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Financial Analysts and Information Flows in the Markets

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Contents

Introduction

Volatility of stock market valuations has significantly increased over the last two decades. The value of modern company is less and less based on physical assets, meanwhile intangible assets: intellectual property, patents, human resources - are much more difficult to asses. The perception of a company becomes a cornerstone of valuation and any minor corporate news is capable to unsettle financial markets.

Managers quite often are better informed than the market and they remain the main source of the news for outsiders. They bring information into the markets in two ways: with the announcements and with the actions. However the executives have not a full control over the information: part of it is produced outside. External analysts collect and scrutinize the information from different sources and provide investors with regular reports on the business of interest.

The aim of this research project is to discuss the information flow between managers, analysts and investors in the financial markets. It examines the official information releases such as quarterly earnings announcements, unofficial flows of information between managers and analysts, and uncertain information as interpretation of managers actions, so-called "signals", used by analysts and investors.

The agency problem coming from informational inequality of the market participants creates numerous opportunities for manipulations. Managers may not only withhold or misinterpret the information, but they are also able to exercise the pressure on third-parties. Financial analysts are not completely independent of company executives: they need to cooperate with managers to get an access to the information and their employers prefer to keep good relationships with the potential clients for investment banking deals. As a result the investors constantly face the challenge how to evaluate the trustworthiness of external information and how to extract the maximum from the news announced. The two first chapters of this thesis discuss particular potential ways to address this challenge.

Chapter 1 adds to the existing literature on analysts' accuracy and conflicts of interests of informational intermediaries in financial markets by studying the problem of trustworthiness of news produced by sell-side analysts. I investigate whether the analysts who are first to switch from positive to negative recommendation about a company are trustworthy. Is it a signal of independence and professionalism or a warning signal of lack of connections with the firm? I find that these analysts have limited access to management-provided information and therefore are not reliable news bringers.

Chapter 2 investigates the abilities of textual analysis of earnings announcement conference calls to provide analysts and investors with valuable incremental information beyond the facts stated by managers. It studies how the negativity of manager's word choice, degree of uncertainty in his speech and other textual clues may help to predict the future earnings and likelihood of financial distress.

The agency problem hits not only investors, but the managers as well. Because the investors aware of potential conflict of interest suspiciously scrutinize any executives' action, the latter lose the flexibility for the actions. As an example, an executive may abstain from rebalancing his portfolio to avoid providing negative signals to the markets by the sale of company's shares. The third chapter examines the possible way to attenuate market reaction to the negative signals. I test whether the companies with more timely and extensive coverage are less constrained by "signaling" problem - losses in value caused by the investors' reaction on managers' actions.

In the rest of this introductive part, I summarize the main questions and findings for each chapter of the thesis.

Summary

Chapter 1: Absence of Access to Management-Provided Information as a Reason to Issue a Sell Recommendation

In this chapter, I aim to investigate whether the analysts, that are first to alarm the investors and issue a negative rating about a company, have a superior access to the company information.

An analyst issuing a "Sell" risks to anger management of the company. Upset managers are able to influence the analysts career and compensation through investment bankers; as well as directly, challenging analysts performance by managing the stream of information he gets. There are numerous ways available to managers to reduce information flow. Managers can exclude analysts from analyst-firm meetings or refuse to answer questions from the analyst during conference calls. And even Regulation of Fair Disclosure (FD) adopted by Security and Exchange Comission (SEC) in 2000, cannot really prevent managers from refusing to return phone calls or canceling, under some plausible excuse, prescheduled meetings with the analyst.

To avoid conflicts with followed companies, analysts replace "Sell" with "Hold" whenever possible. Womack (1996) finds that buy-rating issues occur 7 times more often than sell.

Mikhail et al. (2004) discover that sell recommendations represent only 6% of their sample.

In this paper I try to understand who those analysts giving negative recommendations are: better informed forecasters with tighter relationship with the company or those who have no access to management-provided information. I test two hypotheses the *Reasonable Confidence* hypothesis and the *Nothing to Lose* hypothesis.

The Reasonable Confidence hypothesis suggest that analysts issuing a “Sell” are willing to take this risk, because they are extremely confident in their opinion. This confidence can be explained by better-than-average previous results or by superior access to the information, tighter relationship with the firm. The latter should also reflect in the better-than-average forecasts. Nothing to Lose hypothesis assumes that the analysts who issue a first “Sell” about a firm are not afraid to do it, because they had no guidance and access to information in the first place. Since it is not possible to lose anything you do not possess, the non-cooperating company can serve as a painless sacrifice in order to build a reputation of “independence”. Issuing a “Sell” about a reluctant-to-provide-information firm may also serve as “Your help or your rating” threat to other companies followed by the analyst. The last but not the least motivation to issue a “Sell” about a company refusing to cooperate is an ordinary revenge. The losses, analysts voluntary accept by issuing a “Sell” in revenge for being ignored, are consistent with the experiments on negative reciprocity. Fehr and Gachter (2000) document that many people deviate from self-interested behavior in a reciprocal manner. In this particular case, analysts are ready to bear losses if, by doing so, they can punish the firm which was hostile to them.

Since the management-provided information is unobservable, I use the forecast accuracy, as a proxy for it. Thats why my main concern now is the dependence between recommendation type and previous forecast accuracy. I use a panel of firms covered by analysts over the period 1993-2007 from I/B/E/S database. I use probit model to test for dependence of previous accuracy on the decision to issue a first “Sell”. My second test concerns the change in analysts accuracy after he has issued a first “Sell”. I perform it with the aid of a linear regression of a dummy for first “Sell” recommendation on change in accuracy, controlling for change in forecasts frequency and change in age of the forecasts.

I find that issuing a first negative recommendation about a firm is negatively correlated with the forecast accuracy of the same analyst about this firm in the previous period. This finding supports the hypothesis that the analyst issuing a first “Sell” has a weak cooperation with the firm being covered. I find that not only the analysts previous period performance, but also his average forecast accuracy is inferior relative to the performance of his more-optimistic-in-their-recommendations colleagues. However, his accuracy does not deteriorate further. It means that the management of the covered firm does not reduce the guidance and the information flow despite the issue of the negative recommendation. The most natural explanation why managers did not punish the analyst despite the predictions of Chen and Matsumoto (2006) is because the amount of guidance has already reached the lowest limit, by the time the negative recommendation was issued.

Chapter 2: What Do Managers Say Between The Lines?

In this project, in collaboration with Richard Zeckhauser, we apply textual analysis techniques to conference calls transcripts to examine how past results influence the choice of words and how future results can be forecasted with words chosen. Our aim is to analyze what do managers talk about and whether they reveal unintentionally their true vision about the future. We hypothesize that the choice of words during conference calls cannot be fully explained by informational content of the conference call. It is influenced as well by the mood of managers - their expectations about the future and internal information they release intentionally or unintentionally.

This chapter seeks to contribute to the existing literature on several dimensions. First, it discusses how the past results influence the managers choice of words. Second, it explores whether there is a predictive power in what managers say. As opposed to previous research looking into the companies future (Demers and Vega (2008)), we concentrate on operating performance rather than financial one. While stock prices and returns are subject to perception of the public, which depends on managers speeches, real earnings should be independent of what the markets do feel.

We collected data on S&P 500 companies earnings announcements for the period of 2002 to 2009 (appearing in the index as of 01.03.2007) and largest bankrupt companies appearing in Chapter 11 Library in 2008- 2009. Conference calls transcripts are from Thomson Reuters; price and returns data is from CRSP; earnings and forecasts data is from I/B/E/S.

We find that managers negativity and certainty are influenced more by earnings surprise, than by the change in earnings over the past quarter or capital gain. We examine differences in prepared and improvised parts of managers speeches as they might signal uncertainty, fraud or insincerity. We observe that the differences increase when managers have to present poor results. However, we were not able to find predictive power in these differences. We also find that managers tend to switch the conversation from present to past responding analysts questions when questions are more hostile. We show that negativity of managers words unexplained by past results can serve to predict future earnings of the company. The resulting forecasts however do not outperform consensus forecasts of financial analysts. The most important finding is the ability of textual analysis to provide incremental information when used concurrently with classical bankruptcy prediction model by Altman (1968). The degree of manager's negativity and uncertainty are as important for classificatory model, as classical financial ratios.

Chapter 3: Signaling Attenuation Effect and Sell-side Analysts

In chapter 3 I investigate the impact of analyst coverage of companies regular news on market reaction to less expected events.

When taking decisions on company financing or constructing their own portfolios, managers should take into consideration signaling problem. Access to insider information makes every managers action a possible source of information. Ross (1977) brought up signaling issues in capital structure decisions. Myers and Majluf (1984) build a model showing that firms may pass up valuable investment opportunities, being constrained by signaling effect of equity issue. Fama and Jensen (1983) discuss how insider trading provides negative signal to the market.

I follow the research idea of Kelly and Ljungqvist (2007) who found that better coverage improves the informational efficiency. I hypothesize that timely and active sell-side analysis makes investors less sensitive to new information coming from other sources (besides analysts reports). And therefore, managers are less constrained by signaling issues if they arrange intensive sell-side coverage of the company.

Using U.S. data from 1998 through 2008 obtained from I/B/E/S, SDC Platinum, CRSP and Thomson Financial, I find that markets react less intensively to insider sales after more active and timely coverage of earnings announcements.

Timely analysts coverage either improves market efficiency and insider trade indeed does not bring a news to the markets, or it makes investors believe in higher efficiency and move their attention elsewhere. Insiders, as if they are aware of this phenomenon, are more likely to sell their shares after earnings announcements with timely forecast revisions. The effect persists controlling for market reaction to earnings announcement and company size and is valid for earnings surprises with positive as with negative surprises.

Chapter 1

Absence of Access to Management-Provided Information as a Reason to Issue a Sell Recommendation

Issuing of a sell recommendation is costly for a financial analyst because of the negative reaction of investment bankers and managers of the covered firm. This paper examines the reasons why some analysts still issue "Sells" despite the risks involved. I find that the analysts who issue the first sell recommendation about a firm, despite being more experienced, were on average worse forecasters for this firm than their more optimistic colleagues. Thus, I reject the hypothesis that the first sell recommendations are issued by better informed analysts. I conclude instead that analysts are ready to issue a first sell recommendation when they have not much to lose in terms of management-provided information. This hypothesis is also supported by the fact that the issue of a first "Sell" has no negative impact on further accuracy. This means that the management does not (can not) punish for these negative recommendations by reducing information provided. Probably, because information supply was already reduced to the minimum.

1.1 Introduction

This paper aims to answer the following question: who are the analysts that issue first negative ratings about a company. An analyst issuing a "Sell" risks angering two powerful forces: investment bankers and management of the company. The investment bankers are able to influence directly the analyst's career and compensation; the management of the company has impact on analyst's performance by managing the stream of information. Recounting his experience as a stock analyst, Reingold (2007) writes "Sell ratings offer little payoff to a Wall Street analyst. <...>If a stock falls or performs in line with the market, the Wall Street analyst who rated that stock Hold or Neutral looks almost as good to his clients as the one who rated it Sell. As a result, analysts didn't have much incentive to go out on a limb with a much riskier Sell rating, even before the banking pressure emerged". Confirming his own words Dan Reingold issued "Sell" only three times during his 14-year career. Empirical research gives evidence that he is not alone in his opinion. Womack (1996) finds that buy-rating issues occur 7 times more often than sell. Mikhail, Walther, and R.Willis (2004) discover that sell recommendations represent only 6% of their sample.

Despite the lack of incentives to issue a "Sell", there are analysts still issuing sell recommendations. Among 41,192 analysts appearing in I/B/E/S recommendations file from 1993 to 2007, 60.5% have issued a sell recommendation at least once . What makes these analysts courageous enough to issue a "Sell" and especially a first "Sell"? Well negotiated contract may protect analyst against investment bankers' pressure. So I expect to see more experienced analysts to be more prone to issue sell recommendations. The second menace to analyst's career is resentful management limiting his access to necessary information. There is no contract that can protect an analyst from managers' decision to reduce his access to information and to refuse to guide him. Though there are numerous ways available to managers to reduce information flow. Managers can exclude analysts from analyst-firm meetings or refuse to answer questions from the analyst during conference calls. And even Regulation of Fair Disclosure (FD) adopted by Security and Exchange Comission (SEC) in October 2000, cannot really prevent managers from refusing to return phone calls or canceling, under some plausible excuse, prescheduled meetings with the analyst.

I suppose that an analyst can be sure that company's management will not cut access to information and guidance, if both already were at the minimum level. Since it is not possible to lose anything you do not possess, the non-cooperating company can serve as a painless sacrifice in order to build a reputation of "independence" [1] or to reach any other goals. Since the adoption in September 2002 of NASD Rule 2711 that required security firms to disclose

[1]Hilary and Shon (2007) show that the market does not see sell recommendations as signs of analysts' reliability (inversely, investors assign lower credibility to analysts who issue "Sells"), but we still do not know if the analysts realize it.

the fractions of recommendations that are in each category, analysts have new incentives to issue "Sell" from time to time. Issuing a "Sell" about a reluctant-to-provide-information firm may also serve as "Your help or your rating" threat to other companies followed by the analyst. The last but not the least motivation to issue a "Sell" about a company refusing to cooperate is an ordinary revenge. The losses, analysts voluntary accept by issuing a "Sell" in revenge for being ignored, are consistent with the experiments on negative reciprocity. Fehr and Gachter (2000) document that many people deviate from self-interested behavior in a reciprocal manner. In this particular case, analysts are ready to bear losses if, by doing so, they can punish the firm which was hostile to them.[2])

An alternative guess why analysts issuing a "Sell" are willing to take this risk, is that they are extremely confident in their opinion. This confidence can be explained by better-than-average previous results or by superior access to the information. The latter should also reflect in the better-than-average forecasts.

In this paper I try to understand who those analysts giving bold negative recommendations are: better informed forecasters or those who have no access to management-provided information. Since the management-provided information is unobservable, I use the forecast accuracy, as a proxy for it. That's why my main concern now is the dependence between recommendation type and previous forecast accuracy.

In my analysis I distinguish 3 types of recommendations: positive recommendations (both kinds of buy and neutral), first sell recommendations (I do not make difference between strong sell and moderate sell) and the "Sell"- followers. I call the sell recommendation "first" if there were no other valid negative recommendations at the moment of its issue. A recommendation about a firm is valid until its author issues another recommendation for the same firm or a 6-month period expires[3]. Otherwise, the sell recommendation is called "Sell"-follower. The reasons for such a separation between leaders and followers are the following. First, the one who issues a first "Sell" risks more as his recommendation is more visible. Second, the "Sell"-follower may be issued as a reaction on the previously issued negative recommendation. In my sample the first "Sells" represent 5.9% of the total sample size; the "Sell"-followers represent 4.5%.[4] To exclude the effect of herding behavior I study

[2]An example of negative reciprocity is found in ultimatum bargaining experiments. In these experiments, two players have to agree on the division of a sum of money. One player (the Proposer) proposes a division and the other player (the Responder) can either accept the division, in which case the proposal is implemented, or reject the division, in which case both players receive nothing. It has been shown in numerous experiments that if the Proposer offers less than 30% of the money, the Responder rejects the proposal with high probability – even if by doing so he is clearly worse off (Fehr and Gachter (2000)

[3]I choose six-month upper limit for recommendation validity consistent with Womack (1996) findings that analyst recommendations retain investment value for up to six months.

[4]Such a high percentage of sell recommendations in my sample (total 10.4%) is due to the fact that I exclude the firm-quarters with only one kind of recommendations (only positive or only negatives). Thus, I exclude numerous firm-quarters without any sell recommendations.

only first "Sells" and then check if my results also hold for the "Sell"-followers.

I use a panel of firms covered by analysts over the period 1993-2007 from I/B/E/S database. I use probit model to test for dependence of previous accuracy on the decision to issue a first "Sell". My second test concerns the change in analyst's accuracy after he has issued a first "Sell". I perform it with the aid of a linear regression of a dummy for first "Sell" recommendation on change in accuracy, controlling for change in forecasts' frequency and change in age of the forecasts.

I find that issuing a first negative recommendation about a firm is negatively correlated with the forecast accuracy of the same analyst about this firm in the previous period. This finding supports the hypothesis that the analyst issuing a first "Sell" has a weak cooperation with the firm being covered. I find that not only the analyst's previous period performance, but also his average forecast accuracy is inferior relative to the performance of his more-optimistic-in-their-recommendations colleagues. However, his accuracy does not deteriorate further. It means that the management of the covered firm does not reduce the guidance and the information flow despite the issue of the negative recommendation. The most natural explanation why managers do not punish the analyst despite the predictions of Chen and Matsumoto (2006), is because the amount of guidance has already reached the lowest limit, by the time the negative recommendation was issued.

Studying "Sell"-followers recommendations, I find that their authors have on average less experience. Meanwhile, prior the issue of a negative recommendation, they are not less accurate than their colleagues issuing "Buy" and "Neutral". Their forecast performance, however, tends to worsen after the negative recommendation has been issued. This is consistent with Chen and Matsumoto (2006) findings and can be considered as a consequence of the reduction of management-provided information.

The paper is organized as follows: section 1.2 discusses the previous literature, section 1.3 develops the main working hypotheses and the corresponding empirical strategies, section 1.4 briefly describes the data and presents the main empirical results. Section 1.6 concludes.

1.2 Literature review

The economic literature describes many reasons for optimistic bias in financial analysts' recommendations: career concerns (Hong and Kubik (2003a)); investment banking pressure (Michaely and Womack (1999)); or fear of management's discontent. The anecdotal evidences of how analysts are"punished" by covered companies due to negative report are numerous on the pages of *Wall Street Journal* and *Business Week* (Siconolfi (1995) Siconolfi (1995), Angwin and Peers (2001), Elstrom (2001), Kelly (2003), Solomon and Frank (2003)). Note, that some of this evidence reflects what was happening after ratification of the Regulation Fair Disclosure (FD).

Chen and Matsumoto (2006) provide empirical evidence of revenge-by-silence, practiced by firms' managers. They deal with unfavorable recommendations, examining the changes in forecast accuracy before and after the unfavorable recommendation issue. Chen and Matsumoto (2006) find that issuing an unfavorable recommendation causes a decrease in the accuracy, which they explain by the decrease in management-provided information. They use two methods to define an unfavorable recommendation: the first is based on the change in an analyst's recommendation, the second is based on the relation of analyst's recommendation to the consensus (average) recommendation. As a result, in their sample of unfavorable recommendations there are not only sell ratings but also "Hold" and "Accumulate" if they represent a downgrade of the analyst's opinion or are more pessimistic than the consensus recommendation.

Lang and Lundholm (1996) as well as Bowen, Devis, and Matsumoto (2002) show that analysts generally benefit from managerial disclosures with increased forecast accuracy. So, it's not surprising that analysts willing to keep their access to important management-provided information avoid sell recommendations Francis and Philbrick (1993a)).

What is pushing an analyst to issue a "Sell" remains unclear. Hilary and Shon (2007) suppose that the incentive may be the desire to look more independent in the eyes of market participants. They also prove that "Sell" recommendations do not add credibility to the analyst.

1.3 Hypotheses and Methodology

In this paper I concentrate my attention mainly on first "Sells"[5] for several reasons. First, analysts issuing "Sell" after some "Sells" were already issued, risk less. Second, the issue of a follower- "Sell" can be a result of herding behaviour.

I see three possibilities to explain what makes analysts courageous enough to issue a first sell recommendation.

- *Hypothesis H1("Nothing to lose" hypothesis)*

  The analyst issuing the first sell recommendation about a firm had no help or guidance from the firm's management.

- *Hypothesis H2 ("Anticipated knowledge" hypothesis)*

[5] I remind to the reader that I call the sell recommendation "first" or "non-preceded" if there were no other valid negative recommendations at the moment of its issue. A recommendation about a firm is valid until its author issues another recommendation for the same firm or a 6-month period expires. Otherwise, the sell recommendation is called "Sell"-follower.

The analyst issuing the first "Sell" has a better access to the information (learns bad news earlier than his colleagues).

- *Hypothesis H3 ("Winner's pride" hypothesis)*

  The analyst issuing a first "Sell" is more self-confident due to his historical superior relative forecast accuracy.

Note that hypotheses H2 and H3 both suppose the superior forecast accuracy of the analyst prior to his first-"Sell" issue.

To test which of hypotheses above holds, I rely on the following two assumptions confirmed by previous literature.

- *Assumption A1:* Company-provided information is an important asset increasing the forecast accuracy of an analysts. (Lang and Lundholm (1996), Bowen, Devis, and Matsumoto (2002))
- *Assumption A2:* Managers unhappy about the coverage usually reduce information provided to unfavorable analyst. (Chen and Matsumoto (2006))

A1 translates in that analysts who have no help from the management should have relatively poor forecast accuracy. If the company-provided information increases the forecast accuracy, the low relative accuracy may be interpreted as a lack of this information. Therefore, I can choose between H1 on the one side and H2 with H3 on the other side by testing if the analysts issuing a first "Sell" had a superior performance in the periods preceding to the "Sell" issue.

