qs. High fog index means low readability. *investor_sent* is firm-specific investor sentiment when managers prepare 10-Q filings, 50 to 57 calendar days before firm's filing date. *roa* is return on assets by firm *i* in quarter *t*. *sue* is standardized earnings surprise by firm *i* in quarter *t*. *accruals* is the earnings of firm *i* in quarter *t* subtract cash flow from operations, scaled by the book value of assets. *earn* is earnings of quarter *t* scaled by the book value of assets. *sd_earn* is the standard deviation of earnings scaled by book value of assets calculated using data from the last four quarters. *ret* is the contemporaneous stock returns by firm *i* in quarter *t*. *sd_ret* is the stock return volatility calculated using 12 months of monthly return data before the fiscal quarter ending date. *logestimates* is natural logarithm of number of analysts following firm *i* in quarter *t*. *btm* is the book value of total assets divided by the market value of equity plus the book value of total liabilities. *tover* is natural logarithm of the number of shares traded divided by the number of shares outstanding on the filing date. *logmarkv* is the natural logarithm of the market capitalization of equity at the end of the quarter before the 10-Q filing date as a proxy for company size. *logGeo* is the logarithm of 1 plus the number of geographic segment. *logBiz* is the logarithm of 1 plus the number of business segment. *MA* is a dummy variable that equal to 1 if a company has M&A this quarter and 0 otherwise. *si* is special item. age is the number of years since a firm appears in CRSP. *leverage* is expressed in percent as the ratio of total liabilities to total assets. *ΔTone, ΔFog, ΔUncertain,* Δ*investor_sent* and Δ*investor_sent2* represent change in optimistic tone, readability, uncertain in 10-Qs and change in firm-specific investor sentiment 50 and 40 days before filing dates. They are subtracted from each signal the mean signal in 10-Qs made within the preceding four quarters and divide by the standard deviation of the signal in the past 10-Q filings made within the preceding four quarters. Δ*investor_sent* is the difference between *investor_sent* at quarter *t* and *investor_sent* at quarter *t*-1. Δ*investor_sent2* is the difference between *investor_sent2* at quarter *t* and *investor_sent2* at quarter *t*-1, where *investor_sent2* is firm-specific investor sentiment 40 to 47 calendar days before firm's filing date, when managers prepare 10-Q filings. Panel A reports the descriptive statistics and Panel B reports correlations matrix.

Panel A: Descriptive Statistics

Variable	*Description*	*N*	*Mean*	*S.D.*	*25th Percentile*	*Median*	*75th Percentile*
Tone	Tone of 10-Qs	13791	-0.01	0.01	-0.01	-0.01	0.00
Fog	Fog Index of 10Qs	13791	19.37	1.71	18.46	19.43	20.30
Uncertain	Propotion of uncertain words in 10Qs	13791	1.34	0.50	1.02	1.31	1.65
investor_sent	investor sentiment	13791	-0.17	0.12	-0.25	-0.20	-0.11
roa	Return on asset		0.02	0.03	0.01	0.02	0.03
sue	Unexpected earnings	13791	-0.13	0.18	-0.23	0.00	0.00
accruals	Accruals	13791	-0.02	0.06	-0.04	-0.02	0.00
earn	Current performance	13791	0.02	0.04	0.01	0.02	0.03
sd_earn	Volatility of current performace	13791	0.01	0.03	0.00	0.01	0.01
ret	Return	13791	0.00	0.03	-0.01	0.00	0.01
sd_ret	Volatility of return	13791	0.10	0.06	0.06	0.08	0.12
lnestimates	Natural log of number of analysts follow	13791	3.62	0.70	3.22	3.74	4.13
btm	Book-to-Market	13791	0.40	0.27	0.22	0.34	0.52
tover	turn over ratio	13791	13.09	0.74	12.59	13.09	13.59
logmarkv	Natural log of market value of equity	13791	8.84	1.29	8.00	8.78	9.66
logGeo	Natural log of number of geographic segments	13791	1.37	0.47	1.10	1.39	1.61
logBiz	Natual log of number of buisness sections	13791	1.25	0.50	0.69	1.39	1.61
MA	Dummy of M&A activitiy	13791	0.02	0.13	-	-	-
si	Special item	13791	-0.01	0.04	0.00	0.00	0.00
age	Firm age	13791	34.95	18.22	18.00	35.00	51.00
leverage	Leverage	13791	0.24	0.12	0.15	0.22	0.30
ΔTone	Change of 10-Qs optimistic tone	7970	-0.08	1.76	-0.77	-0.07	0.72
ΔFog	Change of 10-Qs Fog index	7970	0.27	2.05	-0.69	-0.08	0.81
ΔUncertain	Change of 10-Qs uncertain tone	7970	-0.16	1.29	-0.77	-0.18	0.46
Δinvestor_sent	Change of average investor sentiment 57 to 50 calendar days before filing date	7970	0.00	0.17	-0.08	0.00	0.08
Δinvestor_sent2	Change of average investor sentiment 47 to 40 calendar days before filing date	7970	0.00	0.19	-0.07	0.00	0.11

Panel B: Correlation Matrix (p-value in parentheses)