To compute the relative forecast accuracy of an analyst, I consider the last forecast issued by each analyst prior to the company's earnings announcement. I compute the Absolute Forecast Error (AFE) of the analyst i for the firm j in the quarter t as the absolute value of the difference between the last forecast and the actual value.

$$AFE_{ijt} = |Actual_{jt} - Forecast_{ijt}|\,, \tag{1.1}$$

where $Actual_{jt}$ stays for the actual earnings of the firm j at the quarter t,
and $Forecast_{ijt}$ is the last earnings forecast of the analyst i for the firm j in the quarter t.

The forecast accuracy strongly depends on the firm and quarter characteristics. Thus, to be able to compare the analysts' forecast accuracy in different periods for different firms, I need to define a Relative Forecast Accuracy (further *Accuracy*) measure. I use the scaling method described by Clement and Tse (2005):

$$Accuracy_{ijt} = \frac{\max_k(AFE_{kjt}) - AFE_{ijt}}{\max_k(AFE_{kjt}) - \min_k(AFE_{kjt})} \tag{1.2}$$

Note that $Accuracy_{ijt}$ is simply a scaled version of AFE_{ijt}. It is normalized to take values in the interval from 0 to 1. The higher the *Absolute Forecast Error* is, the lower is the *Accuracy*. $Accuracy_{ijt} = 1$ corresponds to the best forecast, $Accuracy_{ijt} = 0$ corresponds to the worse forecast.

In section 1.5 I make a robustness check using other measures for relative accuracy, suggested in Clement (1999).

In the regressions below I use several control variables such as broker size, age of forecast, analyst's experience etc. These variables are shown to strongly affect the accuracy of financial analyst and can also influence the inclination of an analyst to issue a first-"Sell". It is convenient to work with relative quantities rather than with absolute ones. I perform the normalization of all the control variables used in an exactly identical manner by the following formula:

$$Control\ Variable_{ijt} = \frac{Raw\ Variable_{ijt} - \min_k(Raw\ Variable_{kjt})}{\max_k(Raw\ Variable_{kjt}) - \min_k(Raw\ Variable_{kjt})} \tag{1.3}$$

Here $Control\ Variable_{ijt}$ is the control variable used in the regressions below which corresponds to the underlying raw variable. I define the underlying raw variables in Tables 1.1 and 1.6.

[Table 1.1 insert here]

[Table 1.6 insert here]

The indexes ijt here means the analyst i, the firm j and the quarter t, as before.

I introduce two dummy variables:

1. $First\ Sell_{ijt}$ equals 1 if an analyst i issues a sell recommendation about a firm j in a period t which is not preceded by other valid negative recommendations, 0 otherwise;

2. $Follower\ Sell_{ijt}$ equals 1 if an analyst i issues a sell recommendation about a firm j in the period t which is preceded by some other one, 0 otherwise.

To choose between H1 on the one side and H2 with H3 on the other side I test how the issuance of the negative recommendation in period t is related to the analyst's accuracy in the preceding period $t-1$. If the latter is negatively correlated with the former I reject H2 with H3 and H1 remains. If the latter is positively correlated I reject H1. Formally, I use probit regression, explaining $First\ Sell$ at time t by $Accuracy$ at time $t-1$ controlling for analyst characteristics at time t:

$$
\begin{aligned}
& y* = const + \beta \times Accuracy_{ij(t-1)} + \sum_{n=1}^{N} \gamma_n \times Control\ Variable_{ijtn} + \varepsilon_{ijt} \\
& y = 1[y* > 0] \\
& P(y = 1 | Accuracy_{ij(t-1)}, Control\ Variable_{ijtn}) = \\
& = P(y* > 0 | Accuracy_{ij(t-1)}, Control\ Variable_{ijtn}) = \\
& = \Phi(const + \beta \times Accuracy_{ij(t-1)} + \sum_{n=1}^{N} \gamma_n \times Control\ Variable_{ijtn})
\end{aligned}
\tag{1.4}
$$

where $First\ Sell_{ijt}$ is a dummy variable characterizing the type of the recommendation,

Φ is the standard normal cumulative distribution function,

$Accuracy_{ij(t-1)}$ is a relative forecast accuracy,

β and γ_n are corresponding regression coefficients,

$Control\ Variable_{ijtn}$ are N control variables obtained by scaling the variables from Table 1.1,

ε_{ijt} is an error term, that by assumption has a standard normal distribution and is independent of explanatory variables.

H1 predicts $\beta < 0$, H2 and H3 predict $\beta > 0$

It is possible that analysts issue bold sell recommendation because they base their opinion on erroneous forecast. To exclude this effect I provide another test for dependence between the kind of the recommendation and the previous analyst's performance, taking as a measure of past performance average forecast accuracy of an analyst. I compute *Average Accuracy* of an analyst i for the firm j as an average of his accuracy in every period preceding the moment of the recommendation issue.

$$
\begin{aligned}
& Average\ Accuracy_{ijt} = \frac{\sum_{\tau=1}^{T} Accuracy_{ij\tau}}{T}, \\
& \text{where } T = t - 1
\end{aligned}
\tag{1.5}
$$

Besides the change of previous accuracy measure the regression model remains the same as equation 1.4.

$$
\begin{aligned}
&y* = const + \beta \times Average\ Accuracy_{ijt} + \sum_{n=1}^{N} \gamma_n \times Control\ Variable_{ijtn} + \varepsilon_{ijt} \\
&y = 1[y* > 0] \\
&P(y = 1 | Average\ Accuracy_{ij(t-1)}, Control\ Variable_{ijtn}) = \\
&= P(y* > 0 | Average\ Accuracy_{ij(t-1)}, Control\ Variable_{ijtn}) = \\
&= \Phi(const + \beta \times Average\ Accuracy_{ij(t-1)} + \sum_{n=1}^{N} \gamma_n \times Control\ Variable_{ijtn})
\end{aligned}
\tag{1.6}
$$

The assumption A2 provides me a second way to test if H1 holds. A2 asserts that if the analyst has had some help from the company's management, he would lose it with a high probability as a result of his bold negative recommendation. At the same time, if the quality of the forecasts issued after the first "Sell" issue does not deteriorate, we can say that the amount of company-provided information before and after the first-"Sell" remains the same. The only situation when these two statements can be true simultaneously is when the analyst did not have much information about the company even before he issued a first-"Sell". This is exactly what the hypotheses H1 states. Therefore to confirm H1 is sufficient to check that the change of the analyst's accuracy between the quarter $t-1$ and $t+1$ is not correlated with the recommendation the analyst issues at the period t. To check this I use the following regression:

$$\Delta Accuracy_{ijt} = const + \beta_1 \times First\ Sell_{ijt} + \beta_2 \times \Delta Age_{ijt} + \beta_3 \times \Delta Frequency_{ijt} + \varepsilon_{ijt} \tag{1.7}$$

where $\Delta Accuracy_{ij} = Accuracy_{ij(t+1)} - Accuracy_{ij(t-1)}$,

$Frequency$ is the number of the forecasts issued by an analyst for the firm during the quarter of concern;

Age (age of the forecast) is the number of days between the forecast issue and the earnings-announcement date.

$\Delta Age_{ijt} = Age_{ij(t+1)} - Age_{ij(t-1)}$,

$\Delta Frequency_{ijt} = Frequency_{ij(t+1)} - Frequency_{ij(t-1)}$,

$const$ is a regression intercept,

β_n are corresponding regression coefficients,

ε_{ijt} is the regression residual.

To extend my analysis to the follower-sell recommendations, I exclude the first sell recommendations from my sample and run regressions similar to (1.4), (1.6) and (1.7), replacing $First\ Sell$ variable by $Follower\ Sell$.

1.4 Data and Empirical results

1.4.1 Data

My primary data source is Institutional Brokers Estimate System (I/B/E/S). This database has a strong advantage over other commonly used databases (First Call and Zacks), as it includes all of the major brokerage houses and provides a unique code for each analyst.[6] This allows me to track the forecasts and recommendations issued by the same analyst in different periods. Ljungqvist, Malloy, and Marston (2008) have put the reliability of I/B/E/S database under the question. They have discovered that the data from the same time period changes from one download to another due to alterations, deletions, additions and anonymizations of records. In response to this working paper, Thomson Financial has attempted to purge the 2007 and later versions of I/B/E/S databases of the data errors that existed in earlier versions. Given that Thomson Financial has for the most part purged its data of the problems documented by Ljungqvist, Malloy, and Marston (2008) and that I have downloaded my dataset in February 2008, I may hope that my research would not be biased due to Thomson Financial “processing errors”.

The I/B/E/S investment recommendation database starts in October 1993, and includes both brokerage house-specific recommendations and standardized I/B/E/S recommendations. The standardized I/B/E/S recommendations are integer ratings from 1 through 5, corresponding to ”strong buy”, ”buy”, ”hold”, ”underperform” and ”sell”.

My initial sample consists of all firms listed in I/B/E/S files from 1993 to 2007. For this period I have data on 1,561,063 issued recommendations (among them 135,141 recommendations given by anonymous analysts) and 1,581,632 quarter forecasts (among them 13,941 forecasts given by anonymous analysts).

I filter my dataset in order to fulfill the following requirements:

- Actual earnings, analyst and broker identification codes should be available.
- Earnings announcement date should be within SEC filing requirements defined as 48 days from the end of the fiscal quarter for quarters one to three and 93 days for the fourth quarter.[7]
- Both kind of analysts (issuing and not issuing a “Sell) should be present for the firm-quarter j, t. This requirement is necessary because of my choice of accuracy measure.

[6] Zacks does not include large houses such as Merill Lynch, Goldman Sachs, and DLJ. First Call does not identify individual analysts, which precludes tracking the analysts and merging the earnings forecast and investment recommendation databases.

[7] SEC filings are due 45 days after the end of the quarter for fiscal quarters 1-3 and 90 days for quarter 4. I add 3 more days following Chen and Matsumoto (2006) who adjusted this period for weekends/holidays.

> If we consider the periods with only buy (or only sell) recommendations, we will assign all accuracies from 0 to 1 to the recommendations of same kind. The periods with both kinds of recommendations are of interest because they allow us to range accuracy of analysts giving sell recommendations among accuracy of analysts recommending "Buy".

I drop the top 1% and bottom 1% forecast errors to avoid the influence of extreme outliers.

I identify the analysts who issue a first "Sell" recommendation in quarter t and has issued the quarterly forecast in the prior quarters.

For the last forecast of each analyst issued prior to earnings announcement in each period I compute the absolute forecast error using (1.1). Then I compute the relative forecast accuracy for each analyst-firm-quarter dimension using (1.2). I compute $Accuracy_{ijt}$ for the analyst i, firm j, and quarter t only if there are at least three different analysts forecasting for this firm in this quarter. I compute $Average\ Accuracy_{ijt}$ for all quarters preceding the recommendation issue. The average number of quarters used to compute $Average\ Accuracy_{ijt}$ is 9.5.

Table 3.1 reports summary statistics for the whole sample of observations.

[Table 3.1 insert here]

1.4.2 Previous accuracy test

To test whether the analysts issuing first "Sell" are more accurate prior to the recommendation issue, I run the regressions (1.4) and (1.6). Table 1.3 presents the results obtained.

[Table 1.3 insert here]

The results in the 1.3 show that the analysts are more disposed to give a negative first rating when they have lower forecast accuracy in the past. This allows me to reject H2 and H3.

The H1 is supported by the significance of negative coefficients at $Accuracy$ and $Average\ Accuracy$ variables. Other significant coefficients (at variables $analyst's\ experience$ and $analyst's\ workload$) are positive as I expected under H1. Higher workload may explain why the analyst has a weak interaction with every single company management. The higher experience provides additional safety to the analyst: experienced analysts are able to better negotiate their contracts, protecting themselves from investment bankers' pressure.

I check if my analysis can be expanded for all negative recommendations. I exclude the first sell recommendations from my database and compare the accuracy of analysts with negative and non-negative recommendations. Table 1.4 presents the results.

[Table 1.4 insert here]

I find that the only analyst's characteristic pushing an analyst to issue a follower-"Sell" is his low relative experience. There is no connection between the issue by an analyst of a follower-"Sell" and his previous forecast accuracy. So analysts who issue "Sell" about a firm with already published negative rating do not differ in term of their accuracy from analyst issuing "Hold" or "Buy". This result is predictable if we suppose that issue of follower-"Sell" represents only minor risks for analysts comparable with first-"Sell" issue. In cases of particularly poor stock performance any analyst may issue a "Sell", just those who are not willing to take the risk will wait to be preceded by others.

1.4.3 Change in accuracy test

To carry out another test of H1 I look if the relative accuracy of the analyst drops after his first "Sell" issue. Formally, I test the hypothesis that β coefficient at $First\ Sell$ dummy in the regression (1.7) is different from 0. I present the results in Table 1.5.

[Table 1.5 insert here]

The p-Value of 0.462 on $First\ Sell$ variable means that the regression coefficient is not significantly different from 0 at any conventional level of significance. So there is no dependence between the fact of issuing a first sell recommendation and a change in forecast accuracy. I interpret this as an absence of the informational punishment for the issuance of the first negative recommendation.

Meanwhile, the coefficient on $Follower\ Sell$ variable is significant at 3% level of significance. The issue of a follower-"Sell" has a negative impact on future forecast accuracy. No theory explains why the managers are less angry with the first negative recommendations issuers than following ones. Probably, they are not. Likely, they are just unable to use their standard "punishment" with respect to these analysts, because there is no guidance to reduce.

1.4.4 Present and future accuracy

The knowledge, that an analyst issuing first-"Sell" is on average less precise than other analysts in the period before the recommendation was issued, has little practical value - we do not need a tool to predict the past. What can be really interesting for investor is to know to what extend he can rely on the forecast issued simultaneously with or after the first-"Sell".

Based on the my above results, I conclude that firm's management did not collaborate with the analyst who issues a first-"Sell" before the recommendation was issued. It should be still the case in the period of recommendation issue. If it is true, forecasts, issued in the same period as a first sell recommendation, should be also less accurate comparing to forecasts of other analysts. I test this prediction with the aid of regression (1.8). Regression (1.9) tests if the accuracy in the next period after the first-"Sell" issue is still relatively low.

$$Accuracy_{ijt} = const + \beta \times First\ Sell_{ijt} + \sum_{n=1}^{N} \gamma_n \times Control\ Variables_{ijt} + \varepsilon_{ijt} \tag{1.8}$$

$$Accuracy_{ij(t+1)} = const + \beta \times First\ Sell_{ijt} + \sum_{n=1}^{N} \gamma_n \times Control\ Variables_{ij(t+1)} + \varepsilon_{ijt} \tag{1.9}$$

Control variables I use for these regressions will differ from previous one. I include two factors hardly influencing relative forecast accuracy: forecast's age and frequency of forecasts. Table 1.6 displays control variables used for the model.

Table 1.7 presents the results.

[Table 1.7 insert here]

The knowledge, that analysts issuing a first "Sell" have less management-provided information than their colleagues and, therefore are less accurate, can help us make corrections while considering their forecasts issued simultaneously with the rating.

1.5 Robustness checks and additional tests

For robustness check I use a second relative accuracy measure, following the methodology offered by Clement (1999) Clement (1999). Proportional mean absolute forecast error (PMAFE): measured as the difference between the absolute forecast error of analyst i forecasting firm j's earnings for the quarter t and the average absolute forecast error across all analyst forecasts of firm j's quarter$t$ earnings, expressed as a fraction of the average absolute forecast error across all analyst forecasts of firm j's quarter$t$ earnings.

$$Accuracy_{ijt} = \frac{DAFE_{ijt}}{\overline{AFE_{jt}}}$$
$$\text{where } DAFE_{ijt} = AFE_{ijt} - \overline{AFE_{jt}}$$

AFE_{ijt} is the absolute forecast error for analyst i's forecast of firm j for quarter t, and $\overline{AFE_{jt}}$ is the mean absolute forecast error for firm j for year t.

Table 1.8 presents the results obtained.

[Table 1.8 insert here]

1.6 Conclusion

This paper presents an evidence that the analysts issuing the first sell recommendations about a firm were on average less precise in their forecasts about this firm before the"Sell" was issued. I also provide evidence that the forecast accuracy of the analysts who issue a first sell recommendation does not decrease in response to the negative recommendation issue. This finding suggests that they do not experience the reduction of management-provided information as the result of their negative recommendations. As previous empirical studies have discovered (Chen and Matsumoto (2006)) managers tend to punish analysts for unpleasant ratings by decreasing the amount of information provided. But such a punishment is not possible if managers have already reduced his cooperation with an analyst to the minimum. This explain why managers do not "punish" analysts who issue a first "Sell" and also clarify why such analysts have no fear to step over the safe neutral line. I conclude that an issue of a first "Sell" is a sign of a weak cooperation between the management and the analyst in the first place. This information can help investors considering a forecast, issued by an analyst simultaneously (in the same period) with a first sell recommendation.

Table 1.1: Control Variables: Analyst Characteristics

The table displays control variables, which explain the event of the first "Sell" issue.

Control variable	Definition / Computation	Expected sign of the corresponding regression coefficient	Comment
Analysts experience	The number of years the analyst is present in I/B/E/S files before the period of interest	positive	Experienced analysts should be better protected against the pressure from the investment bankers. They have less need to sustain management access. And they are more disposed to issue a bold opinion.
Analyst's firm-specific experience	The number of years the analyst issues forecasts on the firm prior the quarter of interest	positive under H2 or H3	The longer an analyst follows a firm, the better he should be informed about its current state.
Broker size	The number of analysts working for the broker in the period of interest	positive	Larger brokers have superior resources. Analysts employed by larger brokers are not so much dependent on firm-provided information.
Analyst's workload	The number of firms the analyst is following during the current quarter	positive under H1	Analyst who follows larger number of companies may have less tight relationship with each particular company.

Table 1.2: Summary statistics

The data is collected from I/B/E/S database for the years 1993-2007 and exclude the the recommendations given by anonymous analysts. Previous period accuracy takes values from 0 to 1 and is computed by the following formula:

$$Accuracy_{ijt} = \frac{\max_k(AFE_{kjt}) - AFE_{ijt}}{\max_k(AFE_{kjt}) - \min_k(AFE_{kjt})},$$

where (AFE_{kjt}) is an absolute forecast error of the analyst k for the firm j in the quarter t.

$$Average\ Accuracy_{ijt} = \frac{\sum_{\tau=1}^{T} Accuracy_{ij\tau}}{T}$$

Other variables are those discussed in Table 1.1, scaled to the interval [0;1], by the means of the following formula:

$$Control\ Variable_{ijt} = \frac{Raw\ Variable_{ijt} - \min_k(Raw\ Variable_{kjt})}{\max_k(Raw\ Variable_{kjt}) - \min_k(Raw\ Variable_{kjt})}$$

	First-Sell recommendations				Follower-Sell recommendations				Positive recommendations			
	N	Mean	Median	SD	N	Mean	Median	SD	N	Mean	Median	SD
Previous period accuracy	7780	0.568	0.641	0.380	5088	0.588	0.667	0.370	150491	0.586	0.667	0.380
Average accuracy	7908	0.553	0.571	0.236	5172	0.575	0.592	0.245	154476	0.567	0.586	0.265
Broker size	5926	0.468	0.345	0.445	4306	0.459	0.344	0.434	116748	0.470	0.359	0.443
Analyst's workload	16281	0.438	0.375	0.376	10545	0.370	0.276	0.355	330346	0.410	0.333	0.356
Analyst's firm experience	14748	0.526	0.500	0.377	10189	0.398	0.333	0.338	308876	0.404	0.333	0.358
Analyst's general experience	20246	0.523	0.500	0.347	13998	0.376	0.333	0.300	385002	0.427	0.364	0.342

Table 1.3: Past Forecasts Accuracy and the First-"Sell" Issue

This table presents the results of probit regressions. The dependent variable is $First\ Sell$, a dummy variables equal 1 for a first sell recommendation, 0 for all other recommendations. First regression tests whether the decision to issue first "Sell" depends on the previous period accuracy. Second regression uses past average accuracy as explaining variable.

$$P(First\ Sell_{ijt} = 1) = \Phi(const + \beta \times Accuracy_{ij(t-1)} + \sum_{n=1}^{N} \gamma_n \times Analyst\ Characteristics_{ijt})$$

$$P(First\ Sell_{ijt} = 1) = \Phi(const + \beta \times Average\ Accuracy_{ijt} + \sum_{n=1}^{N} \gamma_n \times Analyst\ Characteristics_{ijt})$$

Relative Forecast Accuracy is an absolute forecast error of the last forecast of the analyst i for the firm j before earnings announcement after the quarter t, scaled using the following formula.

$$Accuracy_{ijt} = \frac{\max_k(AFE_{kjt}) - AFE_{ijt}}{\max_k(AFE_{kjt}) - \min_k(AFE_{kjt})}$$

Analyst characteristics, all scaled to range from 0 to 1 within each firm-quarter, are $Analysts\ experience$ - the number of years the analyst is present in I/B/E/S files; $Analyst's\ firm\ specific\ experience$ - the number of years the analyst issues forecasts on the firm prior the quarter of interest; $Broker\ size$ - the number of analysts working for the broker; $Analyst's\ workload$ - the number of the firms the analyst is following during this quarter.
Z-statistics are in parentheses.
By the stars, I denote a significance level of less than 5%, 1% and 0.1%.

	Model 1		Model 2	
	Coefficients	Marginal Effects	Coefficients	Marginal Effects
Accuracy	-0.075***	-0.007		
	(-4.15)			
Average accuracy			-0.132***	-0.013
			(-4.73)	
Broker size	-0.013	-0.001	-0.015	-0.002
	(-0.83)		(-0.97)	
Analyst's workload	0.070***	0.007	0.071***	0.007
	(4.38)		(4.43)	
Analyst's firm experience	0.006	0.001	0.007	0.001
	(0.37)		(0.41)	
Analyst's general experience	0.144***	0.014	0.139***	0.014
	(7.98)		(7.79)	
Constant	-1.731***		-1.699***	
	(-100.33)		(-81.17)	
N	106313		108078	
Pseudo R^2	0.0039		0.0039	

* p<0.05, ** p<0.01, *** p<0.001

Table 1.4: Past Forecasts Accuracy and Follower-Sell Issue

This table presents the results of probit regressions. The dependent variable is *Follower Sell*, a dummy variables equal 1 for a follower-sell recommendation, 0 for non-negative recommendations. First-"Sell" recommendations are excluded from the sample. First regression tests whether the decision to issue follower "Sell" depends on the previous period accuracy. Second regression uses past average accuracy as explaining variable.

$$P(Follower\ Sell_{ijt} = 1) = \Phi(const + \beta \times Accuracy_{ij(t-1)} + \sum_{n=1}^{N} \gamma_n \times Analyst\ Characteristics_{ijt})$$

$$P(Follower\ Sell_{ijt} = 1) = \Phi(const + \beta \times Average\ Accuracy_{ijt} + \sum_{n=1}^{N} \gamma_n \times Analyst\ Characteristics_{ijt})$$

Relative Forecast Accuracy is an absolute forecast error of the last forecast of the analyst i for the firm j before earnings announcement after the quarter t, scaled using the following formula.

$$Accuracy_{ijt} = \frac{\max_k(AFE_{kjt}) - AFE_{ijt}}{\max_k(AFE_{kjt}) - \min_k(AFE_{kjt})}$$

Analyst characteristics, all scaled to range from 0 to 1 within each firm-quarter, are *Analysts experience* - the number of years the analyst is present in I/B/E/S files; *Analyst's firm specific experience* - the number of years the analyst issues forecasts on the firm prior the quarter of interest; *Broker size* - the number of analysts working for the broker; *Analyst's workload* - the number of the firms the analyst is following during this quarter.
Z-statistics are in parentheses.
By the stars, I denote a significance level of less than 5%, 1% and 0.1%.

	Model 1		Model 2	
	Coefficients	Marginal Effects	Coefficients	Marginal Effects
Accuracy	-0.015	-0.001		
	(-0.75)			
Average accuracy			-0.009	-0.001
			(-0.31)	
Broker size	-0.014	-0.001	-0.012	-0.001
	(-0.82)		(-0.71)	
Analyst's workload	-0.011	-0.001	-0.008	-0.001
	(-0.58)		(-0.47)	
Analyst's firm experience	-0.008	-0.001	-0.010	-0.001
	(-0.43)		(-0.49)	
Analyst's general experience	-0.178***	-0.014	-0.179***	-0.014
	(-8.65)		(-8.77)	
Constant	-1.680***		-1.687***	
	(-90.53)		(-74.68)	
N	101303		103006	
Pseudo R^2	0.0038		0.0038	

* p<0.05, ** p<0.01, *** p<0.001

Table 1.5: Change in Relative Forecast Accuracy after the "Sell" issue

This table reports the influence of issuing first sell / follower-sell recommendation on the change in relative forecast accuracy, controlling for change in forecasts' age and frequency.

$$\Delta Accuracy_{ijt} = const + \beta_1 \times First\ Sell_{ijt} + \beta_2 \times Follower\ Sell +$$
$$+ \beta_3 \times \Delta Age_{ijt} + \beta_4 \times \Delta Frequency_{ijt} + \varepsilon_{ijt}$$

$\Delta Accuracy$ stays for difference between the $Accuracy$ in the quarters preceding and following the quarter when the"Sell" was issued.
If the sell recommendation was issued at time period t, then

$$\Delta Age_{ijt} = Age_{ij(t+1)} - Age_{ij(t-1)};$$
$$\Delta Frequency_{ijt} = Frequency_{ij(t+1)} - Frequency_{ij(t-1)}$$

$Frequency$ is the number of the forecasts issued by an analyst for the firm during the quarter of concern; Age (age of the forecast) is the number of days between the forecast issue and the earnings-announcement date. $First\ Sell$ ($Follower\ Sell$) is a dummy variables equal 1 if the analyst has issued a first sell recommendation (sell recommendation) and 0 otherwise.
By the stars, I denote a significance level of less than 5%, 1% and 0.1%.

	Δ Accuracy N = 75 623				
Variables	Coeff.	t-Stat.	p-Value	[95% Conf.	Interval]
Intercept	0.004*	2.74	0.006	0.001	0.009
First Sell	-0.007	-0.74	0.462	-0.024	0.011
Follower Sell	-0.021*	-2.24	0.025	-0.039	-0.003
Δ Age	-0.136***	-36.58	0.000	-0.143	-0.0128
Δ Frequency	0.024***	6.68	0.000	0.016	0.031
$\bar{R}^2$	0.027				

* p<0.05, ** p<0.01, *** p<0.001

Table 1.6: Control Variables for Current and Future Accuracy

The table displays variables influencing on relative forecast accuracy.

Control variable	Definition / Computation	Expected sign of the corresponding regression coefficient	Comment
Analyst's experience	The number of years the analyst is present in I/B/E/S files before the period of interest	positive	Clement (1999) finds that accuracy is positively associated with analyst experience. However Jacob et al (1999) find that positive association between experience and accuracy decreases if controlled for firm-specific experience.
Analyst's firm-specific experience	The number of years the analyst issues forecasts on the firm prior the quarter of interest	positive	First, due to "learning by doing" an analyst may improve his forecasting ability. Second, the better an analyst understands the company he follows, the more likely he will not be replaced.
Broker size	The number of analysts working for the broker in the period of interest	positive	The broker size is considered as a proxy for resources available to the analysts.
Analyst's workload	The number of firms the analyst follows during this quarter	negative	The workload of an analyst is the proxy for analyst's care and attention.
Forecasts' frequency	The number of forecasts issued by an analyst for the firm during the quarter of concern	positive	The higher frequency is associated with the timely updates of the forecasts.
Age of forecast	The number of days between the forecast issue and the earnings-announcement date	negative	The later an analyst issues a forecast, more he can profit from increased amount of information.

Table 1.7: Forecasts Accuracy and the First-"Sell" Issue

Model 1 examines if the relative accuracy in the period of first "Sell" issue is affected by this step:
$Accuracy_{ijt} = const + \beta \times First\ Sell_{ijt} + \sum_{n=1}^{N} \gamma_n \times Control\ Variables_{ijt} + \varepsilon_{ijt}$
Model 2 describes a dependence between a first "Sell" issue and a next period accuracy:
$Accuracy_{ij(t+1)} = const + \beta \times First\ Sell_{ijt} + \sum_{n=1}^{N} \gamma_n \times Control\ Variables_{ij(t+1)} + \varepsilon_{ijt}$
Relative Forecast Accuracy is an absolute forecast error of the last forecast of the analyst i for the firm j before earnings announcement after the quarter t, scaled using the following formula.
$Accuracy_{ijt} = \frac{\max_k(AFE_{kjt}) - AFE_{ijt}}{\max_k(AFE_{kjt}) - \max_k min(AFE_{kjt})}$
$First\ Sell$ is a dummy variables equal 1 for a first sell recommendation, 0 for all other recommendations.
Analyst and forecast characteristics, all scaled to range from 0 to 1 within each firm-quarter, are $Analysts\ experience$ - the number of years the analyst is present in I/B/E/S files; $Analyst's\ firm\ specific\ experience$ - the number of years the analyst issues forecasts on the firm prior the quarter of interest; $Broker\ size$ - the number of analysts working for the broker; $Analyst's\ workload$ - the number of the firms the analyst is following during this quarter; $Forecasts'\ frequency$ - the number of the forecasts issued by an analyst for the firm during the quarter of concern; $Age\ of\ forecast$ - the number of days between the forecast issue and the earnings-announcement date.
T-statistics are in parentheses.
By the stars, I denote a significance level of less than 5%, 1% and 0.1%.

	Model 1 $Accuracy_{ijt}$	Model 2 $Accuracy_{ij(t+1)}$
First Sell	-0.026***	-0.024***
	(-5.51)	(-4.43)
Broker size	0.013***	0.010**
	(4.83)	(3.24)
Analyst's workload	-0.012***	-0.015***
	(-3.84)	(-4.49)
Analyst's firm experience	0.013***	-0.002
	(4.50)	(-0.48)
Analyst's general experience	-0.007*	-0.004
	(-2.10)	(-1.14)
Age of forecast	-0.132***	-0.139***
	(-48.45)	(-47.65)
Forecast's frequency	0.034***	0.021***
	(13.36)	(7.21)
Constant	0.648***	0.669***
	(242.42)	(216.72)
N	148889	126450
$\bar{R}^2$	0.027	0.029
RMS error	0.362	0.360

* p<0.05, ** p<0.01, *** p<0.001

Table 1.8: Past PMAFE and the First-“Sell” Issue

This table presents the results of probit regressions. The dependent variable is $First\ Sell$, a dummy variables equal 1 for a first sell recommendation, 0 for all other recommendations. First regression tests whether the decision to issue first “Sell” depends on the previous period accuracy. Second regression uses past average accuracy as explaining variable.

$$P(First\ Sell_{ijt} = 1) = \Phi(const + \beta \times PMAFE_{ij(t-1)} + \sum_{n=1}^{N} \gamma_n \times Analyst\ Characteristics_{ijt})$$

$$P(First\ Sell_{ijt} = 1) = \Phi(const + \beta \times Average\ PMAFE_{ijt} + \sum_{n=1}^{N} \gamma_n \times Analyst\ Characteristics_{ijt})$$

$PMAFE_{ijt}$ is an absolute forecast error of the last forecast of the analyst i for the firm j before earnings announcement after the quarter t, scaled using the following formula.

$$Accuracy_{ijt} = \frac{DAFE_{ijt}}{\overline{AFE_{jt}}}$$
$$\text{where } DAFE_{ijt} = AFE_{ijt} - \overline{AFE_{jt}}$$

Analyst characteristics, all scaled to range from 0 to 1 within each firm-quarter, are $Analysts\ experience$ - the number of years the analyst is present in I/B/E/S files; $Analyst's\ firm\ specific\ experience$ - the number of years the analyst issues forecasts on the firm prior the quarter of interest; $Broker\ size$ - the number of analysts working for the broker; $Analyst's\ workload$ - the number of the firms the analyst is following during this quarter.
Z-statistics are in parentheses.
By the stars, I denote a significance level of less than 5%, 1% and 0.1%.

	Model 1		Model 2	
	Coefficients	Marginal Effects	Coefficients	Marginal Effects
PMAFE	-0.019* (- 2.46)	-0.002		
Average PMAFE			-0.043** (–3.22)	-0.005
Broker size	-0.009 (-0.60)	-0.001	-0.009 (-0.60)	-0.001
Analyst's workload	0.074*** (4.58)	0.007	0.075*** (4.69)	0.008
Analyst's firm experience	-0.012 (-0.71)	-0.001	-0.011 (-0.68)	-0.001
Analyst's general experience	0.116*** (6.36)	0.012	0.113*** (6.23)	0.011
Constant	-1.721*** (-123.84)		-1.720*** (-124.27)	
N	97251		97980	
Pseudo R^2	0.0025		0.0026	

* p<0.05, ** p<0.01, *** p<0.001

Chapter 2

What Do Managers Say Between The Lines?

(in collaboration with Prof. Richard Zeckhauser)

Because managers are thought to possess important insider information, the numerous investors pay attention not only to the factual information managers announce, but also to a way how they tell it. The short-term market returns after the earnings announcement have been shown to depend heavily on managers choice of words (after controlling for qualitative information involved). Our aim is to investigate whether this market behavior is rational and analysis of managers choice of words can provide rewarding information about future companys fundamentals. We start by studying how past results influence the managers choice of words. We find that the unexpected part of earnings earnings surprise influences the use of both positive and negative words, while stock returns and changes in earnings affect the use of negative words only. We examine differences in the prepared and the improvised parts of managers speech, as they might signal uncertainty, fraud, or insincerity. We observe the increase in these differences during the period preceding a bankruptcy and, more generally, in association with the necessity to present poor results. We show that the degree of negativity of the managers words, which is unexplained by past performance, helps to predict the future earnings of the company. We also document that, as early as four quarters before a companys bankruptcy, the verbal negativity of its managers becomes significantly higher than in viable companies, even after controlling for the companies performances. The quantified word choice of a manager contains incremental information for bankruptcy prediction, when used in the classificatory model concurrently with accounting ratios.

2.1 Introduction

The managers of companies commit to host quarterly-earnings-announcement conference calls independently of their company's performance and of their desire to talk to the public. A typical conference call includes a discussion of the past, a preview of the future, and answers to the analysts' questions. The goal of the managers, it is normally asserted, is to present their company's results in the way that is most beneficial to the company's value. It would be natural to expect that managers would try to persuade analysts and investors that their company had a bright future. However, they do not want to set unrealistic expectations; the market severely penalizes companies that fall short. Equally important, managers cannot significantly misrepresent the truth in a way that would risk expensive litigation and reputational damage. Their concern about the legitimacy of baseless statements causes managers to be more negative in their statements than they would like, or to add a shade of uncertainty to their positive statements.

A Boston-based consulting firm, Business Intelligence Advisors (BIA), employs former CIA officers to verify the sincerity of top managers during their public presentations. Its analysis of verbal and nonverbal clues during conference calls appears to have value, as several important hedge funds employ BIA services.[1] BIA deception detection services use the CIA intelligence techniques of analyzing gestures, words, context, voice, changes in presentation style, and many other details. Complaints, detour phrases, selective memory, and overly courteous responses may serve as warning signs for BIA, whose work is not limited to textual analysis. Without trying to compete with BIA in unveiling corporate paltering[2], we expand upon its ideas on searching for textual clues in order to extract more relevant news from public disclosures.

We believe that managers' choice of words is determined by all the information they have. This includes information about the past, most of which either already has been disclosed or soon will be, as well as insider information or, more accurately, the managers' expectations for the future, which they are not obliged to disclose. Therefore, the choice of words during a conference call cannot be fully explained by the quantitative information describing the past quarter's performance: expected and unexpected earnings, unadjusted and abnormal stock return, etc. Word choice is influenced also by the mood of the managers, their expectations for the future, and internal information they do or do not intend to reveal.

This paper has two goals: first, to study how a company's past performance influences

[1] http://www.politico.com/news/stories/0110/32290.html

[2] The American Heritage Dictionary defines paltering as acting misleadingly or insincerely. Other dictionaries talk about deliberate ambiguity and withholding information. For a more detailed description of different paltering practices and discussion on existing and potential ways to control them see Schauer and Zeckhauser (2009).

the manager's speech, and second, to see whether the manager's words that are not explained by the past might help to predict the future. In looking at a company's future, we choose to concentrate on its future earnings rather than its stock price performance. While stock prices and returns are subject to public perceptions and depend on the managers' speech[3], real earnings are, in most cases[4], independent of such influences.

Consistent with our hypothesis, we find that negative elements in managers' speech, which are not justified by previous performance, are associated with significantly lower future earnings. This finding would be of only moderate interest if analysts correctly incorporated such information. However, we document that financial analysts fail to capture this "soft" information in their forecasts. They therefore, make forecasts that exceed actual earnings for companies whose managers reveal such elements.

We wished to go beyond the improved prediction of earnings. Can the words of managers provide refine estimates of salient events in a firm's future? To address this question, in our final empirical study we use the natural experiment of the recent financial turmoil with its substantial toll of bankruptcies to study how the prospect of an imminent bankruptcy influences the manager's word choice. The goal is to learn whether there is a way to improve our ability to foresee an elevated risk of bankruptcy by noting how managers speak. We find that the threat of bankruptcy significantly impacts the managerial tone (level of optimism or pessimism). Three to four quarters before a company's bankruptcy, a manager's tone becomes significantly more negative than one would expect based on his company's historical performance. We test whether we can improve classical bankruptcy prediction models by adding textual analysis data. We find that adding variables quantifying manager's tone and the degree of uncertainty of his speech improve classificatory ability of the model based on financial ratios only.

Our study differs from, and is complementary to, existing textual-analysis studies of management-expressed news. First, we use a different source of information conference call transcripts. Previous textual-analysis studies focused on management-produced 10-K filings, corporate annual reports, and press releases accompanying earnings-announcements, and on media news content about companies. Conference call transcripts are similar in content to earnings press releases, but are less formalized. They also include an improvised section when

[3]Kahneman and Tversky (1981) have shown that framing can affect the outcome (i.e., the choices one makes) of choice problems. Investment decisions, therefore, depend on how the quantitative news are framed by the managers.

[4]There are still some extreme cases in the durable goods industries or financial services, where the perception of company stability has a direct impact on sales. Jensen and Meckling (1976) provide an example of a computer industry: "There, the buyer's welfare is dependent to a significant extent on the ability to maintain the equipment, and on continuous hardware and software development. Furthermore, the owner of a large computer often receives benefits from the software developments of other users. Thus, if the manufacturer leaves the business or loses his software support and development experts because of financial difficulties, the value of the equipment to his users will decline".

managers respond to questions. Thus, we are able to examine a new question: How does the content of improvised speech differ from the content of a carefully prepared document or formal speech? To draw an analogy, we are learning what a witness in a trial might say under cross examination, as opposed to in response to the prepared questions of his lawyer.

Second, we consider the use of both positive and negative words. The only concurrent study which uses positive and negative word counts combines them into a single variable by subtracting negative words from positive words. (Demers and Vega (2008).) To measure the negative flavor of comments, we use the ratio of negative to positive words, instead of simple word counts or frequencies of appearance.[5]

Third, we avoid using generic dictionaries such as Diction or General Inquirer, which misrepresent the tone of financial news (Loughran and McDonald (forthcoming)). Instead we construct our own checklists, assigning the non-neutral words most frequently used in conference calls to positive or negative categories based on their use in the conference calls. For a robustness check, we use the adjusted "Fin-Neg" lists offered by Bill McDonald on his personal web-page.[6] This lists are based on Harvard dictionary classification, but adjusted to financial terminology.

Our study relates most closely to the recent work by Demers and Vega (2008), which uses quarterly-earnings press releases as its prime information source, and argues in terms of net optimism as indicated by positive, minus negative words. Though our methods are similar, we aim to explore different problems. Instead of forecasting future returns (market reaction to the managers' words) as do Demers and Vega (2008), we seek to predict the company's real performance. We investigate whether, by their choice of words, managers disclose internal information and shed light on the earnings prospects of their company and the extreme event of bankruptcy.

The rest of this paper is organized as follows. In Section 2, we describe the literature regarding the application of textual analysis to corporate reporting. In Section 3, we describe our data and give a brief overview of the methods we employ. In Section 4, we examine how quarterly performance influences a manager's negativity and his use of obfuscating speech. In Section 5, we investigate whether the managers' word choice provides insight into future earnings, and whether financial analysts successfully integrate this information into their forecasts. In Section 6, we see how a manager's word choice can help us to recognize prospects for imminent bankruptcy. Section 7 summarizes and concludes.

[5]Word count is the number of appearance of a category of words in a speech. Frequency of appearance is the ratio of a category's word count to the total number of words in a speech.

[6]www.nd.edu/~mcdonald/Word_Lists.html

2.2 Previous literature: textual analysis of companies' provided information

There are several text sources of company-provided information used for textual analysis: comments by company spokesman quoted by the media (Ober, Zhao, Davis, and Alexander (1999)); 10K annual reports (Li (2006), Loughran and McDonald (forthcoming)); and quarterly earnings announcements (Demers and Vega (2008) and Davis, Piger, and Sedor (2008)).