	Tone	Fog	Uncertain	investor_sent	ΔTone	ΔFog	ΔUncertain	Δinvestor_sent	roa	sue	accruals	earn	sd_earn
Fog	-0.310	1											
	(<0.001)												
Uncertain	-0.459	0.268	1										
	(<0.001)	(<0.001)											
investor_sent	0.027	-0.006	-0.025	1									
	(0.001)	(0.468)	(0.003)										
ΔTone	0.353	-0.062	-0.102	0.001	1								
	(<0.001)	(<0.001)	(<0.001)	(0.893)									
ΔFog	-0.064	0.369	-0.009	-0.008	-0.077	1							
	(<0.001)	(<0.001)	(0.316)	(0.351)	(<0.001)								
ΔUncertain	-0.100	-0.034	0.394	-0.007	-0.134	-0.054	1						
	(<0.001)	(<0.001)	(<0.001)	(0.436)	(<0.001)	(<0.001)							
Δinvestor_sent	-0.013	-0.001	-0.007	0.681	-0.004	0.023	-0.005	1					
	(0.254)	(0.936)	(0.491)	(<0.001)	(0.727)	(0.050)	(0.632)						
roa	0.100	-0.070	-0.015	0.017	0.069	-0.016	-0.007	0.009	1				
	(<0.001)	(<0.001)	(0.078)	(0.040)	(<0.001)	(0.071)	(0.424)	(0.411)					
sue	0.193	-0.172	-0.247	0.011	0.001	0.026	0.042	-0.008	-0.039	1			
	(<0.001)	(<0.001)	(<0.001)	(0.172)	(0.929)	(0.004)	(<0.001)	(0.464)	(<0.001)				
accruals	0.105	-0.072	-0.092	0.016	0.052	-0.057	0.008	-0.015	0.409	0.042	1		
	(<0.001)	(<0.001)	(<0.001)	(0.060)	(<0.001)	(<0.001)	(0.361)	(0.168)	(<0.001)	(<0.001)			
earn	0.084	-0.046	-0.027	0.011	0.055	-0.014	-0.011	0.006	0.775	-0.029	0.623	1	
	(<0.001)	(<0.001)	(0.002)	(0.164)	(<0.001)	(0.121)	(0.221)	(0.592)	(<0.001)	(0.001	(<0.001)		
sd_earn	-0.120	0.035	0.100	-0.025	-0.024	0.019	0.027	0.006	-0.131	0.011	-0.221	-0.133	1
	(<0.001)	(<0.001)	(<0.001)	(0.003)	(0.007)	(0.0351	(0.003)	(0.563)	(<0.001)	(0.199)	(<0.001)	(<0.001)	
ret	-0.0121	-0.0001	0.0047	-0.0174	-0.0101	0.0020	-0.0030	0.0047	-0.0167	-0.0098	-0.0309	-0.0233	0.0128
	(0.156)	(0.994)	(0.579)	(0.041)	(0.273)	(0.824)	(0.744)	(0.679)	(0.049)	(0.251)	(<0.001)	(0.006)	(0.134)
sd_ret	-0.1575	0.0805	0.2149	-0.0467	-0.0408	0.0456	0.0396	-0.0003	-0.1466	0.0430	-0.1559	-0.1350	0.2389
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.978)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
lnestimates	-0.2258	0.1930	0.2904	0.0188	-0.0315	0.0108	-0.0120	-0.0009	0.0847	-0.4082	-0.0966	0.0537	-0.0116
	(<0.001)	(<0.001)	(<0.001)	(0.027)	(<0.001)	(0.241)	(0.1944)	(0.937)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.172)
btm	-0.1056	0.0677	-0.0181	-0.0052	-0.0245	0.0232	-0.0190	0.0148	-0.2788	-0.1254	-0.0755	-0.1846	0.0417
	(<0.001)	(<0.001)	(0.033)	(0.539)	(0.008)	(0.012)	(0.039)	(0.192)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
tover	-0.2634	0.2735	0.4469	-0.0036	-0.0344	0.0175	0.0115	-0.0035	-0.0611	-0.3271	-0.1116	-0.0567	0.1498
	(<0.001)	(<0.001)	(<0.001)	(0.672)	(<0.001)	(0.057)	(0.214)	(0.755)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
logmarkv	-0.1623	0.1001	0.1093	0.0207	-0.0264	-0.0212	-0.0136	0.0034	0.1818	-0.1636	0.0097	0.1362	-0.1024
	(<0.001)	(<0.001)	(<0.001)	(0.015)	(0.004)	(0.022)	(0.142)	(0.761)	(<0.001)	(<0.001)	(0.257)	(<0.001)	(<0.001)
logGeo	-0.1747	0.0747	0.1494	-0.0065	0.0007	-0.0132	0.0111	0.0147	0.0101	-0.1306	0.0289	0.0132	0.0252
	(<0.001)	(<0.001)	(<0.001)	(0.443)	(0.936)	(0.154)	(0.231)	(0.194)	(0.236)	(<0.001)	(<0.001)	(0.120)	(0.003)
logBiz	-0.1131	0.0797	-0.0243	-0.0076	0.0131	-0.0242	-0.0347	0.0220	-0.0335	-0.1001	0.0565	-0.0159	-0.0631