The two most researched characteristics of a financial text are 1) degrees of positivism (optimism) or negativism (pessimism) and 2) certainty versus uncertainty. The common method applied is to use either counts or frequencies of specific groups of words in the text. Most authors prefer word counts when dealing with certainty/uncertainty (Li (2006); Ober, Zhao, Davis, and Alexander (1999)), and frequencies when measuring "optimism" or "pessimism" ratios of total number of positive or negative words to the number of words in the speech (Davis, Piger, and Sedor (2008); Tetlock (2007)). Demers and Vega (2008) use frequencies measuring optimism and pessimism, certainty and uncertainty, their prime variables are net optimism and net certainty - differences in corresponding frequencies.

The major issue that has been explored by finance researchers in this area is the market's reaction to the "soft information" in a company's news. Demers and Vega (2008) and Davis, Piger, and Sedor (2008) observe a significant market response to managers' net optimism after the earnings announcements. Demers and Vega (2008) find that the unexpected component of managers' net optimism is significantly associated with short-window returns, and that it also predicts post-earnings-announcement drift. Both studies use Diction[7] software to classify words.

Demers and Vega (2008) also find that the level of certainty expressed in managers' language is inversely associated with a firm's abnormal return volatility. Use of more uncertain words and wavering language in managerial earnings announcements is associated with abnormal, idiosyncratic stock volatility.

The papers of Ober, Zhao, Davis, and Alexander (1999) and Li (2006) are devoted entirely to certainty measures. Ober, Zhao, Davis, and Alexander (1999) find that the corporate expression of certainty in public business discourse is not affected by organizational profitability status or by industry type. They find that a significant difference in the use of certainty words exists between oral and written corporate communications.

Li (2006) reduces the list of uncertain words to the words "risk" and "uncertainty" (in

[7] http://www.dictionsoftware.com/ The software applies an algorithm, which 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.

different forms) and measures managers' risk sentiment by the frequency of these words in the annual corporate reports. Li finds that an increase in the use of these words is associated with lower earnings in the following year. A portfolio, constructed by buying stocks of the firms with a minor increase of risk sentiment in annual reports and by shorting shares of the firms with a large increase in risk sentiment, generates significant positive annual abnormal returns.

The only above-mentioned research that does not apply generic word classifications is Loughran and McDonald (forthcoming). That work not only avoids using Diction or General Inquirer [8], software but shows how the Harvard Dictionary, the basis for generic textual-analysis software, misclassifies words in financial contexts (for example, "liability" or "taxes"). They find that almost three-fourths of the negative-word counts according to the Harvard list are attributable to words that are often not negative in a financial context. That paper offers two solutions: a) adjusted lists, which classify words according to their usual meanings in a financial context; and b) term weighting. Loughran and McDonald (forthcoming) apply both methods to the Management Discussion and Analysis (MD&A) part of annual 10-K filings. They find significant relationships between the words used and filing-date returns, trading volume, and subsequent return volatility. They find no evidence of return predictability. They also link the word lists successfully to earnings surprise in the first quarter, to fraud, and to material weakness.

Textual analysis methods are widely applied to the information coming not only from insiders, but also from other agents on the market, such as analysts or media. Several works relate market returns to the qualitative content of such news. Tetlock (2007) measures the tone of the Wall Street Journal market coverage section and finds that media variables affect both returns and trading volumes. Engelberg (2009) finds that the frequency of negative words in the media news has predictability for asset prices. Tetlock, Saar-Tsechansky, and Macskassy (2008) extend the approach, adding companies' fundamentals to the analysis. They find that a higher frequency of negative words in firm-specific news stories is associated with lower firm future earnings, and that the stock market briefly underreacts to the information embedded in the negative words.

The attempts to extract qualitative information from companies' reports go beyond textual analysis. Mayew and Venkatachalam (2009) measure managers' affects during conference calls, applying vocal-emotion-analysis software to audio recordings. They find that managers' displays of positive and negative affect are respectively positively and negatively related to contemporaneous stock returns and to future unexpected earnings.

[8]more information about General Inquirer software can be found at http://www.wjh.harvard.edu/∼inquirer/. The main differences between GI and Diction are word-lists and the handling of homographic terms. Demers and Vega (2008) find that GI's negativity (positivity) sentiment and Diction's pessimism (optimism) sentiment are correlated measures (ρ=0.40).

2.3 Data and methods

Our analysis is based on the S&P 500 companies appearing in the index as of 01.03.2007, and the largest bankrupt companies appearing in the Chapter 11 Library© in 2007-2009.

Thomson Reuters has transcripts for 451 companies of the S&P 500 list; it is the source of the conference call transcripts that we use. Our sample includes earnings announcements for the period from 2004 to 2009. Earnings and forecasts data is from I/B/E/S. Price and returns data is from CRSP.

Wishing neither to misclassify words nor to get the result out of the black box, we avoid using generic software. We elaborate the list of positive, negative, and uncertain words, based on the most frequently used words in conference calls. First, we compute the appearances of all words in all managers' speeches during all conference calls in our sample. Then, from among the most frequently used words, we choose the words belonging to three following groups: 1) positive words, 2) negative words, and 3) words of uncertainty. We present the complete list of chosen words in Table 2.1. Words in the groups are ordered by their frequency of usage.

[Table 2.1 insert here]

To test the robustness of our analysis of the choice of words, we use the alternative word lists compiled by Loughran and McDonald (forthcoming) . These lists comprise the Harvard IV GI lists, adjusted for financial terminology. This classification contains 2,337 negative, 353 positive, and 285 uncertain words. Here are some examples of words in the Loughran and McDonald classification (referred to also in this paper as the "extensive classification"): negative - abandon, bridge, caution; positive - able, beautiful, charitable; uncertain - abeyance, clarification, depend.

Tetlock, Saar-Tsechansky, and Macskassy (2008) express a concern that positive word counts do not properly reflect the attitude of the speaker because such words are frequently negated. We correct the number of positive words to account for negation. We exclude a positive word from the count when one of three negation words (no, not, none) occurs among the three words preceding the positive word.

We measure a speech's negativity as the ratio of negative words to positive words. We distinguish the negativity of each prepared presentation from that of its Q&A session, as these two parts are fundamentally different. A presentation is prepared and proofread in advance, whereas answers must to some extent represent improvisations.

Table 2.2 presents summary statistics on the frequencies of different kinds of words used in a manager's speech, as well as on variables describing company's performance.

[Table 2.2 insert here]

The earnings surprise for an announcement is the difference between the actual earnings for the quarter recorded in I/B/E/S and the mean analyst forecast included in the I/B/E/S detail file during the 30 days before the quarterly earnings announcement, divided by the stock price 5 trading days before the announcement.

Table 2.3 presents summary statistics of different kinds' of words frequencies in managers' speeches as well as on companies' performance.

[Table 2.3 insert here]

The earnings surprise for an announcement is the difference between the actual earnings for the quarter recorded in I/B/E/S and the mean analyst forecast included in the I/B/E/S detail file during the 30 days before the quarterly earnings announcement, divided by the stock price 5 trading days before the announcement.

Let $e_{t,j}$ be the earnings announced for the company j at quarter t and $\hat{e}_{t,j}$ be the corresponding consensus forecast. Denote by $P_{t,j}$ the price of shares of company j 5 trading days before the announcement in quarter t. The earnings surprise s_t, j is

$$s_{t,j} = \frac{e_{t,j} - \hat{e}_{t,j}}{P_{t,j}} \tag{2.1}$$

The quarter capital gain is the difference in stock price 5 trading days before earnings announcement, minus the stock price 5 trading days after the previous earnings announcement, divided by the later.

Let $P_{j,t-1,+5}$ be the stock price for the company j 5 days after an earnings announcement for quarter $t-1$ and let $P_{j,t,-5}$ be the stock price for the company j 5 days before an earnings announcement for quarter t. Then the quarter-end capital gain price is

$$Capital\_gain_{jt} = \frac{P_{j,t,-5} - P_{j,t-1,+5}}{P_{j,t-1,+5}} \tag{2.2}$$

The quarter change in earnings is the earnings at quarter t, minus the earnings in quarter $t-1$, scaled by the stock price 5 days before the earnings announcement.

$$\Delta Earnings_{jt} = \frac{Earnings_{jt} - Earnings_{jt-1}}{Price_{t,-5}} \tag{2.3}$$

We provide more details on other variables' computations in the corresponding chapters.

2.4 What do managers talk and not talk about?

This section has two goals. First, it determines the most important performance measures for a company's management. This is important in order to understand the logic of managers' actions and to evaluate to what extent their interests are aligned with the interests of shareholders. It is also an important step to undertake before using textual analysis as a forecasting tool. Before looking at the future through the managers' choice of words, we need to understand how the past performance drives that choice.

Second, it examines how the character of reporting is modified in relation to the changes a company's performance. Here we are interested not so much in what is said, but in what is *meant to be said*. Do the managers omit something, deliberately obfuscating the truth? The BIA service would check this by measuring the time gap before answering a question and the trembling of the voice; it might also use video images when available. We suggest below several measures, which may help to identify paltering, when using only a written transcript.

2.4.1 Interpreting quarter results.

Managers host a quarterly conference call to announce and comment on earnings in the prior quarter. It would be natural to assume that, as the earnings discussion is the purpose of the call, the quality of earnings should be the most important factor determining the managers' mood and consequently the word choice. It is possible, however, that the managers, and perhaps the investors, care more about some other results. The best way to determine which performance characteristics are most important to the managers is to investigate how the changes in those characteristics influence the managers' tone.

To measure that tone, we employ the variable $Negativity$, equal to the ratio of the number of negative words to the number of positive words.

$$Negativity = \frac{Negative\ words}{Positive\ words} \tag{2.4}$$

We use the following OLS model to test which factors most influence the $Negativity$ measure.

$$\begin{aligned} Negativity_t = Const + \beta_1 Capital\_gain_{t,t-1} + \beta_2 \Delta Earnings_{t,t-1} + \beta_3 Surprise\_decile_t + \\ + \beta_4 Market\_return_{t,t-1} + \epsilon \end{aligned} \tag{2.5}$$

where $Capital\_gain_{t,t-1}$ the percentage stock return for the period between two earnings announcements, is computed according to (2.2).

$\Delta Earnings_{t,t-1}$ the change in earnings between two earnings announcements, normalized by the stock prices is computed by (2.3).

$Surprise_t$ is the earnings surprise the difference between the actual earnings in quarter t and the average analysts' forecast issued 30 days prior to the earnings announcement, scaled by the stock price 5 trading days before the announcement is computed by (2.1).

When a firm underperforms expectations and the surprise is negative, the $Surprise\_decile$ will take values from -5 (for the largest negative surprises) to -1 (for the smallest surprises). Positive surprises are similarly divided into quintiles, taking the values from 1 to 5 from smallest to largest.

$Market\_return_{t,t-1}$ is the equally weighted market return for the period starting 5 days after an earnings announcement for the quarter $t-1$ and ending 5 days prior to the earnings announcement for the quarter t.

The fixed-effects model controls for the peculiarities in announcement style of different companies. In fact, managers have their particular vocabularies, and some of them have a penchant for using more positive/negative/uncertain words than others.

The results of estimations are in table 2.4.

[Table 2.4 insert here]

Table 2.5 displays estimates using the same models, with the only difference being that we compute the negativity ratio using the extensive classification lists suggested by Loughran and McDonald (forthcoming) - the *FinList*. We make this analysis to check the robustness of our results and also to investigate whether the results are driven by the most frequently used words or by those used rarely. This analysis checks whether our results are robust and also investigates if they are driven by the most frequently used words or by the words rarely used.

[Table 2.5 insert here]

The tables show that the results do not depend on the choice of word classification list. When the extensive classification is used, regression coefficients change insignificantly.

The tone of the presentations prepared in advance is stronger impacted by the performance characteristics than the tone of the improvised answers to the analysts' questions. The change in earnings compared to the previous quarter plays an important role in determining the managers' tone. Capital gain impacts the tone of the presentations, even after controlling for the general market performance. However, in the model explaining manager's tone in improvised answers, the coefficient at Capital gain variable is not statistically significant on any conventional level.

Besides the change in earnings, managers care significantly about the difference between actual earnings and market expectations. These findings confirm the importance to managers of beating the market expectations, as described by Degeorge, Patel, and Zeckhauser (1999). The findings are robust whether we use as a regressor in the model the surprise's deciles or the surprise itself. The coefficient of determination is, however, higher for the models with deciles.

Market returns during the past quarter are negatively correlated with the negativity of managers' speech. This means that when the markets are down, managers reflect it in their speech and do not try to sweeten the news with overwhelming enthusiasm and positiveness to encourage the public.

The negativity of the managers' answers to the analysts' questions is significantly correlated with the negativity of the analysts' questions, more negative questions receiving more negative answers.

To disentangle the effect on negativity caused by negative words and positive words, we make the same kind of analysis for frequencies of each category. The results are in Table 2.6 for the shorter classification and in Table 2.7 for the *FinList*.

[Table 2.6 insert here]

[Table 2.7 insert here]

We find that the managers' use of negative words can be explained much more easily than their use of positive words. Adjusted R^2 is noticeably lower for the positive words' frequencies.

Two characteristics are significantly associated with the use of positive words: earnings surprise and market returns. The frequency of negative words in the presentations is negatively and significantly correlated with two more factors: capital gain during the quarter and change in earnings. However, we were unable to reject the hypothesis that the use of negative words in questions and answers is independent of the change in earnings. Negative words become more frequent when the economy worsens, when the shareholders experience capital loss, or when the firm's earnings fall below the analysts' forecasts. Earnings surprise appears to be one of the most crucial results discussed by the managers and questioned by the analysts.

2.4.2 Paltering.

Conference calls are an important means of dissemination of a company's news. The goal of managers, it is normally asserted, is to present a company's results in the way that is most beneficial to the company's value. It would be natural to expect that managers, even when they have poor results to present, would try to persuade investors that their money is not too greatly at risk. However, at the same time, the managers' efforts to keep value up are subject to the constraint that they not significantly misrepresent the truth in a way that would risk expensive litigation and reputational damage. The other constraint is the necessity to keep market expectations regarding future earnings at a reasonable level, in a way that these expectations can be met.

In this subsection, we investigate what managers do not talk about. We ask which parameters of a past company's performance may incline a manager to omit, obfuscate, or avoid certain subjects.

We identify several patterns of evasive behavior and analyze their correlations to the firm's performance. The indicative patterns studied are:

1. Use of specific "uncertain" words or constructions (see the classification in Table 2.1).

2. Significant differences in negativity between presentations (prepared speech) and answers (improvised speech).

   When preparing a presentation, managers, aware of the great importance of every word, carefully ponder the possible impact of each locution. When improvising answers, managers, without the luxury of time for crafting responses, instinctively avoid saying anything negative. When taken by surprise by a provocative question, managers might be inclined to sweeten the truth. Corporate lawyers are unable to intervene to prevent managers' improvised sugarcoating and to ensure that they do not cross the acceptable line of puffery. In fact, in 2/3 of our observations, more negativity is expressed in the presentations than in the answers. The average negativity in the presentations is significantly greater than in answers.

3. Using a "wrong" tense.

   Presentations should announce and explain past results. Answers should clarify missed points, explain the current situation, or give a preview of the future. If too few sentences in the presentation are in the past tense, the managers are possibly misleading the listeners by diverting their attention from actual outcomes to events that have not yet happened. If too many answers use the past tense, it means either that the managers have prepared an insufficient or unclear announcement, or that the managers are avoiding talking about the present and the future. Summarizing, we would suspect paltering activity when the use of the past tense declines in the managers' presentation and increases in their answers.

   We investigate how the choice of verb tenses shifts with the changes in the company's or the market's performance. We are also interested in whether the choices of tense and the negativity in the managers' tones are related. When managers have bad news to communicate, do they spend more time than usually explaining present corrective measures and projecting future successful undertakings? For automated recognition of verb tenses we extensively used Natural Language Toolkit library[9] in the following way:

- for each sentence, all words in it were tagged with Part-of-Speech tags (POS tagging[10]) ;
- then each tagged sentence was chunked into Name and Verb phrases
- for each verb phrase, its tense is deduced from the POS tag of the first word with a number of heuristics to correct the most common errors of POS tagging;
- if a sentence contains several verb phrases, its tense is defined as a most common tense among its phrases. If a most common tense is not defined, the sentence tense is not defined.

After we have assigned the tenses to each sentence we classify them as describing past present or future with the announcement day as a reference point[11]

We find that, in the prepared presentations, higher earnings surprise is associated with greater use of the past tense. In managers' improvised answers, earnings surprises are positively correlated with the use of the future tense. However, the difference in the size of these effects is negligible.

The correlation of the negativity in the managers' tone with their choice of tense is much more significant. A higher negativity level coincides with more extensive talk about the past.

Table 2.8 presents the results of the the tense-usage analysis.

[Table 2.8 insert here]

The constant shows that, normally, more than half of the phrases in presentations use the past tense and more than half of the phrases in questions and answers use the present tense. We see that the choice of tense is correlated with the managers' negativity. The more negative the managers are, the more their talk is about the past. The effect is stronger pronounced for the prepared speech than for the improvised

[9]www.nltk.org

[10]POS tagging and sentence chunking are implemented using standard statistical methods from NTLK library. For more details see http://streamhacker.com/2008/11/10/part-of-speech-tagging-with-nltk-part-2/; http://streamhacker.com/2009/02/23/chunk-extraction-with-nltk/ and http://streamhacker.com/2008/12/29/how-to-train-a-nltk-chunker/.

[11]The difficulties here arise with the classification of present perfect tense. We classify it for our use as the past-oriented speech, according to the definition of Merriam-Webster dictionary: "present perfect is a verb tense that expresses action or state completed at the time of speaking"

answers. Apparently, they try not to talk about the present and future unless the general tone can be positive.

4. Switching to a different time frame.

   Another evasive tactic is to switch the tense when answering an analyst's question. Switching a tense can be a way to avoid a liability, or, in other cases, it can be an effort to attract the public's attention to a more glorious period (usually somewhere in the future).

   An example of time orientation switch is an answer given by Lehman Brothers' CEO Dick Fuld on the second-quarter 2008 conference call. A Bank of America analyst asked, "Are you guys seeing any impact, some of the rumors circulating in the marketplace, driving a reduction in client activity or counter parties pulling away from Lehman?" Dick Fuld switched to present perfect from present, referring to the time preceding the announcement and answered: "We've seen nothing significant across prime broker balances, derivatives, secured lending markets, short end unsecured markets, we've seen nothing significant." Despite formally both question and answer are in present tense, the answer was oriented to the time preceding the announcement.

   Managers switch the time frames in both directions. Analysts get future projections when asking about achieved results. In uncertain times, questions about the current activities or the future opportunities of a company are answered with glorious stories about past successes. The switches from the past are almost four times more frequent in our sample than switches to the past. On average, in a conference call, 43% of questions using the past tense receive an answer oriented to the present or future. The proportion of future-tense questions receiving past-tense answers is 11%.

   Are switches in time frame strategic? If so, they should relate to conditions of the company. Table 2.9 examines this question.

   [Table 2.9 insert here]

   Past performance has a low impact on managers' inclinations to switch tenses. When the financial performance of a quarter is particularly good (for both the company and the market in general), managers like to look back even when not asked to do so. Higher earnings surprise, however, decreases the proportion of questions about the present or future, which do not receive answers regarding the same time frame. The more aggressive the questions are, the more inclined to switch to the past the managers are.

The only factor we find that impacts managers' desire to avoid talk about the past is the negativity of the questions. The more negative the questions are, the less managers switch the time-frame replying to the past-oriented questions.

In Table 2.10, we present correlations of different evasive measures with each other, with the manager's tone, and with past performance.

[Table 2.10 insert here]

We also investigate how the use of these paltering techniques by managers impacts market efficiency. Table 2.11 presents the coefficients of regressions explaining the following variables: the forecast revision frequency, the variance of analysts' forecasts, and the speed of analysts' reactions to the announcement. We control for market return during the quarter as a proxy for the stability of the economy.

[Table 2.11 insert here]

Negativity is positively associated with revision frequency and variance of forecasts. It is negatively correlated with the speed of analysts' reactions. This means that higher degrees of negativity coincides with higher degrees of uncertainty for analysts. Higher concentration on discussions of the past in the managers' presentations leads to faster and better-grounded reactions, with fewer revisions by analysts. Inversely, concentration on the past in the answers obscures the situation and makes analysts ponder longer before issuing a new forecast. An unexpected result is that a greater frequency of uncertain words reduces revision frequency. We should keep in mind, however, that the frequency of revisions is low not only when analysts get exhaustive information and do not need to adjust it later, but also when the information is so uninformative that there is no point in changing the forecast.