	(<0.001)	(<0.001)	(0.004)	(0.373)	(0.156)	(0.009)	(<0.001)	(0.052)	(0.0001	(<0.001)	(<0.001)	(0.063)	(<0.001)
MA	0.0555	-0.0363	-0.0296	0.0155	-0.0323	0.0277	0.0239	0.0032	0.0332	0.1003	0.0408	0.0212	0.0264
	(<0.001)	(<0.001)	(0.001)	(0.069)	(0.001)	(0.003)	(0.010)	(0.775)	(<0.001)	(<0.001)	(<0.001)	(0.013)	(0.002)
si	0.0816	-0.0382	-0.0478	0.0136	0.0508	-0.0391	-0.0031	-0.0143	0.4967	-0.0042	0.7116	0.7473	-0.2736
	(<0.001)	(<0.001)	(<0.001)	(0.111)	(<0.001)	(<0.001)	(0.734)	(0.208)	(<0.001)	(0.618)	(<0.001)	(<0.001)	(<0.001)
age	-0.0035	-0.0313	-0.1870	-0.0044	0.0401	-0.0441	-0.0530	0.0135	-0.0275	-0.0351	0.1290	0.0031	-0.1112
	(0.680)	(<0.001)	(<0.001)	(0.603)	(<0.001)	(<0.001)	(<0.001)	(0.233)	(0.0012	(<0.001)	(<0.001)	(0.718)	(<0.001)
leverage	0.0684	-0.0530	-0.0747	-0.0097	0.0273	0.0076	-0.0113	0.0014	0.0270	0.0252	0.1147	0.0213	-0.0150
	(<0.001)	(<0.001)	(<0.001)	(0.252)	(0.003)	(0.412)	(0.221)	(0.898)	(0.002)	(0.003)	(<0.001)	(0.012)	(0.077)

	ret	sd_ret	lnestimates	btm	tover	logmarkv	logGeo	logBiz	MA	si	age	leverage
sd_ret	0.0223	1										
	(0.009)											
lnestimates	-0.0066	-0.0520	1									
	(0.437)	(<0.001)										
btm	0.0223	0.1128	-0.1495	1								
	(0.009)	(<0.001)	(<0.001)									
tover	0.0035	0.4478	0.3643	0.0998	1							
	(0.679)	(<0.001)	(<0.001)	(<0.001)								
logmarkv	-0.0092	-0.2896	0.6157	-0.3406	-0.0676	1						
	(0.282)	(<0.001)	(<0.001)	(<0.001)	(<0.001)							
logGeo	0.0033	0.0225	0.1479	-0.0408	0.1172	0.1755	1					
	(0.701)	(0.008)	(<0.001)	(<0.001)	(<0.001)	(<0.001)						
logBiz	0.0001	-0.1388	0.0070	0.1187	-0.1042	0.2125	0.2156	1				
	(0.987)	(<0.001)	(0.413)	(<0.001)	(<0.001)	(<0.001)	(<0.001)					
MA	-0.0064	0.0626	-0.0391	-0.0946	-0.0122	-0.0164	-0.0361	-0.0752	1			
	(0.454)	(<0.001)	(<0.001)	(<0.001)	(0.152)	(0.054)	(<0.001)	(<0.001)				
si	-0.0223	-0.0979	-0.0236	-0.0264	-0.0717	0.0323	-0.0135	0.0282	-0.0155	1		
	(0.009)	(<0.001)	(0.006)	(0.002)	(<0.001)	(<0.001)	(0.114)	(0.001)	(0.067)			
age	-0.0016	-0.2722	-0.1030	0.1353	-0.2650	0.1879	0.1743	0.4226	-0.0899	0.0404	1	
	(0.854)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)		
leverage	0.0121	-0.0508	-0.0867	-0.2104	-0.0934	-0.0039	-0.0215	0.0343	0.0258	-0.0064	0.1138	1
	(0.154)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.649)	(0.012)	(<0.001)	(0.002)	(0.453)	(<0.001)	

Table 3.2
Tone in 10-Qs and Firm-specific Investor Sentiment

Dependent Variable	Tone		
	(1)	(2)	(3)
	Overall	High	Low
constant	-0.003	-0.013**	0.003
	(-0.61)	(-2.40)	(0.59)
investor_sent	**0.001***	0.003*	0.001
	(1.64)	(1.76)	(1.38)
high		-0.001*	
		(-1.69)	
high*investor_sent		**-0.004***	
		(-1.71)	
low			-0.001
			(-1.54)
low*investor_sent			**-0.004***
			(-1.91)
roa	0.013**	-0.006	0.038***
	(2.38)	(-0.91)	(4.59)
sue	-0.000	-0.001	0.000
	(-0.46)	(-0.77)	(0.18)
accruals	0.004	0.003	0.005*
	(1.55)	(1.32)	(1.80)
earn	0.001	0.016**	-0.007
	(0.36)	(2.15)	(-1.55)
sd_earn	-0.005	-0.005	-0.009
	(-0.98)	(-0.96)	(-1.51)
ret	0.002	-0.001	0.002
	(1.34)	(-0.42)	(1.11)
sd_ret	-0.003	-0.004	-0.002
	(-1.13)	(-1.32)	(-0.59)
logestimates	-0.000	-0.001**	-0.000
	(-1.42)	(-2.11)	(-0.69)
btm	-0.003***	-0.003***	-0.004***
	(-3.55)	(-3.47)	(-3.56)
tover	0.000	0.001*	-0.000
	(0.38)	(1.81)	(-0.58)
logmarkv	0.000	0.001**	-0.000
	(0.99)	(2.24)	(-0.03)
logGeo	-0.001	0.000	-0.001
	(-0.50)	(0.15)	(-1.12)
logBiz	-0.001*	-0.001	-0.001
	(-1.94)	(-1.16)	(-0.80)
MA	0.001*	0.001**	0.000
	(1.90)	(2.47)	(0.58)
si	-0.005*	-0.011***	-0.010***
	(-1.71)	(-8.67)	(-6.93)
crisis	-0.011***	0.003	-0.001
	(-9.20)	(0.78)	(-0.25)
age	0.000***	0.000***	0.000***
	(8.04)	(6.84)	(6.40)
leverage	-0.004*	-0.003*	-0.005*
	(-1.76)	(-1.77)	(-1.84)
Quarter FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	13791	8091	5700
Adjusted R^2	17.70%	17.70%	18.40%

The table reports the regression of investor sentiment on the tone of subsequent 10-Qs from 1994 to 2014. *Tone* represents the optimistic tone in 10-Qs. Column 1 uses whole sample, columns 2 and 3 use investor sentiment at top 50% and bottom 50%, respectively. *investor_sent* is firm-specific investor sentiment when managers prepare 10-Q filings, 50 to 57 calendar days before firm's filing date. *high* and *low* are dummy variables. *high* equals to 1 if investor sentiment is on the top 5% per quarter per industry, otherwise 0. *low* equals to 1 if investor sentiment is on the bottom 5%, otherwise 0. Heteroskedasticity-robust standard errors are clustered by firm. t-statistics are reported in parentheses. *, **, and *** represent significance level of 10%, 5%, and 1%, respectively. All other variable definitions are as reported in Table 3.1.

Table 3.3
Change of Tone in 10-Qs and Firm-specific Investor Sentiment

Dependent Variable	Δtone		
	(1)	(2)	(3)
	high vs. low	high to low	low to high
constant	3.379	-1.083	-0.220
	(1.34)	(-0.94)	(-0.24)
Δinvestor_sent	0.503***	0.221	-0.021
	(2.77)	(1.25)	(-0.19)
below_average	0.070		
	(1.47)		
Δinvestor_sent*below_average	**-0.571****		
	(-2.24)		
$O_{t-1}P_t$		0.065	
		(0.88)	
Δinvestor_sent*$O_{t-1}P_t$		**-0.801****	
		(-2.03)	
$P_{t-1}O_t$			0.050
			(0.68)
Δinvestor_sent*$P_{t-1}O_t$			**0.543***
			(1.73)
roa	5.539**	4.099	4.541**
	(2.49)	(1.42)	(2.15)
sue	0.071	0.010	0.034
	(0.42)	(0.09)	(0.39)
accruals	0.777	0.578	0.500
	(1.20)	(0.77)	(0.87)
earn	-1.831	-1.263	-1.397
	(-1.21)	(-0.70)	(-0.97)
sd_earn	1.078	1.294	1.230**
	(1.54)	(0.84)	(1.99)
ret	0.312	-0.108	0.303
	(0.52)	(-0.14)	(0.57)
sd_ret	-0.022	-0.201	-0.229
	(-0.03)	(-0.26)	(-0.42)
logestimates	-0.024	-0.052	-0.043
	(-0.35)	(-0.68)	(-0.67)
btm	-0.674***	-0.407**	-0.432***
	(-4.02)	(-2.20)	(-3.31)
tover	-0.245***	-0.228***	-0.218***
	(-3.24)	(-2.88)	(-3.37)
logmarkv	-0.043	-0.021	-0.023
	(-0.70)	(-0.30)	(-0.40)
logGeo	-0.004	-0.106	-0.046
	(-0.03)	(-0.79)	(-0.44)
logBiz	0.049	0.132	0.086
	(0.44)	(1.05)	(0.87)
MA	-0.322	-0.335	-0.298
	(-1.52)	(-1.47)	(-1.59)
si	0.448	0.951	0.896
	(0.47)	(0.87)	(0.92)
age	-0.029***	-0.033***	-0.021***
	(-7.84)	(-6.63)	(-6.86)
leverage	0.151	0.138	0.083
	(0.38)	(0.31)	(0.24)
Quarter /Year/ Firm FE	Yes	Yes	Yes
Observations	7970	7970	7970
Adjusted R^2	4.50%	3.80%	4.70%

The table reports the regression of the change of tone on the change of investor sentiment. *ΔTone* is the change of tone in the current 10-Qs, subtracted by the prior quarter. *Δinvestor_sent* is the change of investor sentiment at current quarter and last quarter. *below_average* equals to 1 if a firm has below average firm-specific investor sentiment for quarter *j* (i.e. pessimistic firm-specific investor sentiment compare with peers in the same quarter), otherwise 0. $O_{t-1}P_t$ is a dummy variable, which equals to 1 if investor sentiment was in high investor sentiment group at quarter *t-1* and is in low investor sentiment group at quarter *t*, otherwise 0. $P_{t-1}O_t$ is a dummy variable, which equals to 1 if investor sentiment was in low investor sentiment group at quarter *t-1* and is in high investor sentiment group at quarter *t*. Heteroskedasticity-robust standard errors are clustered by firm. t-statistics are reported in parentheses. *, **, and *** represent significance level of 10%, 5%, and 1%, respectively. All other variable definitions are as reported in Table 3.1.