2.5 Predictive power of textual analysis

The goal of this section is to find out whether the textual analysis has any value for forecasting future performance of a company. The association of "soft" (not factual) information expressed by managers and future performance of the companies was a core of several studies, concentrated mostly on stock returns[12]. As stock returns are in large a result of market reaction to "soft" information itself, we focus on operational performance and financial stability of the companies.

[12]Engelberg (2009), Demers and Vega (2008), Tetlock, Saar-Tsechansky, and Macskassy (2008)

2.5.1 Forecasting earnings.

Thousands of professional financial analysts constantly endeavor to provide timely and accurate forecasts of the earnings of the companies they follow. On average, there are 13 analysts issuing a report on every S&P 500 company each quarter. With their research being available to the public, does it make sense to work on independent predictions by examining such details as excessive managers' negativity? It would make sense under two conditions: 1) The degree of managers' negativity contains certain internal information; and 2) Analysts do not systematically capture this information in their forecasts.

The first statement hypothesizes that a manager at the moment of the earnings announcement of quarter t already has some idea of what to expect in the quarter $t+1$. He might reveal his insight unintentionally, or possibly without noticing. Alternatively, he might reveal it intentionally to avoid possible legal consequences or to bring down the market's expectations. This means that the component of the managers' negativity unexplained by past results provides information about that company's prospects. This argument yields the first testable hypothesis of the *information leak*.

- *INFORMATION LEAK H_{IL0}: The managers reveal information about future earnings of the company by choosing (consciousnessly or subconsciousnessly) the presentation tone.*

To test this hypothesis we formulate an alternative statement:

- *INFORMATION LEAK H_{ILa} : The managers' negativity above/below the benchmark in the earnings announcement is not correlated with the earnings in the next quarter.*

In order to understand whether the analysts' forecasts can be improved if adjusted according to the degree of the managers' negativity we test the following set of hypotheses.

- *WISE ANALYSTS H_{WA0} : Analysts' forecasts capture the tone of managers' speech, and their forecast errors do not depend on the degree of the managers' negativity above or below the benchmark.*

- *WISE ANALYSTS H_{WAa} : Managers' tone is informative about earnings, after taking into account analysts' estimates.*

To test whether we can reject the two alternative hypotheses above, we first estimate the benchmark, the normal level of negativity justified by the company's past performance. We use the model 2.5, including firm fixed effects, to explain the managers' choice of words by the company's and the market's past performances. Then, for every observation, starting from January 2006, we estimate the "normal" degree of negativity based on all preceding data. We call the difference between actual negativity and the fitted value "Negativity Residual" (NRP for presentations and NRA for answers). Negativity residuals measure the excessive negativity - the negativity which cannot be justified by past performance. Under our hypothesis, positive residuals would signal managers' expectations of lower earnings in the future, while negative residuals would mean that managers feel more secure about the future than one could expect given the past results.

To investigate whether this new measure adds information to forecast earnings, we compare two models. The first one equation (6) explains the earnings in quarter t+1 by the earnings in the two preceding quarters, the size (decile) of earnings surprise at quarter t, and the market returns during the quarter t.

To test whether these alternative hypotheses can be rejected the first step is to estimate the benchmark, the normal level of negativity, justified by the company past performance. We use the model 2.5, including firm fixed effects, to explain the managers' choice of words by past company's and market's performances. Then, for every observation starting from January 2006[13] we estimate the "normal" degree of negativity based on all preceding data. We call the difference between actual negativity and fitted value - *Negativity Residual* (*NRP* for presentations and *NRA* for answers). Negativity residuals measure the excessive negativity - the negativity which can not be justified by the past results. Under our hypothesis positive residuals would signal lower earnings in the future, while negative residuals would mean that managers feel more secure about the future than one can expect given the past results.

To investigate whether this new measure can add value to the forecasting of earnings we compare two models. The first one - equation 2.6 - explains earnings in quarter $t+1$ by the earnings in two preceding quarters, size (decile) of earnings surprise at quarter t and market returns during the quarter t.

$$Earnings_{t+1} = Const + \beta_1 Earnings_t + \beta_2 Earnings_{t-1} + \beta_3 Surprise\_decile_t + \beta_4 Market\_return_t + \epsilon \quad (2.6)$$

The second model - equation 2.7 - includes $Negativity\_residuals_t$ both NRP (for presentations) and NRA (for answers to analysts). As the residuals of different sign may have different correlations with future earnings, we separate positive and negative residuals, by multiplying them on dummy variables.

[13]this choice is dictated by the necessity to have enough preceding observations to estimate the model

$$
\begin{aligned}
Earnings_{t+1} = {} & Const + \beta_1 Earnings_t + \beta_2 Earnings_{t-1} + \beta_3 Surprise\_decile_t + \\
& + \beta_4 Market\_return_t + \beta_5 NRP_t \times SignDummy_P + \beta_6 NRP_t \times (1 - SignDummy_P) + \\
& + \beta_7 NRA_t \times SignDummy_A + \beta_8 NRA_t \times (1 - SignDummy_A) + \epsilon
\end{aligned} \tag{2.7}
$$

where $SignDummy$ is equal to 1 if negativity residuals (NRA or NRA accordingly to the index) are positive and 0 otherwise.

We also test whether the knowledge of negativity residuals can make any input into the model after we have taken into consideration the financial analysts' forecasts. We compute analysts' consensus following the earnings announcement to the quarter t as average of all forecasts valid on the third day after earnings announcement. We assume that three days period is sufficient for analysts to incorporate new information. According to previous research, analysts forecasts revisions cluster around earnings announcements (Bagnoli, Levine, and Watts (2002), Zhang (2008)) with most revisions falling on the day of announcements or next trading day.[14]

Table 2.12 presents the results of our estimations. To be able to compare adjusted R^2 for different models, all of them are tested on the same group of observations.

[Table 2.12 insert here]

The results are robust to use of extended financial lists of words classification offered by Loughran and McDonald (forthcoming).

[Table 2.13 insert here]

The results reject H_a1 hypothesis as we see that excessive negativity is positively correlated with future earnings. Despite analysts' forecasts are one of the best estimators for future earnings, we get higher adjusted R^2 when we include negativity residuals into the model. This is the first, but not yet sufficient, evidence that analysts do not fully incorporate information contained in managers' negativity into their forecasts.

Despite cases with negative negativity residuals are almost twice more common, than positive residuals, the coefficients at negative residuals are statistically insignificant at any conventional level. Positive residuals have predictive power while negative residuals do not. When manager is excessively negative both in presentation and answers, it signals lower earnings in the future. The negativity below expected level can not help in forecasting future earnings.

[14] Zhang (2008) asserts that depending on the year, about 26-53% of analysts revise their forecasts within 1 day after earnings announcement.

The fact adjusted R^2 is higher for the model which supplements analysts' consensus with negativity residuals, than for the one with consensus as the only explanatory variable, does not prove superiority of model analysis over the use of analysts' predictions. Investors usually do not include analysts' forecasts as a parameter in some linear model, they take it at the face value. We find no significant differences between the mean values of scaled forecast errors of analysts' consensus and obtained using the fitted values for regressions with negativity residuals.

As we are not yet able to forecast earnings with the help of textual analysis better than analysts, the next reasonable try to use our knowledge would be to help adjust analysts' forecast. The next question we ask is whether managers' negativity is correlated with analysts' forecast error. Answering this question we are going to test H_a2

We define $Forecast\ Error$ (FE) as the difference between consensus forecast and actual earnings, scaled by the price to ensure comparability of errors for different quarters and firms.

$$FE_t = \frac{(Consensus\ forecast_{t-1,t} - Actual_t)}{Price_{t-1}} \tag{2.8}$$

where $Consensus\ forecast_{t-1,t}$ is the average of all forecasts for quarter t outstanding 3 days after earnings announcement for quarter $t-1$; $Price_{t-1}$ is the stock price at the day of quarter $t-1$ earnings announcement.

We estimate the following OLS model

$$\begin{aligned} AFE_{t+1} = Const &+ \beta_1 Market\ return_{t+1} + \beta_2 Revision\ Frequency_{t+1} + \\ &+ \beta_3 NRP_t \times SignDummy_P + \beta_4 NRP_t \times (1 - SignDummy_P) + \\ &+ \beta_5 NRA_t \times SignDummy_A + \beta_6 NRA_t \times (1 - SignDummy_A) + \epsilon \end{aligned} \tag{2.9}$$

where $AFE_{t+1} = |FE_{t+1}|$ is the $Absolute\ Forecast\ Error$. We use market returns and revision frequency as proxies for the quarter-firm complicated for forecasting, when markets are not stable and/or new information comes lately after earnings announcements.

To avoid that the results are driven by errors-outliers, we winsorize[15] $Absolute\ Forecast\ Errors$ at top 1% of observations.

[Table 2.14 insert here]

Negativity above the level justified by the previous performance is positively correlated with both forecast error and absolute forecast error. It means that positive and negative

[15]To winsorize means to transform extreme values: the extreme observations takes values of the boundary observation.

errors do not change in a similar way. Positive errors (expectations are above actual earnings) become larger and possibly more frequent when managers are excessively negative. This would happen when analysts overestimate the future earnings. Thus, analysts do not incorporate sufficiently excessive negativity into their forecasts.

With higher revision frequency and worse performing market, the absolute errors go up as well as forecast errors do. Positive negativity residuals (excessive negativity) remain significant in the model with controls.

Interestingly, the negativity below normal level (computed with the short classification) decreases absolute forecast error without a significant effect on forecast error. In other words, it decreases general uncertainty. The absolute errors are smaller with lower residuals, but it involves both positive and negative errors. Excessively positive managers either can provide more exact information for analysts to ground their forecasts or have better tools to manage the earnings to be closer to the estimate. The difference in the results obtained with short and long word classifications is driven by extreme negative NRP of the extensive list. When extreme observations are winsorized at 1%, the coefficients at negative residuals become significant comparably with the model based on short-listed words.

For better understanding of what happens with forecast errors at different levels of negativity, we provide the table 2.15.

[Table 2.15 insert here]

Generally, analysts errors are biased toward negative - actual earnings exceed analysts' forecasts. Previous literature has shown that managers benefit from reporting earnings that are higher than the analysts' forecasts (Bartov, Givoly, and Hayn (2002), Kasznik and McNichols (2002), Brown and Caylor (2005), Matsumoto (2002)) . As consequence they can manage earnings (Degeorge, Patel, and Zeckhauser (1999)) or incentivize analysts to issue lower forecasts (Ke and Yu (2006), Francis and Philbrick (1993b), Hong and Kubik (2003b)).

We see on our sample, that when managers are excessively negative about the future, share of cases with positive forecast errors rises. Negative errors tend to be smaller than positive errors in absolute value which is consistent with the concept of companies taking a "big bath" when not able to meet or beat analysts' expectations.

Negative forecast errors increases in absolute value with increase of negativity residuals. This mean that when firms are beating forecasts despite excessive negativity, are beating them by larger amount. This means that analysts may incorporate some of information contained in the speech negativity into the analysis. However, mean of positive errors increases at much larger rates and also the frequency of positive errors goes up with increase in excessive negativity. Analysts forecasts happen to be too upward biased despite the managers having excessively negative attitude.

As we reject both alternative hypotheses, we come to the conclusion, that negativity above benchmark contains valuable information about next quarter earnings and can serve to adjust analysts' forecasts.

2.5.2 Forecasting bankruptcy.

The use of accounting information to predict bankruptcy or financial distress was pioneered by Beaver (1966), Beaver (1962) and Altman (1968). First to add qualitative information to the bankruptcy prediction models, Tennyson, Ingram, and Dugan (1990) analyzed two kinds of managers' narrative disclosures: President's Letter and Management's Discussion and Analysis of Results. They use the WORDS program developed by Harway and Iker (1969) to assign factor loadings to several content groups. They find that for the Management Analysis the quantity of words focused on the firm growth and expansion is negatively correlated with the likelihood of bankruptcy. For the Presidents' Letter the increase in use of the words focused on specific internal problems is increasing the likelihood of bankruptcy.

The aim of our research is to continue the investigation on how textual analysis can help in forecasting financial distress. The financial crisis of 2007-2009 has led to a huge number of bankruptcy filings. We use these cases as a natural experiment to study the "language" of bankruptcy. We focus particularly on two parameters: negativity of the speech and degree of evasive behavior.

We formulate two following hypotheses:

- *BANKRUPTS' CHANGING TONE HYPOTHESIS* H_{B1}: A systematic difference exists between the negativity of the speech of firms approaching bankruptcy and firms that are not.

- *BANCRUPTCY PREDICTABILITY HYPOTHESIS* H_{B2}: Words' choice contains information useful for classifying firms ex-ante into bankrupt and non-bankrupt groups when considered in addition to accounting ratios.

We use the list of bankrupts with assets of over 100 million dollars from the Chapter 11 Library. Despite the length of the list of bankrupts, only a few of the companies have their conference call transcripts in the StreetEvents database. After we exclude companies for which the data is unavailable in any of our 3 data sources (StreetEvents, CRSP, I/B/E/S), we stay with 50 bankrupt companies. We randomly select 100 non-bankrupt companies from the S&P 500 (2007) list, keeping the proportions of the various industries the same as for the bankrupt companies. For the bankrupt companies, we define the *Distance* variable, measuring the distance from an earnings announcement to the bankruptcy in quarters. *Distance* is equal to 1 for the last earnings announcement before filing for Chapter 11. We examine up to 6 quarters prior to the bankruptcy.

Graphs on Figure 2.1 plot the changes of managers' tone in the time.

[Figure 2.1 insert here]

These graphs, however, do not account for the very important factor of the general mood in economy during a specific time period. This creates a bias: most bankruptcy cases happen in times of trouble when the overall economy does poorly and the degree of negativity in anyone's speech is higher. To avoid this bias, we compute the abnormal negativity as the difference between the managers' negativity and the average negativity for all firms in the sample in the same quarter.

$$Abnormal\ negativity_{it} = Negativity_{it} - \sum_{i=1}^{N} Negativity_{it} \times \frac{1}{N} \tag{2.10}$$

where i is a firm, t is a quarter and N is a number of firms in the quarter. To compute the average negativity, we use observations of both future-bankrupt and never-bankrupt companies. In the same way we compute abnormal frequency of positive and negative words.

Graphs on Figure 2.2 plot the tone measures adjusted by the average.

[Figure 2.2 insert here]

This graphical interpretation are consistent with the BANKRUPTS' CHANGING TONE HYPOTHESIS H_{B1}. We see that abnormal negativity, as well as the frequency of the negative words have tendency to rise with the bankruptcy approaching. This behavior is more pronounced for the prepared speeches than for improvised answers to analysts' questions. The frequency of positive words in presentations picks three quarters before the bankruptcy, while in answers it changes smoothly and drops in the last earnings-announcement-conference-call before the bankruptcy. Apparently, three to four quarters before the bankruptcy the eloquence of the managers still can persuade the public that the company is solvent and has some perspectives. However, subject to litigation risks, managers mostly keep the excessive positivism in the prepared speech in the well proof-read sentences. The abnormal frequency of negative words becomes alarming one year before bankruptcy and declines a quarter after to rise again later.

We test now the H_{B1} hypothesis using the same sample of 50 bankrupt companies and 100 non-bankrupt. The sample includes earnings-announcements-conference-calls for the period from 2003 to 2009.

Table 2.16 presents the coefficients of OLS regressions, testing how the distance to the bankruptcy impacts managers' tone. The basic model has the abnormal negativity on the left-hand side. The explanatory variables are distance-from-bankruptcy dummies and company-performance-variables proven to have an impact on negativity in the previous sections. Baseline observations are observations for non-bankrupt companies and observations preceding a bankruptcy by more than 6 quarters. Second model differs in a way that dependent variable is non-adjusted negativity, and to compensate the absence of adjustment we add controls for each quarter as regressors. Third model estimates the association of "unexplained" negativity with distance to bankruptcy and has negativity residuals as a dependent variable.

[Table 2.16 insert here]

In all three models, the coefficients are statistically significant on the dummies for distances of 4 and less quarters before the bankruptcy. The coefficients, however, do not increase monotonously with the shrinking of the distance to the bankruptcy. The largest coefficients are on the dummies of distances of three and two quarters before the bankruptcy.

Our second hypothesis, the BANCRUPTCY PREDICTABILITY HYPOTHESIS H_{B2} posits that textual analysis has an incremental information content for bankruptcy prediction when combined with the financial statement information. To test H_{B2} we develop a classificatory model using a logistic regression for the accounting ratios. A second classificatory model uses measure of tone and evasiveness concurrently with accounting ratios. We test the H_{B2} on 6 different horizons. We keep one observation for each bankrupt firm on a specified distance from the bankruptcy. Then we select randomly one observation for each of non-bankrupt firms in the way that for each quarter in the sample with a bankrupt observation there are three observations for non-bankrupt companies. The non-bankrupts companies are selected from S&P 500 list. In our classificatory models we utilize the same financial ratios used by Altman (1968) in his seminal work:

- Liquidity ratio (LR) = working capital divided by total assets;
- Cumulative profitability ratio (CPR)= retained earnings divided by total assets;
- Return on assets (ROA) = earnings before interest and taxes divided by total assets;
- Solvency ratio (SR) = market value of equity divided by the book value of total debt;
- Capital-turnover ratio (CTR) = sales divided by total assets.

Textual analysis explanatory variables are abnormal negativity and quantity of uncertain words. The regressand is a Bankruptcy dummy equal to 1 if the firm is going to file for Chapter 11 after the period specified for each regression.

Table 2.17 describes the classification success for both models in six setups with changing distances from bankruptcy. The percentages of correct classifications and pseudo-R2 presented are the average values of ten independent trials with randomly selected non-bankrupt observations.

[Table 2.17 insert here]

The combined model has a classification accuracy higher than the financial ratio model alone for any of 6 quarters preceding the bankruptcy. We observe the largest superiority of the combined model in the period around of one year or three quarters before the bankruptcy. The incremental information value of textual analysis is the smallest in a last quarter before a bankruptcy.

If we exclude textual analysis variables from the joint model for the conference call four quarters before the bankruptcy, we increase average number of classification mistakes by 68%, while the exclusion of ROA increases mistakes number by 57%, of cumulative profitability ratio - 55%, of liquidity ratio - 18%, of solvency ratio - 16%, of capital-turnover ratio - 6%. Median increase of classification mistakes is 80% for exclusion of textual analysis variables; 60% for ROA; 60% for cumulative profitability ratio; 20% for solvency ratio; 10% for liquidity ratio; and 10% for capital-turnover ratio.

These findings are robust to the use of extensive FinList classification. We reject the null hypothesis and state that textual analysis appears to contain useful information in addition to financial data for bankruptcy forecasting.

2.6 Conclusion

We apply textual analysis techniques to the earnings announcements transcripts with the aim of investigating whether internal information about a company's future may leak through the managers' choice of words. We find that the textual analysis of conference calls does not require extensive word classifications. Analysis of only the most frequently used positive and negative words yields the same effects as the use of much more extensive word lists. Our first significant finding is that the most important factor determining managers' tone on the earnings-announcement conference call is the difference between the analysts' expectations and the actual earnings. The change in earnings during the quarter and the stock returns influence the frequency of negative words used by the managers. That is not, however, the case for positive words.

Second, we find that Negativity Residuals excessive negativity, which cannot be explained by past performance are negatively correlated with future earnings. This finding suggests that, by using a proportion of positive and negative wordings, managers shed light on their company's prospects. Analysts fail to incorporate the managers' tone into their forecasts. Excessive negativity increases the gap between actual results and analysts' expectations. We document that higher negativity is associated with larger uncertainty, as reflected in the higher frequency of forecast revisions, larger variance in forecasts, and slower analysts' reactions to the earnings announcements. Though our model tested out of sample does not provide better forecasts than those of financial analysts, it helps to form more justified expectations by adjusting the analysts' forecasts.

We analyze several measures of evasive activities which can be undertaken by managers. We find that the intensity of evasive behavior is positively correlated with the negativity of the managers' speech. When answering analysts' questions, managers change the time references more often when they have to report poor results and when the analysts' questions become more aggressive.

Finally, we study how the managers' speech changes as a bankruptcy approaches. We find that significant changes in negativity occur up to 4 quarters before the bankruptcy. When the tone of managers becomes significantly more negative than that of their peers and is not justified by their company's recent performance, bankruptcy can be expected.

Adding textual analysis measures of tone and evasive behavior to classical bankruptcy prediction model of Altman (1968) we significantly improve our classification abilities.

Summarizing, our results suggest that textual analysis can contribute to the ability to predict not only market returns, but also physical company performance.

Short list FinList (extensive classification)

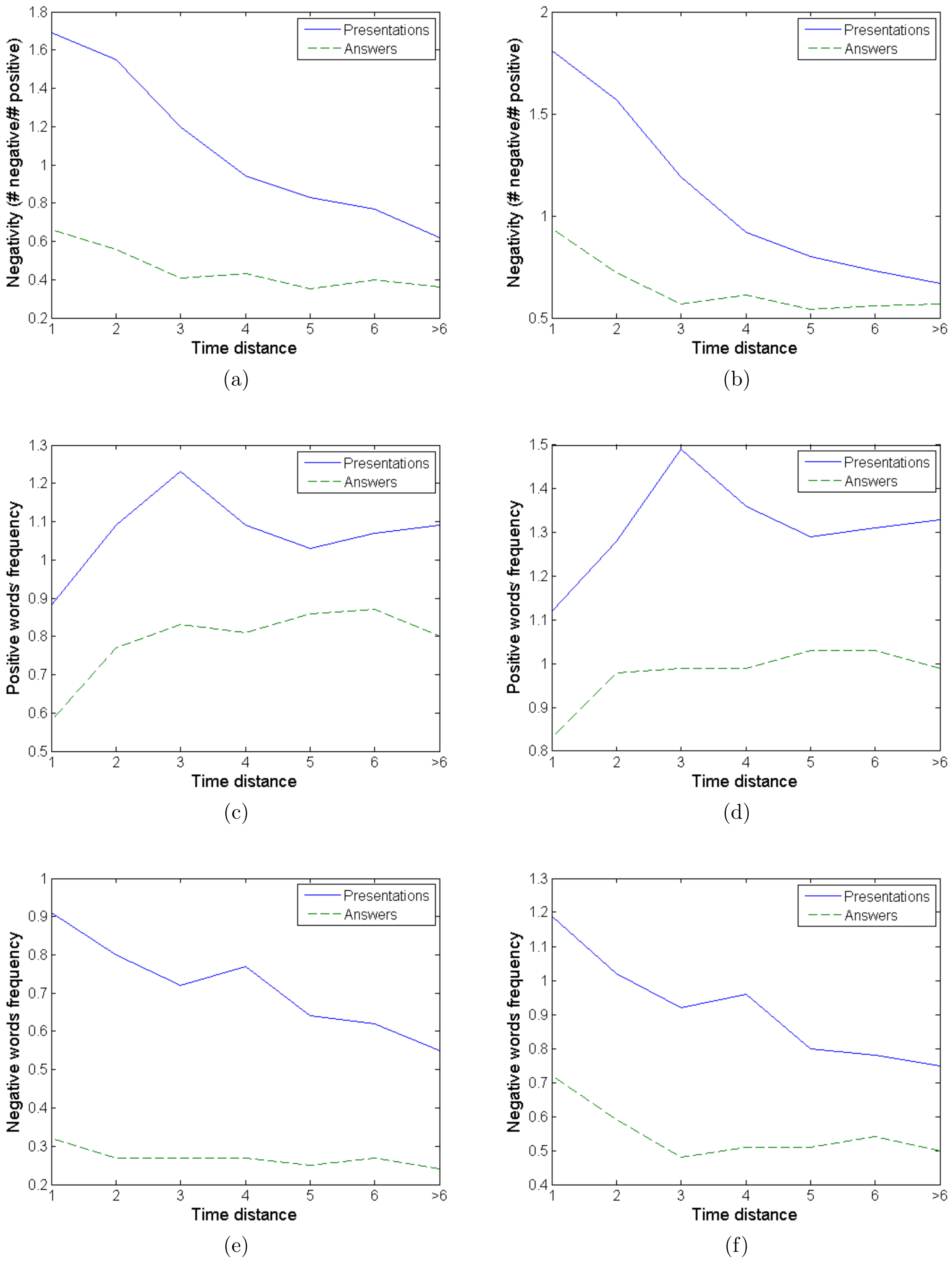

Figure 2.1: Evolution of the managers' tone before a bankruptcy

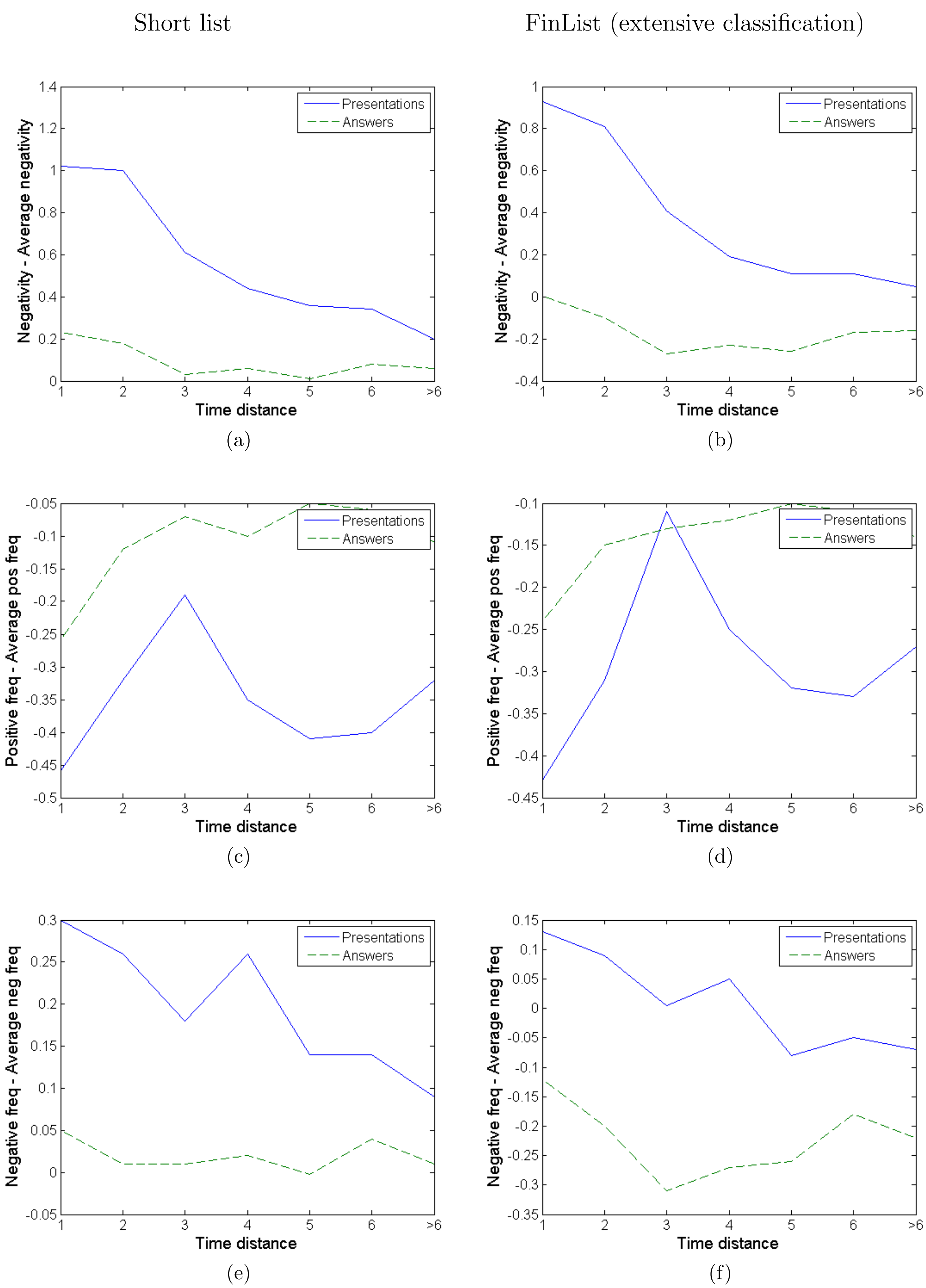

Figure 2.2: Tone of future bankrupts compared to average

Table 2.1: Word classification by groups

We compute the frequencies of all words appearing in managers' speechs during conference calls (initial earnings announcements and answers to analysts' questions). Then, from among the most frequent words we choose the words belonging to three groups: 1) positive words; 2) negative words; 3) words of uncertainty. The words appear in the order of frequency of their use, within their categories.

N	Positive	Negative	Uncertainty/Paltering
1	growth	decline	think
2	good	risks	may
3	strong	risk	expect
4	opportunities	loss	anticipate
5	opportunity	negative	believe
6	improvement	uncertainties	maybe
7	positive	difficult	compared
8	grow	losses	guess
9	growing	below	knowledge
10	improved	declined	expected
11	improve	pressure	expectations
12	grew	reduce	assumptions
13	ability	incorrect	assume
14	strength	decrease	assuming
15	gain	inaccuracies	projections
16	success	decreased	forecast
17	favorable	tough	fairly
18	advantage	challenging	generally
19	outstanding	challenges	perhaps
20	improving	declines	roughly
21	improvements	volatility	reasonable
22	confident	weakness	plans
23	successful	problem	efforts
24	stronger	lost	preliminary
25	comfortable	challenge	possible
26	excellent	slowdown	planning
27	nice	difficulty	expecting
28	confidence	problems	estimates
29	profitable	declining	predict
30	attractive	negatively	forecasting
31	optimistic	worse	forecasts
32	benefited	uncertainty	pretty
33	exciting		approximately
34	wins		might
35	safe		wondering
36	successfully		enough
37	grown		hope
38	strengthen		potential
39	encouraging		comparison
40	perfect		assumption

Table 2.2: Summary statistics

Table describes main variables we use in this paper.

Variable	Description
	Text variables
$Words$	number of words in the presentations or answers to analysts' questions;
$Phrases$	number of sentences in the presentations or answers to analysts' questions;
$Negative$	number of negative words, can be computed for answers or presentations according to either word classification: our short classification or FinList offered in Loughran and McDonald (forthcoming);
$Positive$	number of positive words, can be computed for answers or presentations according to either word classification: our short classification or FinList offered in Loughran and McDonald (forthcoming);
$Uncertain$	number of uncertain words, can be computed for answers or presentations according to either word classification: our short classification or FinList offered in Loughran and McDonald (forthcoming);
$Negativity$	ratio of number of negative words to number of positive words in the same section of a conference call;
R_Past	ratio of sentences in the past tense to number of all sentences in the specific part of a conference call;
$R\_Present$	ratio of sentences in the present tense to number of all sentences in the specific part of a conference call;
R_Future	ratio of sentences in the future tense to number of all sentences in the specific part of a conference call;
$Switch\_from\_past$	share of analysts' questions oriented toward the past which get an answer oriented toward the future or present;
$Switch\_to\_past$	share of analysts' questions oriented toward future or present which get an answer oriented toward the past.
	Company performance
$Capital\_gain$	stock return over the period from previous earnings announcement;
$\Delta Earnings$	change in earnings scaled by share price;
$Surprise$	difference between actual earnings and average of analysts' forecasts issued in 30 days before earnings announcement, scaled by the stock price;
$Earnings$	quarterly earnings per share announced in the conference call.

Table 2.3: Summary statistics

Table presents summary statistics for all variables described in table 2.2.

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Speech length				
$Words\_Presentations$	3923.909	1658.64	5	18094
$Words\_Answers$	3986.422	1567.314	22	21371
$Phrases\_Presentations$	168.988	73.114	1	819
$Phrases\_Answers$	179.59	72.274	2	958
Negative words				
$Negative\_Presentations$	16.856	13.14	0	170
$Negative\_Presentations\_FinList$	32.041	22.749	0	447
$Negative\_Answers$	8.851	6.937	0	150
$Negative\_Answers\_FinList$	30.322	17.605	0	445
Positive words				
$Positive\_Presentations$	56.832	34.272	0	296
$Positive\_Presentations\_FinList$	65.607	36.301	0	332
$Positive\_Answers$	36.57	20.055	0	191
$Positive\_Answers\_FinList$	45.684	23.109	0	276
Negativity				
$Negativity\_Presentations$	0.391	0.411	0	8
$Negativity\_Presentations\_FinList$	0.587	0.475	0	12
$Negativity\_Answers$	0.304	0.335	0	10
$Negativity\_Answers\_FinList$	0.789	0.744	0	41
Uncertainty words				
$Uncertainty\_Presentations$	37.979	20.017	0	188
$Uncertainty\_Presentations\_FinList$	26.054	14.805	0	204
$Uncertainty\_Answers$	61.081	29.153	0	295
$Uncertainty\_Answers\_FinList$	28.497	15.458	0	201
Frequency of tense change				
$Switch\_from\_past$	0.433	0.203	0	1
$Switch\_to\_past$	0.112	0.071	0	1
Company performance				
$Capital\_gain$	0.067	0.805	-0.987	55.653
$\Delta Earnings$	-0.006	0.37	-27.196	2.318
Absolute Surprise, unscaled	0.092	0.715	0	58.747
Positive surprise, unscaled	0.065	0.127	0	2.82
Negative surprise, unscaled	-0.165	1.33	-58.747	0
Surprise	-0.004	0.299	-27.452	0.324
Earnings	0.572	1.005	-68.400	8.790

Table 2.4: NEGATIVITY RATIO ANALYSIS. MOST FREQUENTLY USED POSITIVE AND NEGATIVE WORDS

This table presents the results of OLS regressions and fixed-effect regressions, explaining negativity of managers' tone by companies' performance.

$$Negativity_t = Const + \beta_1 Capital\_gain_{t,t-1} + \beta_2 \Delta Earnings_{t,t-1} + \beta_3 Surprise\_decile_t + +\beta_4 Market\_return_{t,t-1} + \epsilon$$

where $Negativity_t$ is the ratio of the number of negative words to the number of positive words; $Capital\_gain_{t,t-1}$ is the change in stock price computed as the stock price 5 trading days before the announcement minus stock price 5 trading days after the preceding quarter announcement, scaled by the latter; $\Delta Earnings_{t,t-1}$ is the difference in actual EPS and previous-quarter EPS, scaled by the price 5 days before earnings announcement; $Surprise_t$ is an earnings surprise - difference between actual earnings in quarter t and average analysts' forecast 30 days preceding the earnings announcement, scaled by the stock price 5 trading days before the announcement. When the firm underperforms expectations and surprise is negative, the *Surprise_decile* will take values from -5 (for largest surprises) to -1 (smallest negative surprises). Positive surprises are divided into quintiles as well, and *Surprise_decile* for positive surprises takes values from 1 to 5. The stars denote the significance levels of less than 5% (*), 1% (**) and 0.1% (***). t-statistics are in parentheses.

Negativity

	Presentations			Answers				Questions
	1	2	3	1	2	3	4	1
$Capital\_gain_{t,t-1}$	-0.025***	-0.019***	-0.010*	-0.013**	-0.009	-0.004	-0.004	-0.018*
	(-4.705)	(-3.479)	(-2.233)	(-2.784)	(-1.901)	(-1.027)	(-1.029)	(-2.225)
$\Delta Earnings_{t,t-1}$	-0.482***	-0.468***	-0.339***	-0.304***	-0.295***	-0.207**	-0.179**	-0.434***
	(-5.887)	(-5.740)	(-5.032)	(-4.431)	(-4.308)	(-3.252)	(-3.032)	(-3.644)
$Surprise\_decile_t$	-0.029***	-0.028***	-0.026***	-0.016***	-0.016***	-0.009***	-0.008***	-0.030***
	(-20.490)	(-19.838)	(-20.803)	(-13.588)	(-12.982)	(-7.758)	(-6.893)	(-14.094)
$Market\_return_{t-1,t}$		-0.487***	-0.507***		-0.301***	-0.204***	-0.237***	-0.581***
		(-10.128)	(-12.714)		(-7.448)	(-5.169)	(-6.464)	(-7.956)
$Questions\_negativity_t$						0.208***	0.150***	
						(33.924)	(24.478)	
$Firm\_fixed\_effects$			X				X	
$Constant$	0.424***	0.426***	0.423***	0.324***	0.325***	0.218***	0.243***	0.502***
	(89.769)	(90.570)	(108.533)	(81.724)	(82.124)	(44.803)	(52.224)	(71.087)
N	8166	8158	8158	8152	8144	7676	7676	7696
adj_R2	0.0594	0.0709	0.0708	0.0273	0.0334	0.1602	0.1594	0.0401

*p<0.05, ** p<0.01, *** p<0.001

Table 2.5: NEGATIVITY RATIO ANALYSIS. EXTENSIVE (FINLIST) CLASSIFICATION OF POSITIVE AND NEGATIVE WORDS

This table is analogous to Table 2.4 with the only difference being that here the *Negativity* is computed based on the word classification offered by Loughran and McDonald (forthcoming). The stars denote the significance levels of less than 5% (*), 1% (**) and 0.1% (***). t-statistics are in parentheses.

	Negativity							
	Presentations			Answers				Questions
	1	2	3	1	2	3	4	1
$Capital\_gain_{t,t-1}$	-0.028***	-0.021**	-0.013*	-0.021**	-0.013	-0.008	-0.010	-0.031
	(-4.440)	(-3.282)	(-2.548)	(-2.699)	(-1.676)	(-1.052)	(-1.453)	(-1.511)
$\Delta Earnings_{t,t-1}$	-0.403***	-0.387***	-0.319***	-0.560***	-0.543***	-0.462***	-0.406***	-0.826**
	(-4.201)	(-4.055)	(-4.196)	(-4.757)	(-4.629)	(-4.107)	(-4.081)	(-2.698)
$Surprise\_decile_t$	-0.038***	-0.037***	-0.032***	-0.028***	-0.027***	-0.020***	-0.018***	-0.065***
	(-22.580)	(-21.986)	(-22.411)	(-13.912)	(-13.373)	(-9.956)	(-9.654)	(-12.087)
$Market\_return_{t-1,t}$		-0.531***	-0.555***		-0.556***	-0.419***	-0.452***	-1.118***
		(-9.436)	(-12.355)		(-8.164)	(-6.131)	(-7.431)	(-6.092)
$Questions\_negativity_t$						0.111***	0.072***	
						(27.226)	(18.076)	
$Firm\_fixed\_effects$			X				X	
$Constant$	0.633***	0.635***	0.629***	0.806***	0.808***	0.592***	0.662***	1.897***
	(114.540)	(115.359)	(142.953)	(121.110)	(121.740)	(58.475)	(69.888)	(106.906)
N	8189	8181	8181	8519	8511	8037	8037	8114
adj_R2	0.0664	0.0763	0.0764	0.0275	0.0349	0.1162	0.1139	0.0260

*p<0.05, ** p<0.01, *** p<0.001

Table 2.6: NEGATIVE AND POSITIVE FREQUENCIES.

This table presents the results of estimation of the following OLS regressions, explaining the frequency of positive and negative words in different sections of a conference call by the company's performance.

$$Word\ frequency_t = Const + \beta_1 Capital\_gain_{t,t-1} + \beta_2 \Delta Earnings_{t,t-1} + \beta_3 Surprise\_decile_t + \\ + \beta_4 Market\_return_{t,t-1} + \epsilon$$

where $Word\ frequency_t$ is the number of words of specific category (positive, negative, uncertain) per 100 words in the conference call section. $Capital\_gain_{t,t-1}$ is the change in stock price computed as the stock price 5 trading days before the announcement, minus stock price 5 trading days after the preceding quarter announcement, scaled by the later; $\Delta Earnings_{t,t-1}$ is the difference in actual EPS and previous quarter EPS, scaled by the price 5 days before earnings announcement; $Surprise_t$ is an earnings surprise - the difference between actual earnings in quarter t and average analysts' forecast 30 days preceding the earnings announcement, scaled by the stock price 5 trading days before the announcement. When the firm underperforms expectations and surprise is negative, the *Surprise_decile* will take values from -5 (for largest surprises) to -1 (smallest negative surprises). Positive surprises are divided into quintiles as well, and *Surprise_decile* for positive surprises takes values from 1 to 5.
The stars denote the significance levels of less than 5% (*), 1% (**) and 0.1% (***). t-statistics are in parentheses.

Frequency

	Presentations		Answers		Questions	
	Negative	Positive	Negative	Positive	Negative	Positive
$Capital\_gain_{t,t-1}$	-0.018***	0.014	-0.007**	0.002	-0.007**	0.003
	(-4.721)	(1.632)	(-3.272)	(0.333)	(-2.830)	(0.615)
$\Delta Earnings_{t,t-1}$	-0.164**	0.150	-0.055	0.111	-0.057	0.058
	(-2.895)	(1.164)	(-1.811)	(1.427)	(-1.461)	(0.784)
$Surprise\_decile_t$	-0.018***	0.024***	-0.005***	0.014***	-0.008***	0.013***
	(-18.228)	(10.640)	(-9.122)	(10.532)	(-11.855)	(9.694)
$Market\_return_{t-1,t}$	-0.406***	0.174*	-0.152***	0.168***	-0.229***	0.178***
	(-12.214)	(2.290)	(-8.586)	(3.678)	(-9.586)	(3.930)
$Constant$	0.459***	1.415***	0.229***	0.898***	0.255***	0.704***
	(140.696)	(190.009)	(131.825)	(200.737)	(110.682)	(161.135)
N	8177	8177	8177	8177	7785	7785
adj_R2	0.0675	0.0157	0.0236	0.0163	0.0345	0.0149

*p<0.05, ** p<0.01, *** p<0.001

Table 2.7: NEGATIVE AND POSITIVE FREQUENCIES: EXTENDED CLASSIFICATION

This table is analogous to Table 2.6 with the only difference being that here the $Negativity$ is computed based on the word classification offered by Loughran and McDonald (forthcoming). The stars denote the significance levels of less than 5% (*), 1% (**) and 0.1% (***). t-statistics are in parentheses.