Table 3.4
Readability in 10-Qs and Firm-specific Investor Sentiment

Dependent Variable	Fog		
	(1)	(2)	(3)
	Overall	High	Low
constant	16.775***	17.583***	16.909***
	(17.18)	(18.16)	(15.01)
investor_sent	**-0.230****	-0.144	-0.627***
	(-2.17)	(-0.39)	(-2.66)
high		0.089	
		(1.31)	
high*investor_sent		**0.247**	
		(0.52)	
low			0.121
			(1.42)
low*investor_sent			**0.520***
			(1.75)
roa	-1.736**	-4.231***	-2.508**
	(-2.12)	(-3.12)	(-2.19)
sue	0.425***	0.234	0.358**
	(2.86)	(1.59)	(2.37)
accruals	0.430	-0.201	0.987**
	(0.92)	(-0.45)	(2.10)
earn	0.766	2.352***	0.126
	(1.29)	(3.56)	(0.33)
sd_earn	0.016	1.300	-0.560
	(0.02)	(1.29)	(-0.48)
ret	-0.874**	-0.495	-0.889**
	(-2.43)	(-1.50)	(-2.34)
sd_ret	0.006	0.074	-0.471
	(0.01)	(0.17)	(-0.99)
logestimates	0.017	-0.012	-0.028
	(0.22)	(-0.18)	(-0.45)
btm	0.375**	0.353**	0.200
	(2.33)	(2.15)	(1.25)
tover	0.137**	0.079	0.153**
	(2.34)	(1.38)	(2.52)
logmarkv	-0.002	0.028	-0.054
	(-0.03)	(0.45)	(-0.80)
logGeo	-0.172	-0.233*	-0.183
	(-1.18)	(-1.69)	(-1.19)
logBiz	0.090	0.136	0.147
	(0.67)	(1.17)	(1.16)
MA	0.113	0.147	0.188
	(0.73)	(1.06)	(1.18)
si	-0.681	2.442***	2.631***
	(-1.40)	(10.45)	(9.59)
crisis	2.550***	-1.374*	-1.208**
	(9.44)	(-1.95)	(-2.42)
age	-0.027***	-0.034***	-0.022***
	(-7.67)	(-10.08)	(-4.83)
leverage	0.168	0.428	0.175
	(0.35)	(0.94)	(0.40)
Quarter FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	13791	8091	5700
Adjusted R^2	16.00%	23.20%	20.00%

The table reports the regression of Fog index on investor sentiment from 1994 to 2014. *Fog* represents the Fog index 10-Qs. Column 1 uses all sample, columns 2 and 3 use investor sentiment at top 50% and bottom 50%, respectively. *investor_sent* is firm-specific investor sentiment 50 to 57 calendar days before firm's filing date, when managers prepare 10-Q filings. *high* and *low* are dummy variables. *high* equals to 1 if investor sentiment is on the top 5%, otherwise 0. *low* equals to 1 if investor sentiment is on the bottom 5%, otherwise 0. Heteroskedasticity-robust standard errors are clustered by firm. t-statistics are reported in parentheses. *, **, and *** represent significance level of 10%, 5%, and 1%, respectively. All other variable definitions are as reported in Table 3.1.

Table 3.5
Change of Readability in 10-Qs and Firm-specific Investor Sentiment

Dependent Variable	ΔFog		
	(1)	(2)	(3)
	high vs. low	high to low	low to high
constant	3.856	3.957***	4.001***
	(1.25)	(2.62)	(2.67)
Δ*investor_sent*	-1.365***	-0.455**	-0.425**
	(-2.59)	(-2.21)	(-2.14)
below_average	-0.037		
	(-0.26)		
Δinvestor_sent*below_average	**1.534***		
	(1.75)		
$O_{t-1}P_t$		0.012	
		(0.08)	
$\boldsymbol{\Delta investor\_sent*O_{t-1}P_t}$		**-0.008**	
		(-0.01)	
$P_{t-1}O_t$			0.096
			(1.10)
$\boldsymbol{\Delta investor\_sent*P_{t-1}O_t}$			**0.510**
			(1.15)
roa	6.351	-0.129	-0.794
	(1.07)	(-0.06)	(-0.36)
sue	0.358	-0.012	0.088
	(1.16)	(-0.05)	(0.35)
accruals	2.38	-0.133	0.736
	(0.94)	(-0.14)	(0.77)
earn	-0.814	0.682	1.021
	(-0.38)	(0.83)	(1.23)
sd_earn	-3.706	-0.876	0.765
	(-1.00)	(-0.35)	(0.30)
ret	-6.593**	-1.708	-1.092
	(-2.12)	(-1.63)	(-1.12)
sd_ret	-0.808	-0.462	-0.041
	(-0.43)	(-0.46)	(-0.04)
logestimates	0.001	0.081	0.071
	(0.01)	(0.75)	(0.63)
btm	0.847**	0.730**	0.783***
	(2.01)	(2.54)	(2.61)
tover	0.01	-0.060	-0.083
	(0.05)	(-0.59)	(-0.82)
logmarkv	0.113	0.070	0.110
	(0.79)	(0.80)	(1.26)
logGeo	-0.51	0.201	0.143
	(-0.88)	(1.09)	(0.79)
logBiz	0.007	0.110	0.115
	(0.02)	(0.70)	(0.74)
MA	0.914	0.304	0.286
	(0.90)	(1.15)	(1.10)
si	-4.788	-1.787*	-2.491**
	(-1.45)	(-1.65)	(-2.10)
age	-0.026***	-0.049***	-0.049***
	(-9.83)	(-12.10)	(-11.66)
leverage	-0.094	0.603	0.486
	(-0.34)	(1.08)	(0.94)
Quarter /Year/ Firm FE	Yes	Yes	Yes
Observations	7970	7970	7970
Adjusted R^2	3.20%	7.20%	7.00%

The table reports the regression of the change of readability on the change of investor sentiment. ΔFog is the Fog index in the current 10-Qs, subtracted by the prior quarters and divide by the standard deviation of the tone in the past 10-Q filings made within the preceding four quarters. *Δinvestor_sent* is the change of investor sentiment at current quarter and last quarter. *below_average* equals to 1 if a company has below average firm-specific investor sentiment for quarter j (i.e. pessimistic firm-specific investor sentiment compare with peers in the same quarter), otherwise 0. $O_{t-1}P_t$ is a dummy variable, which equals to 1 if investor sentiment was in high investor sentiment group at quarter t-1 and is in low investor sentiment group at quarter t, otherwise 0. $P_{t-1}O_t$ is a dummy variable, which equals to 1 if investor sentiment was in low investor sentiment group at quarter t-1 and is in high investor sentiment group at quarter t. Heteroskedasticity-robust standard errors are clustered by firm. t-statistics are reported in parentheses. *, **, and *** represent significance level of 10%, 5%, and 1%, respectively. All other variable definitions are as reported in Table 3.1.