	Frequency					
	Presentations		Answers		Questions	
	Negative	Positive	Negative	Positive	Negative	Positive
$Capital\_gain_{t,t-1}$	-0.025***	0.011	-0.013**	-0.000	-0.016*	0.004
	(-3.920)	(1.421)	(-2.609)	(-0.039)	(-2.257)	(0.756)
$\Delta Earnings_{t,t-1}$	-0.229*	0.096	-0.130	0.094	-0.130	0.054
	(-2.444)	(0.799)	(-1.713)	(1.119)	(-1.242)	(0.722)
$Surprise\_decile_t$	-0.032***	0.027***	-0.013***	0.016***	-0.017***	0.014***
	(-19.618)	(12.992)	(-9.939)	(10.972)	(-9.314)	(10.440)
$Market\_return_{t-1,t}$	-0.663***	0.209**	-0.578***	0.192***	-0.405***	0.141**
	(-12.040)	(2.957)	(-13.192)	(3.952)	(-6.500)	(3.161)
$Constant$	0.866***	1.622***	0.790***	1.137***	1.230***	0.817***
	(160.269)	(234.054)	(184.661)	(239.965)	(203.884)	(189.469)
N	8198	8198	8543	8543	8184	8184
adj_R2	0.0712	0.0228	0.0362	0.0167	0.0183	0.0152

*p<0.05, ** p<0.01, *** p<0.001

Table 2.8: Tense usage analysis.

This table presents the results of OLS regressions explaining the frequencies of the tenses used by managers during earnings-announcement conference calls. Frequencies are stated in percentages.
The stars denote the significance levels of less than 5% (*), 1% (**) and 0.1% (***). t-statistics are in parentheses.

	Frequency in %								
	Presentations			Answers			Questions		
	Past	Present	Future	Past	Present	Future	Past	Present	Future
$Capital\_gain_{t,t-1}$	-0.061	-0.073	0.134*	0.057	-0.129	0.072	-0.017	-0.003	0.020
	(-0.491)	(-0.733)	(2.476)	(0.654)	(-1.510)	(1.161)	(-0.146)	(-0.028)	(0.291)
$\Delta Earnings_{t,t-1}$	2.340	-1.732	-0.609	-1.748	1.074	0.674	-2.283	1.112	1.172
	(1.250)	(-1.160)	(-0.749)	(-1.345)	(0.838)	(0.722)	(-1.317)	(0.657)	(1.138)
$Surprise\_decile_t$	0.129***	-0.075**	-0.054***	-0.073**	0.110***	-0.037*	0.024	0.008	-0.032
	(3.854)	(-2.798)	(-3.735)	(-3.131)	(4.774)	(-2.190)	(0.759)	(0.252)	(-1.692)
$Market\_return_{t-1,t}$	3.177**	-3.222***	0.045	2.073**	-1.028	-1.046	2.433*	-3.766***	1.332*
	(2.860)	(-3.638)	(0.094)	(2.689)	(-1.353)	(-1.888)	(2.274)	(-3.602)	(2.095)
$Negativity_{Presentations_t}$	4.075***	-3.583***	-0.491***	1.468***	-1.190***	-0.279*	1.329***	-0.896***	-0.433**
	(16.045)	(-17.695)	(-4.454)	(8.324)	(-6.845)	(-2.201)	(5.315)	(-3.667)	(-2.916)
$Uncertainty_{Presentations_t}$	-0.081***	0.056***	0.025***						
	(-16.333)	(14.088)	(11.741)						
$Uncertainty_{Answers_t}$				-0.041***	0.049***	-0.008***	-0.019***	0.021***	-0.002
				(-17.239)	(20.974)	(-4.769)	(-5.819)	(6.478)	(-0.858)
$Constant$	55.954***	34.150***	9.896***	32.057***	53.099***	14.844***	36.637***	52.149***	11.214***
	(228.427)	(174.831)	(93.011)	(174.268)	(292.986)	(112.357)	(145.322)	(211.747)	(74.859)
N	8158	8158	8158	8158	8158	8158	7762	7762	7762
adj_R2	0.0598	0.0584	0.0202	0.0472	0.0616	0.0034	0.0082	0.0081	0.0016

*p<0.05, ** p<0.01, *** p<0.001

Table 2.9: SWITCHES.

This table presents the results of OLS regressions, explaining the frequency of switching the tenses in Q&A sessions. The dependent variable in regressions 1 and 3 is the share of the questions oriented toward the present or future and getting the answer oriented toward the past, among all future or present-oriented questions. The dependent variable in regressions 2 and 4 is the share of the questions oriented toward the past which get answers oriented toward the future or present, among all past-oriented questions. Explanatory variables are firm- and market-performance characteristics, as well as analysts' *Negativity* (number of negative words to the number of positive words in the analysts questions).
The stars denote the significance levels of less than 5% (*), 1% (**) and 0.1% (***). *t*-statistics are in parentheses.

	Share or answers with switched tense			
	Short classification		FinList classification	
	1	2	3	4
	To Past	From Past	To Past	From Past
$Capital\_gain_{t,t-1}$	0.002*	-0.001	0.003**	-0.001
	(2.509)	(-0.208)	(2.665)	(-0.147)
$\Delta Earnings_{t,t-1}$	0.008	-0.004	0.000	0.000
	(0.548)	(-0.098)	(0.383)	(0.109)
$Surprise\_decile_t$	-0.001*	0.001	-0.000	0.001
	(-1.980)	(1.407)	(-1.472)	(1.163)
$Market\_return_{t-1,t}$	0.031***	0.048	0.028**	0.024
	(3.436)	(1.871)	(3.097)	(0.761)
$Questions\_negativity_t$	0.013***	-0.037***	0.010***	-0.018***
	(5.372)	(-5.351)	(7.400)	(-3.639)
$Constant$	0.108***	0.446***	0.102***	0.450***
	(93.116)	(133.146)	(72.439)	(89.354)
N	7746	7746	8047	8045
adj_R2	0.0059	0.0045	0.0085	0.0016

Table 2.10: CORRELATIONS TABLE: PALTERING MEASURES AND PREVIOUS RESULTS.
This table presents paired correlations of paltering measures and companies' performance. $Uncertainty\_freq$ is the frequency of uncertain words in the conference call; Dif_AP is the absolute difference between manager's $Negativity$ in the prepared presentation and improvised answers; $Past\_P$ and $Past\_A$ are the proportions of the sentences formulated in the past tense in the presentations and answers respectively. $From\_past$ and To_past are the proportions of questions in a specific tense when managers decide to answer in a different tense, over all questions using this tense.
The stars denote the significance levels of less than 5% (*), 1% (**) and 0.1% (***). t-statistics are in parentheses.

Variables	$Negativity_P$	$Negativity_A$	$\Delta Earnings$	$Surprise\_decile$	$Capital\_gain$
$Uncertainty\_freq$	0.07***	0.01	0.02	0.01	-0.02
Dif_AP	0.73***	0.53***	-0.03**	-0.17***	-0.02
$Past\_P$	0.16***	0.04***	0.02	0.01	0.01
$Past\_A$	0.09***	0.12***	-0.01	-0.04***	-0.00
$From\_past$	-0.07***	-0.06***	0.02	0.03**	-0.01
To_past	0.02**	0.05***	-0.00	-0.02	0.00

*p<0.05, ** p<0.01, *** p<0.001

Table 2.11: Paltering and market efficiency.

The dependent variables are 1) Revision frequency in the following quarter (number of revisions, scaled by the number of analysts); 2) Variance of analysts' forecasts outstanding at the end of following quarter; 3) Percentage of analysts covering the firm in the following quarter who react within one working day after the earnings announcement. Indexes P and A relate the variable to the presentation part of a call or to the manager's answers respectively. Dif_AP is the absolute difference in negativity of presentation and answers; Dif_sign_AP is a dummy variable equal to one when negativity of answers is greater than negativity of presentations. $Length\_P$ is the logarithm of the number of sentences in the presentations. Frequencies of past tense in the speech ($Past\_P$ and $Past_A$) are expressed in percentages.

The stars denote the significance levels of less than 5% (*), 1% (**) and 0.1% (***). t-statistics are in parentheses

	Short list			Extensive list		
	Revisions Freq	Variance	Reaction	Revisions Freq	Variance	Reaction
$From\_past$	0.071***	-0.009	-0.034*	0.062**	-0.011	-0.030*
	(3.382)	(-0.621)	(-2.540)	(2.936)	(-0.802)	(-2.210)
$Past\_P$	-0.205***	0.031	0.160***	-0.141**	0.079*	0.122***
	(-3.778)	(0.852)	(4.600)	(-2.615)	(2.197)	(3.527)
$Past\_A$	0.023	0.029	-0.172**	0.126	0.044	-0.235***
	(0.276)	(0.517)	(-3.230)	(1.540)	(0.800)	(-4.441)
$Length_P$	0.010	0.010	-0.014	0.029*	0.018*	-0.033***
	(0.864)	(1.235)	(-1.921)	(2.559)	(2.405)	(-4.525)
$Market\_return_{t-1,t}$	-0.598***	-0.153***	0.205***	-0.619***	-0.180***	0.217***
	(-11.078)	(-4.261)	(5.904)	(-11.443)	(-4.977)	(6.229)
$Uncertainty\_freq$	-0.080***	-0.008	0.048***	-0.036	0.028	-0.032
	(-4.730)	(-0.727)	(4.416)	(-1.422)	(1.679)	(-1.946)
Dif_AP	0.003	-0.113***	0.032*	0.014	-0.061***	0.021*
	(0.155)	(-7.550)	(2.204)	(0.908)	(-5.949)	(2.158)
Dif_sign_AP	-0.000	0.017*	0.023**	-0.012	0.009	0.007
	(-0.036)	(2.192)	(3.010)	(-0.890)	(1.070)	(0.809)
$Negativity\_P$	0.136***	0.197***	-0.093***	0.095***	0.085***	-0.072***
	(6.825)	(14.949)	(-7.277)	(6.970)	(9.313)	(-8.173)
$Negativity\_A$	0.076***	0.093***	-0.117***	0.012	0.068***	-0.039***
	(3.912)	(7.189)	(-9.372)	(0.827)	(6.879)	(-4.151)
$Constant$	0.521***	-0.084*	0.539***	0.381***	-0.153***	0.759***
	(10.280)	(-2.494)	(10.168)	(8.266)	(-4.965)	(15.481)
N	7283	7171	7283	7300	7188	7300
$adjR^2$	0.0452	0.0602	0.0519	0.0353	0.0443	0.0404

*p<0.05, ** p<0.01, *** p<0.001

Table 2.12: PREDICTING FUTURE EARNINGS.

This table presents the results of OLS regressions, explaining earnings in the next quarter by past performance of the company and the market. The full model (column 6) looks as follows:

$$\begin{aligned}Earnings_{t+1} = Const + \beta_1 Earnings_t + \beta_2 Earnings_{t-1} + \beta_3 Surprise\_decile_t + \\ + \beta_4 Market\_return_t + \beta_5 NRP_t \times SignDummy_P + \beta_6 NRP_t \times (1 - SignDummy_P) + \\ + \beta_7 NRA_t \times SignDummy_A + \beta_8 NRA_t \times (1 - SignDummy_A) + \beta_8 Consensus_{t,t+1} + \epsilon\end{aligned}$$

where $Surprise_t$ is an earnings surprise - the difference between actual earnings in quarter t and average analysts' forecast in the 30 days preceding the earnings announcement, scaled by the stock price 5 trading days before the announcement. When the firm underperforms expectations and surprise is negative, the $Surprise\_decile$ will take values from -5 (for largest negative surprises) to -1 (smallest negative surprises). Positive surprises are divided into quintiles as well, and $Surprise\_decile$ for positive surprises takes values from 1 to 5. $Negativity\_residuals_t$ are residuals of the following regression estimated on preceding data with firm fixed-effects.

$$Negativity_t = C + \beta_1 Capital\_gain_t + \beta_2 \Delta Earnings_t + \beta_3 Surprise\_decile_t + \beta_4 Market\_return_t$$

$Analysts\_consensus_{t,t+1}$ is the average forecast for quarter $t+1$ earnings outstanding on the third day after the earnings announcement of quarter t.
To make adjusted R^2 comparable, all regressions are run on the same set of observations (for which all parameters are defined).
The stars denote the significance levels of less than 5% (*), 1% (**) and 0.1% (***). t-statistics are in parentheses

	$Earnings_{t+1}$					
	1	2	3	4	5	6
$Earnings_t$	0.444***	0.428***			0.234***	0.192***
	(21.003)	(20.292)			(8.375)	(6.893)
$Earnings_{t-1}$	0.419***	0.428***			0.355***	0.359***
	(20.545)	(21.130)			(17.031)	(17.426)
$Surprise\_decile_t$	0.023***	0.019***			0.029***	0.025***
	(5.542)	(4.592)			(7.145)	(6.112)
$Market\_return_t$	0.685***	0.609***			0.657***	0.562***
	(5.537)	(4.951)			(5.398)	(4.664)
$NRP_t \times SignDummy_P$		-0.265***		-0.409***		-0.305***
		(-6.237)		(-9.357)		(-7.303)
$NRP_t \times (1 - SignDummy_P)$		-0.143		0.090		-0.091
		(-1.186)		(0.723)		(-0.772)
$NRA_t \times SignDummy_A$		-0.150*		-0.337***		-0.217***
		(-2.458)		(-5.298)		(-3.610)
$NRA_t \times (1 - SignDummy_A)$		0.190		0.304		0.168
		(1.237)		(1.892)		(1.113)
$Consensus_{t,t+1}$			0.885***	0.888***	0.377***	0.418***
			(42.169)	(43.029)	(11.272)	(12.533)
$Constant$	0.031	0.084**	0.011	0.122***	-0.057**	0.003
	(1.708)	(2.934)	(0.559)	(4.174)	(-2.963)	(0.097)
N	3667	3667	3667	3667	3667	3667
adj_R2	0.4000	0.4110	0.3265	0.3542	0.4200	0.4351

* p<0.05, ** p<0.01, *** p<0.001

Table 2.13: Predicting future earnings with extended list.

This table presents the results of OLS regressions, explaining earnings in the next quarter by past performance of the company and the market. The full model (column 4) looks as follows:

$$\begin{aligned}Earnings_{t+1} &= Const + \beta_1 Earnings_t + \beta_2 Earnings_{t-1} + \beta_3 Surprise\_decile_t + \\ &+ \beta_4 Market\_return_t + \beta_5 NRP_t \times SignDummy_P + \beta_6 NRP_t \times (1 - SignDummy_P) + \\ &+ \beta_7 NRA_t \times SignDummy_A + \beta_8 NRA_t \times (1 - SignDummy_A) + \beta_8 Consensus_{t,t+1} + \epsilon\end{aligned}$$

The stars denote the significance levels of less than 5% (*), 1% (**) and 0.1% (***). t-statistics are in parentheses.

	$Earnings_{t+1}$					
	1	2	3	4	5	6
$Earnings_t$	0.497***	0.478***			0.251***	0.199***
	(24.628)	(23.786)			(9.180)	(7.322)
$Earnings_{t-1}$	0.340***	0.344***			0.283***	0.282***
	(18.640)	(19.071)			(15.435)	(15.605)
$Surprise\_decile_t$	0.020***	0.015***			0.028***	0.023***
	(4.951)	(3.707)			(6.974)	(5.712)
$Market\_return_t$	0.767***	0.684***			0.735***	0.633***
	(6.218)	(5.584)			(6.086)	(5.311)
$NRP_t \times SignDummy_P$		-0.224***		-0.399***		-0.275***
		(-5.614)		(-9.888)		(-7.067)
$NRP_t \times (1 - SignDummy_P)$		-0.018		0.122		0.013
		(-0.218)		(1.424)		(0.157)
$NRA_t \times SignDummy_A$		-0.142***		-0.206***		-0.165***
		(-4.522)		(-6.401)		(-5.414)
$NRA_t \times (1 - SignDummy_A)$		0.094		0.135		0.076
		(1.204)		(1.682)		(0.994)
$Consensus_{t,t+1}$			0.906***	0.901***	0.433***	0.482***
			(43.394)	(44.279)	(13.099)	(14.707)
$Constant$	0.045*	0.129***	-0.009	0.127***	-0.063**	0.025
	(2.548)	(4.801)	(-0.452)	(4.597)	(-3.284)	(0.924)
N	3829	3829	3829	3829	3829	3829
adj_R2	0.3884	0.4015	0.3296	0.3658	0.4145	0.4335

* p<0.05, ** p<0.01, *** p<0.001

Table 2.14: NEGATIVITY RESIDUALS, UNCERTAINTY AND FORECAST ERRORS. $WAFE$ is the absolute forecast error winsorized at top 1% observations.
FE is the forecast error - scaled difference between theaverage of all forecasts outstanding 3 days after previous quarter earnings announcement and the actual earnings.
All errors are scaled by the stock price.
NRP and NRA are negativity residuals for presentations and answers, respectively.
$Revision\ frequency$ refers to the number of forecast revisions during the quarter, scaled by the number of analysts covering the firm in this quarter.
By the stars, we denote the significance levels of less than 5% (*), 1% (**) and 0.1% (***). t-statistics are in parentheses.

Panel A: Classification of most frequently used words

	WAFE		FE	
	1	2	3	4
$NRP_t \times SignDummy_P$	0.007***	0.007***	0.005***	0.005***
	(12.876)	(13.909)	(8.514)	(9.023)
$NRP_t \times (1 - SignDummy_P)$	0.005***	0.004**	0.000	0.000
	(3.523)	(2.886)	(0.141)	(0.305)
$NRA_t \times SignDummy_A$	0.005***	0.004***	0.006***	0.005***
	(5.942)	(6.005)	(6.390)	(6.889)
$NRA_t \times (1 - SignDummy_A)$	-0.001	-0.003	-0.003	-0.003
	(-0.580)	(-1.800)	(-1.434)	(-1.545)
$Market\ return_{t+1}$		-0.004**		-0.006***
		(-3.267)		(-3.896)
$Revision\ Frequency_{t+1}$		0.003***		0.003***
		(10.081)		(9.589)
$Constant$	0.004***	0.001**	0.000	-0.002***
	(12.996)	(3.002)	(0.364)	(-6.134)
N	3667	3260	3667	3260
adj_R2	0.0902	0.1585	0.0437	0.1060

Panel B: Extensive word classification - $FinList$

	WAFE		FE	
	1	2	3	4
$NRP_t \times SignDummy_P$	0.008***	0.007***	0.005***	0.005***
	(14.592)	(14.845)	(8.892)	(9.210)
$NRP_t \times (1 - SignDummy_P)$	0.002	0.001	0.000	0.000
	(1.532)	(0.854)	(0.229)	(0.104)
$NRA_t \times SignDummy_A$	0.003***	0.002***	0.002***	0.002***
	(6.086)	(6.345)	(4.553)	(4.676)
$NRA_t \times (1 - SignDummy_A)$	-0.000	0.000	-0.001	-0.000
	(-0.182)	(0.054)	(-0.922)	(-0.132)
$Market\ return_{t+1}$		-0.006***		-0.006***
		(-4.039)		(-3.750)
$Revision\ Frequency_{t+1}$		0.003***		0.004***
		(9.205)		(9.494)
$Constant$	0.004***	0.001**	0.000	-0.002***
	(11.753)	(2.608)	(0.757)	(-5.359)
N	3829	3395	3829	3395
adj_R2	0.1048	0.1649	0.0416	0.0961

* p<0.05, ** p<0.01, *** p<0.001

Table 2.15: MEAN FORECASTS ERRORS CLASSIFIED BY THE SIZE OF NEGATIVITY RESIDUALS.