Table 3.6
Uncertainty in 10-Qs and Firm-specific Investor Sentiment

	Uncertain		
	(1)	(2)	(3)
	Overall	High	Low
constant	0.677**	0.912***	0.437
	(2.32)	(3.02)	(1.44)
investor_sent	**-0.054***	0.127	-0.066*
	(-1.84)	(1.46)	(-1.65)
high		-0.035*	
		(-1.84)	
high*investor_sent		**-0.210***	
		(-1.70)	
low			0.184***
			(3.34)
low*investor_sent			**0.464*****
			(3.73)
roa	-0.022	0.268	-0.039
	(-0.05)	(0.51)	(-0.12)
sue	0.075	0.090	0.080
	(1.12)	(1.25)	(1.37)
accruals	-0.186	-0.130	-0.232
	(-1.36)	(-0.93)	(-1.44)
earn	0.054	-0.088	0.009
	(0.19)	(-0.22)	(0.06)
sd_earn	0.144	0.021	-0.319
	(0.45)	(0.06)	(-0.96)
ret	0.006	-0.083	-0.069
	(0.06)	(-0.52)	(-0.61)
sd_ret	-0.013	0.089	0.014
	(-0.09)	(0.61)	(0.08)
logestimates	0.014	0.033*	0.001
	(0.86)	(1.72)	(0.05)
btm	0.019	0.002	0.006
	(0.50)	(0.03)	(0.13)
tover	-0.004	-0.013	0.020
	(-0.21)	(-0.67)	(0.93)
logmarkv	0.030	0.014	0.029
	(1.60)	(0.72)	(1.33)
logGeo	0.070*	0.063	0.082*
	(1.75)	(1.51)	(1.92)
logBiz	0.017	0.022	0.022
	(0.56)	(0.68)	(0.70)
MA	-0.020	-0.008	-0.004
	(-0.64)	(-0.21)	(-0.10)
si	0.048	-0.446*	0.210
	(0.25)	(-1.91)	(1.21)
crisis	0.967***	0.853***	0.698***
	(16.46)	(15.37)	(16.18)
age	-0.013***	-0.014***	-0.015***
	(-14.62)	(-16.12)	(-16.81)
leverage	-0.130	-0.154	-0.120
	(-1.05)	(-1.20)	(-1.09)
Quarter FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	13791	8091	5700
Adjusted R^2	34.30%	35.70%	32.40%

The table reports the regression of tone on investor sentiment from 1994 to 2014. *Uncertain* represents the proportion of uncertain words in 10-Qs. Column 1 uses all sample, columns 2 and 3 use investor sentiment at top 50% and bottom 50%, respectively. *investor_sent* is firm-specific investor sentiment 50 to 57 calendar days before firm's filing date, when managers prepare 10-Q filings. *high* and *low* are dummy variables. *high* equals to 1 if investor sentiment is on the top 5%, otherwise 0. *low* equals to 1 if investor sentiment is on the bottom 5%, otherwise 0. Heteroskedasticity-robust standard errors are clustered by firm. t-statistics are reported in parentheses. *, **, and *** represent significance level of 10%, 5%, and 1%, respectively. All other variable definitions are as reported in Table 3.1.

Table 3.7
Change of Uncertainty in 10-Qs and Firm-specific Investor Sentiment

Dependent Variable	ΔUncertain		
	(1)	(2)	(3)
	high vs. low	high to low	low to high
constant	-0.625	-2.123**	-1.992**
	(-0.57)	(-2.47)	(-2.31)
Δinvestor_sent	0.257*	0.119	0.092
	(1.78)	(0.96)	(0.77)
below_average	0.037		
	(1.02)		
Δinvestor_sent*below_average	**-0.345***		
	(-1.76)		
$O_{t-1}P_t$		0.057	
		(0.85)	
Δinvestor_sent*$O_{t-1}P_t$		**-0.564***	
		(-1.69)	
$P_{t-1}O_t$			-0.116
			(-1.23)
Δinvestor_sent*$P_{t-1}O_t$			**-0.730***
			(-1.75)
roa	0.482	3.156	1.515
	(0.47)	(1.48)	(1.22)
sue	-0.006	0.102	-0.167
	(-0.05)	(0.62)	(-0.97)
accruals	0.253	0.868	0.394
	(0.52)	(1.44)	(0.64)
earn	-0.317	-2.570	-0.588
	(-0.66)	(-1.58)	(-1.11)
sd_earn	-0.356	0.100	2.662
	(-0.62)	(0.07)	(1.63)
ret	-0.204	-0.327	0.092
	(-0.46)	(-0.59)	(0.15)
sd_ret	-0.537	-0.369	-0.855
	(-1.18)	(-0.54)	(-1.40)
logestimates	0.08	0.153**	0.099
	(1.58)	(2.26)	(1.54)
btm	0.08	-0.021	0.091
	(0.68)	(-0.13)	(0.62)
tover	0.038	0.018	0.032
	(0.82)	(0.33)	(0.57)
logmarkv	0.021	-0.017	0.011
	(0.51)	(-0.35)	(0.24)
logGeo	-0.018	0.015	-0.026
	(-0.20)	(0.14)	(-0.24)
logBiz	-0.049	-0.052	-0.017
	(-0.62)	(-0.59)	(-0.18)
MA	0.035	0.111	0.090
	(0.23)	(0.71)	(0.59)
si	-0.314	0.420	-0.032
	(-0.48)	(0.41)	(-0.04)
age	-0.026***	-0.022***	-0.028***
	(-9.83)	(-6.54)	(-9.96)
leverage	-0.094	0.124	-0.183
	(-0.34)	(0.38)	(-0.54)
Quarter /Year/ Firm FE	Yes	Yes	Yes
Observations	7970	7970	7970
Adjusted R^2	3.20%	4.10%	4.30%

The table reports the regression of the change of uncertainty on the change of investor sentiment. ΔUncertain is the proportion of uncertain words in the current 10-Qs, subtracted by the prior quarters and divide by the standard deviation of the tone in the past 10-Q filings made within the preceding four quarters. *Δinvestor_sent* is the change of investor sentiment at current quarter and last quarter. *below_average* equals to 1 if a company has below average firm-specific investor sentiment for quarter j (i.e. pessimistic firm-specific investor sentiment compare with peers in the same quarter), otherwise 0. $O_{t-1}P_t$ is a dummy variable, which equals to 1 if investor sentiment was in high investor sentiment group at quarter t-1 and is in low investor sentiment group at quarter t, otherwise 0. $P_{t-1}O_t$ is a dummy variable, which equals to 1 if investor sentiment was in low investor sentiment group at quarter t-1 and is in high investor sentiment group at quarter t. Heteroskedasticity-robust standard errors are clustered by firm. t-statistics are reported in parentheses. *, **, and *** represent significance level of 10%, 5%, and 1%, respectively. All other variable definitions are as reported in Table 3.1.

Table 3.8
Regressions of tone, readability and uncertainty of 10-Q filings on firm-specific investor sentiment from an alternative investor sentiment period

	(1)	(2)	(3)
	Tone	Fog	Uncertain
constant	-0.008*	16.877***	0.007**
	(-1.83)	(15.41)	(2.53)
investor_sent2	**0.001*** **	**-0.224***	**0.023**
	(2.80)	**(-1.63)**	**(0.09)**
roa	0.011*	-2.320	0.002
	(1.81)	(-1.62)	(0.55)
sue	-0.000	0.367*	0.001
	(-0.26)	(1.83)	(1.10)
accruals	0.004**	0.348	-0.002*
	(2.11)	(0.62)	(-1.93)
earn	0.001	0.145	-0.001
	(0.11)	(0.18)	(-0.46)
sd_earn	-0.003	2.457*	-0.001
	(-0.86)	(1.84)	(-0.26)
ret	0.001	-1.127***	-0.001
	(0.40)	(-2.59)	(-1.47)
sd_ret	-0.003	-0.692	-0.000
	(-1.35)	(-1.37)	(-0.32)
logestimates	-0.001*	-0.014	0.000
	(-1.90)	(-0.20)	(0.53)
btm	-0.002***	0.344	0.000
	(-3.69)	(1.64)	(0.09)
tover	0.000	0.145**	0.000
	(1.15)	(2.36)	(0.28)
logmarkv	0.001*	-0.013	0.000
	(1.75)	(-0.19)	(1.32)
logGeo	-0.000	-0.203	0.000
	(-0.46)	(-1.42)	(1.02)
logBiz	-0.001	0.159	0.000
	(-1.41)	(1.26)	(1.41)
MA	0.001***	0.108	-0.000
	(2.77)	(0.65)	(-0.02)
si	-0.003	-0.645	0.002
	(-1.56)	(-1.17)	(1.58)
crisis	-0.010***	0.000	0.010***
	(-9.84)	(.)	(19.22)
age	0.000***	-0.028***	-0.000***
	(8.55)	(-6.35)	(-19.92)
leverage	-0.004**	0.267	-0.002*
	(-2.03)	(0.48)	(-1.67)
Quarter FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	10826	10826	10826
Adjusted R^2	17.90%	17.70%	33.20%

The table reports the regression of tone, readability and uncertainty on the change of investor sentiment using alternative investor sentiment. *investor_sent2* is firm-specific investor sentiment when managers prepare 10-Q filings, 40 to 47 calendar days before firm's filing date. Heteroskedasticity-robust standard errors are clustered by firm. t-statistics are reported in parentheses. *, **, and *** represent significance level of 10%, 5%, and 1%, respectively. All other variable definitions are as reported in Table 3.1.

Table 3.9
Regressions of the change of tone, readability and uncertainty of 10-Q filings on the change of firm-specific investor sentiment from an alternative investor sentiment period

Variable	(1) ΔTone	(2) ΔFog	(3) ΔUncertain
constant	3.819***	1.711*	-2.080***
	(4.03)	(1.9)	(-3.03)
Δinvestor_sent2	**0.216***	**-0.342***	**0.247***
	(1.68)	**(-1.95)**	**(1.84)**
below_average	-0.044	0.007	-0.001
	(-0.71)	(0.18)	(-0.04)
Δinvestor_sent2*below_average	**-0.499***	**0.407***	**-0.310***
	(-1.84)	**(1.79)**	**(-1.72)**
roa	3.221*	-3.853***	0.626
	(1.73)	(-3.14)	(0.60)
sue	0.229	-0.077	0.023
	(1.30)	(-0.57)	(0.20)
accruals	0.963	0.835	0.155
	(1.57)	(1.56)	(0.33)
earn	-1.042	2.551***	-0.442
	(-0.90)	(3.54)	(-1.01)
sd_earn	1.320**	-1.099	-0.129
	(2.29)	(-1.00)	(-0.22)
ret	0.478	-0.21	0.028
	(0.89)	(-0.42)	(0.07)
sd_ret	-0.753	0.181	-0.462
	(-1.33)	(0.34)	(-1.07)
logestimate	-0.046	0.057	0.079
	(-0.69)	(0.89)	(1.47)
btm	-0.526***	0.358***	0.154
	(-3.47)	(2.83)	(1.28)
tover	-0.189***	-0.013	0.012
	(-3.24)	(-0.23)	(0.29)
logmarkv	-0.026	0.036	0.018
	(-0.44)	(0.77)	(0.44)
logGeo	-0.023	0.089	0.135
	(-0.19)	(0.89)	-1.49
logBiz	-0.092	0.006	(0.02)
	(-0.83)	(0.04)	(-0.26)
MA	-0.469*	0.152	-0.035
	(-1.90)	(0.70)	(-0.22)
si	0.081	-1.688**	-0.175
	(0.08)	(-2.23)	(-0.30)
age	-0.012***	-0.048***	-0.029***
	(-2.75)	(-29.70)	(-11.64)
leverage	0.359	0.424	0.12
	(0.98)	(1.39)	(0.37)
Quarter FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	7934	7934	7934
Adjusted R2	5.40%	8.60%	3.50%

The table reports the regression of the change of tone, readability and uncertainty on the change of investor sentiment using alternative investor sentiment. *ΔTone, ΔFog, ΔUncertain* and *Δinvestor_sent2* represent change in optimistic tone, readability, uncertain tone in 10-Qs and change in firm-specific investor sentiment between current quarter and prior quarter. *Δinvestor_sent2* is the difference between investor sentiment 40 to 47 days before the filing issue date (isent40) at quarter t and isent40 at quarter t-1. Heteroskedasticity-robust standard errors are clustered by firm. t-statistics are reported in parentheses. *, **, and *** represent significance level of 10%, 5%, and 1%, respectively. All other variable definitions are as reported in Table 3.1.

Table 3.10
Regressions of tone of 10-Q filings on firm-specific investor sentiment using delta control variables

Variable	(1) ΔTone	(2) ΔFog	(3) ΔUncertain
constant	-1.836	4.090***	-0.457
	(-0.88)	(4.30)	(-0.75)
Δinvestor_sent	**0.403****	**-1.238****	**0.268***
	(2.36)	(-2.46)	(1.87)
below_average	0.049	-0.043	0.050
	(1.09)	(-0.32)	(1.44)
Δinvestor_sent*below_average	**-0.546****	**1.409***	**-0.335***
	(-2.23)	(1.63)	(-1.71)
Δroa	-0.955	-1.047	0.091
	(-0.91)	(-0.52)	(0.13)
Δsue	-0.171	0.005	-0.003*
	(-0.88)	(1.01)	(-1.87)
Δaccruals	0.094	-2.005	-0.992
	(0.12)	(-0.36)	(-1.41)
Δearn	6.406***	1.601	-0.426
	(3.24)	(0.99)	(-1.00)
Δsd_earn	-3.489*	-1.484	1.097
	(-1.66)	(-0.48)	(0.96)
Δret	0.462	-4.162**	0.119
	(1.12)	(-2.24)	(0.43)
Δsd_ret	-4.005***	3.978**	1.947***
	(-4.15)	(2.02)	(3.08)
Δ logestimates	-0.049	-0.058	0.105
	(-0.54)	(-0.24)	(1.58)
Δ logBTM	0.283	0.424	-0.265
	(0.94)	(0.38)	(-1.36)
Δtover	-0.188**	-0.072	0.139**
	(-2.50)	(-0.36)	(2.54)
Δ logmarkv	0.701***	-0.613	-0.216**
	(4.79)	(-0.78)	(-2.23)
Δ logGeo	-0.270	-0.626	-0.149
	(-0.82)	(-0.54)	(-0.42)
Δ logBiz	-0.028	-0.686	0.253
	(-0.10)	(-1.26)	(0.98)
MA	-0.376*	0.938	0.001
	(-1.68)	(0.89)	(0.01)
Δsi	2.152	0.248	1.300
	(1.32)	(0.06)	(1.56)
age	-0.020***	-0.038***	-0.029***
	(-4.49)	(-5.65)	(-15.75)
Δleverage	0.828	0.449	-0.529
	(1.53)	(0.38)	(-1.23)
Quarter FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	7692	7692	7692
Adjusted R2	4.80%	3.00%	4.40%

The table reports the regression of the change of tone, readability and uncertainty on the change of investor sentiment,with the change of all control variables. *ΔFog, ΔUncertain* and *Δinvestor_sent* represent the change in optimistic tone, readability, uncertain tone in 10-Qs and the change in firm-specific investor sentiment. *Δinvestor_sent* is the difference between isent50 at quarter *t* and isent50 at quarter *t-1*. *below_average* equals to 1 if a firm has below average firm-specific investor sentiment for quarter *j* (i.e. pessimistic firm-specific investor sentiment compare with peers in the same quarter), otherwise 0. All control variables, except age and *MA*, are measured in the same way as *Δinvestor_sent*, that is, the difference between level at quarter *t* and level at quarter *t-1*. Heteroskedasticity-robust standard errors are clustered by firm. t-statistics are reported in parentheses. *, **, and *** represent significance level of 10%, 5%, and 1%, respectively. All other variable definitions are as reported in Table 3.1.