This table summarizes the mean analyst errors for the different groups we form, based on the size of negativity residuals in the presentations. We create three equal-sized groups for positive and negative residuals - 6 groups overall.
The forecast error is:

$$FE_t = \frac{(Consensus\ forecast_{t-1,t} - Actual_t)}{Price_{t-1}}$$

where $Consensus\ forecast_{t-1,t}$ is an average of all analysts' forecasts for the quarter t outstanding on the third day after earnings announcement of quarter $t-1$; $Actual_t$ are earnings announced in quarter t. Absolute forecast error is:

$$AFE = |FE|$$

WAFE is a winsorized absolute forecast error with top 1% observations replaced.
Revision frequency refers to the number of forecast revisions during the quarter, scaled by the number of analysts covering the firm in this quarter.

$$Revision\ frequency = \frac{Number\ of\ revisions}{Number\ of\ analysts}$$

Panel A reports the results we get using the short positive/negative words list containing the most frequently used words only. Panel B reports the results, using the extensive word classification.

Panel A: Most frequently used words classification

	Negative residuals			Positive residuals		
	1	2	3	1	2	3
Residuals interval	[-0.49;-0.23)	[-0.23;-0.13)	[-0.13;-0]	[+0;0.11]	(0.11;0.36]	(0.36;6.77]
Mean FE	0.0010	0.0008	0.0005	0.0023	0.0042	0.0204
Mean AFE	0.0027	0.0041	0.0046	0.0049	0.0101	0.0276
Mean WAFE	0.0027	0.0033	0.0035	0.0046	0.0068	0.0111
Observations number	818	819	786	443	443	415
Mean of positive FE	0.0054	0.0073	0.0072	0.0084	0.0155	0.0472
Mean of negative FE	-0.0013	-0.0025	-0.0032	-0.0024	-0.0055	-0.0073
% of positive errors	34.35	33.70	35.88	43.12	46.05	50.84
Mean Revision Freq	0.38	0.42	0.42	0.48	0.59	0.62

Panel B: Extensive word classification

	1	2	3	1	2	3
Residuals interval	[-3.61;-0.29)	[-0.29;-0.16)	[-0.16;-0]	[+0;0.15]	(0.15;0.43]	(0.43;5.69]
Mean FE	0.0012	0.0003	0.0000	0.0017	0.0026	0.0330
Mean AFE	0.0037	0.0034	0.0042	0.0068	0.0070	0.0399
Mean WAFE	0.0030	0.0032	0.0036	0.0050	0.0062	0.0128
Observations number	842	837	813	482	458	445
Mean of positive FE	0.0071	0.0054	0.0059	0.0099	0.0111	0.0649
Mean of negative FE	-0.0018	-0.0023	-0.0033	-0.0044	-0.0039	-0.0078
% of positive errors	35.15	34.53	36.29	42.74	43.01	56.18
Mean Revision Freq	0.4112	0.3916	0.4240	0.4914	0.5378	0.6518

Table 2.16: Impact of approaching bankruptcy on the manager's tone.

This table presents the estimates of a regression explaining negativity in the presentations, or negativity residuals (NRP), by the firm's performance and its distance to the bankruptcy. $Distance_i$ is a dummy variable equal to 1 if the number of quarters before the bankruptcy is equal to i and 0 otherwise. The baseline cases are those starting more than 6 quarters before the bankruptcy. Sample includes observations both of bankrupt and non-bankrupt companies.
The stars denote the significance levels of less than 5% (*), 1% (**) and 0.1% (***). t-statistics are in parentheses.

	short classification			extensive classification		
	1	2	3	4	5	6
	Abn negativity	Negativity	NRP	Abn negativity	Negativity	NRP
Surprise_decile	-0.039***	-0.040***		-0.048***	-0.050***	
	(-13.836)	(-13.899)		(-16.023)	(-16.257)	
Market return	0.343***	0.291		0.359**	-0.119	
	(3.389)	(0.948)		(3.221)	(-0.369)	
Capital_gain	-0.008	-0.008		-0.012	-0.012	
	(-1.192)	(-1.249)		(-1.576)	(-1.577)	
$\Delta Earnings$	-0.104*	-0.099*		-0.073	-0.067	
	(-2.438)	(-2.318)		(-1.468)	(-1.345)	
Distance_1	0.808***	0.827***	1.036***	0.464**	0.486**	0.659***
	(5.615)	(5.731)	(5.938)	(2.949)	(3.080)	(3.912)
Distance_2	1.032***	1.039***	1.352***	0.814***	0.838***	1.141***
	(7.671)	(7.693)	(8.059)	(5.188)	(5.321)	(6.532)
Distance_3	1.167***	1.226***	1.621***	0.972***	1.020***	1.409***
	(8.394)	(8.783)	(9.281)	(6.005)	(6.274)	(7.743)
Distance_4	0.485***	0.482***	0.548**	0.253	0.252	0.322
	(3.375)	(3.342)	(3.269)	(1.456)	(1.442)	(1.770)
Distance_5	0.212	0.215	0.285	-0.041	-0.023	0.038
	(1.425)	(1.438)	(1.634)	(-0.244)	(-0.137)	(0.215)
Distance_6	0.194	0.181	0.294	-0.065	-0.072	0.035
	(1.301)	(1.210)	(1.611)	(-0.374)	(-0.410)	(0.185)
Time controls		X	X		X	X
Constant	-0.009	0.562***	0.092*	0.034***	0.826***	-0.019
	(-0.938)	(9.382)	(2.041)	(3.331)	(16.310)	(-0.356)
N	3496	3496	2339	4434	4434	4284
adj R^2	0.1092	0.1529	0.0977	0.0758	0.1020	0.0391

* p<0.05, ** p<0.01, *** p<0.001

Table 2.17: Predicting bankruptcy with logistic regressions.
The table compare the classification accuracy achieved with the logistic model based on accounting ratios only, and the model which includes textual analysis data. We report the percentage of correctly specified observations in two categories: bankrupts and non-bankrupts, as well as overall score. The other measure we compute to assess the quality of two models is a $pseudo - R^2$. The values in the table are the average results obtained in 10 random trials. The classification success depends on the sample selection, thus we have run the regressions on 10 different samples. The number of non-bankrupt companies in each sample is 3 times larger than the number of bankrupt firms.
Panel C shows the difference between values in Panel B and Panel A.

Classification accuracy (Cut Point=0.5)

Panel A: Accounting ratios model						
	6	5	4	3	2	1
Bankrupts	60%	59.7%	74%	76.3%	64.8%	78.1%
Non-bankrupts	94.7%	94.9%	95.6%	93.8%	95.9%	97.7%
Total	86.2%	86%	90.2%	89.5%	88.2%	92.7%
Pseudo R2	0.456	0.470	0.619	0.616	0.511	0.648
Panel B: Joint accounting ratios and speech analysis model						
	6	5	4	3	2	1
Bankrupts	70	72.4	86.8	87.6	76	81.7
Non-bankrupts	95.2	95.3	97.5	97	96.4	97.3
Total	88.9	89.6	94.8	94.7	91.3	93.1
Pseudo R2	0.559	0.582	0.740	0.782	0.598	0.714
Panel C: Differences between two models						
	6	5	4	3	2	1
Bankrupts	10	12.7	12.8	11.3	11.2	3.6
Non-bankrupts	0.5	0.4	1.9	3.2	0.5	-0.4
Total	2.7	3.6	4.6	5.2	3.1	0.4
Pseudo R2	0.103	0.112	0.121	0.166	0.087	0.066

Chapter 3

Signaling Attenuation Effect and Sell-side Analysts

This paper investigates how managers can benefit from timely and active coverage by sell-side analysts. Selling insiders' shares is deemed by the market as a bad signal, and it is in the interest of managers to diminish the negative impact this actions might have on shares' value. I find that companies with timely and intensive analyst coverage experience lower market reaction in response to insider sales. My findings are consistent with Kelly and Ljungqvist (2007) who find that analysts coverage improves market efficiency. By improving market efficiency or making investors believe in higher informational efficiency, sell-side analysts' coverage cushions the effect of negative signals. Managers, as if they were aware of this fact or as if they also believe in stronger efficiency caused by more active coverage, are more likely to sell their shares when their earnings announcements are actively followed by analysts.

3.1 Introduction

One of advantages of efficient markets for the managers is the absence of signaling constraint. In the real world, managers have to consider how the markets can react to their actions, when taking decisions on company financing or rebalancing their own portfolios. The necessity to avoid actions capable to seem to markets a bad signal, may lead to suboptimal decisions. Ross (1977) brought up signaling issues in capital structure decisions. Myers and Majluf (1984) builds a model showing that firms may pass up valuable investment opportunities, being constrained by signaling effect of equity issue. Fama and Jensen (1983) discusses how insider trading provides negative signal to the market.

I argue that if investors at some point of time believe in transparency of a particular company (deservedly or not), they would concentrate their signal-interpreting endeavor elsewhere and managers would benefit from greater flexibility in their decision. The problem of investors' limited attention is discussed by Hirshleifer, Lim, and Teoh (forthcoming), who find that investors' ability to interpret the news is limited and too many news lead to under-reaction. This explains why investors would neglect signals from companies they judge transparent and concentrate their efforts on more opaque firms.

I hypothesize that timely and active sell-side analysis makes investors less sensitive to the signals as it either improves market efficiency or makes the markets believe in greater efficiency. Despite the fact that reputation of sell-side analysts was harmed by numerous scandals in recent years and many papers have been written on the conflict of interest problems they face, investors still use their reports for financial decisions. Zhang (2008) finds that analysts play the role of information conductors: the immediate reaction of financial analysts to company earnings announcements increases the market reaction in the event window and decreases the post-earnings announcement drift. Kelly and Ljungqvist (2007) explore the links between analyst research, informational efficiency, and asset prices. They establish that exogenous reductions in analysts' coverage are followed by less efficient pricing and lower liquidity; greater earnings surprises and more volatile trading around subsequent earnings announcements; increases in required returns; and reduced return volatility. These findings confirm that analysts' coverage generally improves informational efficiency.

My empirical results support my hypothesis. I find that timely and intensive coverage of company's earnings announcements attenuate the market reaction to such negative signals as insider sales. Therefore, managers are less constrained by signaling issues if they arrange intensive sell-side coverage of the company. Insiders, as if they are aware of this phenomena, are more likely to sell their shares after earnings announcements with timely forecast revisions. The effect persists controlling for market reaction to earnings announcement and company size and is valid for earnings surprises with positive, as with negative surprises.

The paper is structured as follows: in the chapter 2 I discuss methods and data, chapter 3 presents the results and chapter 4 concludes.

3.2 Methods and data

The more efficient the market, the less investors need to pay attention to the behavior of managers and to search for potential signals. The active and timely coverage of financial analysts improves market efficiency and also gives to investors the feeling of greater informational transparency. These observations lead me to formulate the following hypothesis.

H1 - Signal attenuation hypothesis: When the coverage of the firm is timely and active, the market reaction to negative signals is weaker.

If managers share my belief expressed in H1, they would try to profit from active and timely analysts' following and undertake more frequently the negative-signal-actions when they get better coverage. Thus comes the second hypothesis:

H2. Managers flexibility hypothesis: Being less constraint by signaling problems, managers are more likely to undertake a "negative signal" action when company is effectively covered by analysts.

I test the hypotheses described above on the cases of most famous and frequent category of negative signals - insider trading. I use I/B/E/S for the data on earnings announcements and analysts forecasts, CRSP for prices and returns information, Thomsons Reuters for SEO and insider trading data. The sample covers 10 years from January 1998 to December 2008.

I exclude from analysis companies with stocks cheaper than a dollar, as well as companies which could not be uniquely identified in all three databases.

Under Rule 10b5-1, the SEC defines illegal insider trading as any securities transaction made when the person behind the trade is aware of nonpublic material information. Some companies pre-announce insider trades schedule to avoid both legal persecution and signaling problems. In this case the insider trade can happen on any day scheduled in advance, but this practice reduces managers' flexibility. Those managers who do not announce insider sale schedules are legally bound to sell during the period of time with minimal uncertainty in the market. As the law considers the quarterly earnings to be nonpublic material information, it moved most of unscheduled insider trades to the "safety zone" - days following earnings announcements (Bettis, Coles, and Lemmon (2000)).

In this paper I consider the insider sales taking place in two weeks following the earnings announcement.

The forecast revisions are mostly needed when there are important company news announced. That's why I proxy the quality of coverage by analysts' reaction to the earnings announcements.

The important parameter influencing both the analysts' reaction and the willingness of managers to sell their shares is the earnings surprise - the unexpected component of the earnings announced. To compute earnings surprise I use the method recommended by Kothari (2001), used in Dellavigna and Pollet (2009).

The earnings surprise for an announcement is the difference between actual earnings for the quarter recorded in I/B/E/S and the mean analyst forecast included in the I/B/E/S detail file during 30 days before the quarterly earnings announcement, scaled by the stock price 5 trading days before the announcement.

Let $e_{t,j}$ be the earnings announced for the company j at quarter t and $\hat{e}_{t,j}$ be the corresponding consensus forecast. Let denote by $P_{t,j}$ the price of shares of company j 5 trading days before the announcement in quarter t. The earnings surprise s_t, j is

$$s_{t,j} = \frac{e_{t,j} - \hat{e}_{t,j}}{P_{t,j}} \tag{3.1}$$

I arrange all earnings surprises into 11 groups. Group 0 corresponds to earnings surprise equal to 0. Groups 1 to 5 corresponds to quintiles of positive surprises. I assign groups -1 to -5 to quintiles of negative surprises. -5 corresponds to the largest in absolute value negative surprise.

Table 3.1 presents summary statistics.

[Table 3.1 insert here]

Tables 3.2 summarizes market reaction to insider sales by analysts responsiveness to the earnings announcements, and 3.3 provides reference on number of how the trade size relates to analysts responsiveness.

[Table 3.2 insert here]

[Table 3.3 insert here]

The average market reaction to insider sale grows with larger share sold. The larger is analysts reaction during a week after the earnings announcement, the weaker is the reaction of the market to insider sale. The intersection of the size of share sold and intensity of analysts' response provides mixed evidence.

3.3 Main results

To test my first hypothesis I estimate the following OLS model.

$$\begin{aligned} CAR_{ISijt} = \alpha + \beta_1 First\_day\_response_{it} + \beta_2 First\_week\_response_{it} + \beta_3 Share\_sold + \\ + \beta_4 First\_day\_response_{it} \times Share\_sold + \beta_5 First\_week\_response_{it} \times Share\_sold + \\ \beta_6 \times Cap\_decile_{it} + \beta_7 Total\_analysts_{i(t+1)} + \sum_{n=1}^{10} \gamma_n \times Surprise\ group_{it} \end{aligned} \tag{3.2}$$

where :
- CAR_{ISijt} is cumulative abnormal return for stock i in the window around the insider sale j after announcement of quarter t results expressed in percentages;
- $First\_day\_response$ is the number of analysts revising their forecasts for the firm i within two days from the announcement of quarter t earnings ([0;1] time interval);
- $First\_week\_response$ is the number of analysts revising their forecasts for the firm i in the first week after announcement of quarter t earnings, but not in the first two days ([2;5] interval);
- $Total\_analysts$ is the number of analysts covering the firm i in the quarter $t+1$;
- Cap_decile_{it} is a decile (computed for each year) of firm's i capitalization;
- $Share\_sold_{ijt}$ is the percantage of shares sold among the shares outstanding.

The coefficients of interest are those on the analysts' response variables: $First\_week\_response$ and $First\_day\_response$, and on interaction terms of analysts' reaction with percentage of shares sold. I include the percentage of shares sold $Share\_sold_{ijt}$ into regression to take into consideration the magnitude of insider sale happened. To control for the size and public interest to the company I use the number of analysts covering the firm and the decile of firm's capitalization. The necessity to introduce into regression the size of earnings surprise is dictated by possible post-earnings announcement drift, as I study the insider trades which happens after the earnings announcement. I include into the model dummies for earnings surprise group.

The estimation results are in Table 3.4

[Table 3.4 insert here]

The timeliness of analysts reaction to the earnings announcements is positively correlated with cumulative abnormal returns around the day when the insider trade takes place. This mean that analysts' activity attenuate the negative reaction to insider sale.

One standard deviation increase in the number of analysts reacting immediately on the earnings announcement results in decrease of market reaction by 0.53%. While one standard deviation increase in the number of analysts reacting in the following week after the earnings announcement results decreases market reaction by 0.43%.

Firms may vary in real or perceived transparency for reasons independent of analysts' coverage. Transparent firms associated with less reaction at the time of insider sales can also attract higher analyst activity. For example, it may be easier to provide more accurate forecasts on their earnings. In this case the effect documented in Table 3.4 might be driven simultaneously by firm's inherent transparency. To avoid this potential explanation I introduce into the model the firm fixed effects. The results are in the Table 3.5.

[Table 3.5 insert here]

The significance of analysts' coverage explaining market reaction holds when fixed effects are introduced.

To test *H2* whether managers are more prone to sell their stocks after earnings announcements with timely and active coverage, I estimate the following logit model.

$$\begin{aligned} P(Insider\ Sale_{it} = 1) = \Phi(c + \alpha_1 \times Response\ dummy_{it} + \alpha_2 \times First\_day\_response_{it} + \\ \alpha_3 \times First\_week\_response_{it} + \beta \times Cap\_decile_{it} + \gamma \times CAR_E\_decile_{it} \\ + \sum_{n=1}^{10} \delta_n \times Surprise\ group_{it} + \sum_{n=1}^{10} \mu_n \times Surprise\ group_{it} \times Response\ dummy_{it}) \end{aligned} \tag{3.3}$$

where :

- $Insider\ Sale_{it}$ is a dummy variable equal to 1 if insiders of firm i sell shares in two weeks after earnings announcement for quarter t;
- $Response\ dummy_{it}$ is a dummy variable equal to 1 if at least one financial analyst revises his forecast for the firm i in the window [0;1], where day 0 is the day of earnings announcement for quarter t;
- $First\_day\_response_{it}$ is a number of financial analysts who revise forecasts for the firm i in the window [0;1], where day 0 is the day of earnings announcement for quarter t;
- $First\_week\_response_{it}$ is a number of financial analysts who revise forecasts for the firm i in the window [2;7], where day 0 is the day of earnings announcement for quarter t;
- Cap_decile_{it} is a decile (computed for each year) of firm's i capitalization;
- CAR_decile_{it} is a decile of cumulative abnormal return for the stock i in the window [0;1] around earnings announcement for quarter t.

Table 3.6 presents the estimation results for four models.

[Table 3.6 insert here]

Table 3.7 shows the marginal effects for these four estimations.

[Table 3.7 insert here]

I find that analysts responsiveness to earnings announcement is positively correlated with the likelihood of insider sales. The effect of analysts' responsiveness depends on the news communicated on the earnings announcement. For the positive news coverage effects on likelihood to sell is stronger.

The marginal effects reveal that earnings announcement has a 5% higher likelihood to be followed by insider sell if analysts react to the earnings announcement immediately. Each additional analysts revising a forecast on a first day after earnings announcement add further 1%.

One possible concern is that the willingness of managers to sell is not dictated by the coverage per se, but by the market reaction to the earlier earnings announcement news, which is stronger when analysts intervene. I include CAR_{EA} decile as a control variable to dismiss this concern. The following graphs illustrates that the observed phenomena can not be fully explained by the effect of analysts' reaction on the price.

Figure 3.1 demonstrate the dependence of insider trades on earnings surprise and analysts' responsiveness. For reference I present 3.2 illustrating frequencies of insider purchases.

[Figure 3.1 insert here]

[Figure 3.2 insert here]

For negative surprises, timely reaction of the analysts coincides with or/and cause stronger price movement down. Thus, if the managers preferences to sell or not are determined by the price mostly, the managers should be less prone to sell after negatives surprise when earnings surprise is negative. Inversely, for positive surprises managers should sell more when analysts are active.

In fact, we see on the Figure 3.1 that the line depicting frequency of insider sales for timely covered companies is always above the line for non-timely covered companies. However, the gap between two lines shrinks on the zone of negative surprises, which is consistent with the logic of price influencing managers' decision.

On the Figure 3.2 we see that for insider purchases (which do not usually play any signaling roles) two lines intersects and behave consistently with the price-driven decision making.

3.4 Conclusion

I reflect on the commonly accepted idea that sell-side analysts improve market efficiency, and investigate the possible consequences of investors and managers believing in this argument. The more market is efficient, the less it makes sense to trade based on so-called signals - interpretations of managers' activities. I hypothesize that a manager gets greater flexibility in his actions when his company is timely and extensively covered by financial analysts. I use the sample of the most frequent negative signals - insider sales - to investigate how the magnitude of market reaction to the signal correlates with the quality of coverage. I find that the market reaction to insider sale is weaker when the firm's earnings announcement gets a more active and timely coverage. Insiders, aware of this phenomena or believing in greater market efficiency brought in by the analysts, are more likely to sell their shares after earnings announcements with timely forecast revisions. The effect persists controlling for market reaction to earnings announcements and company size and is valid for earnings surprises with positive, as with negative surprises.

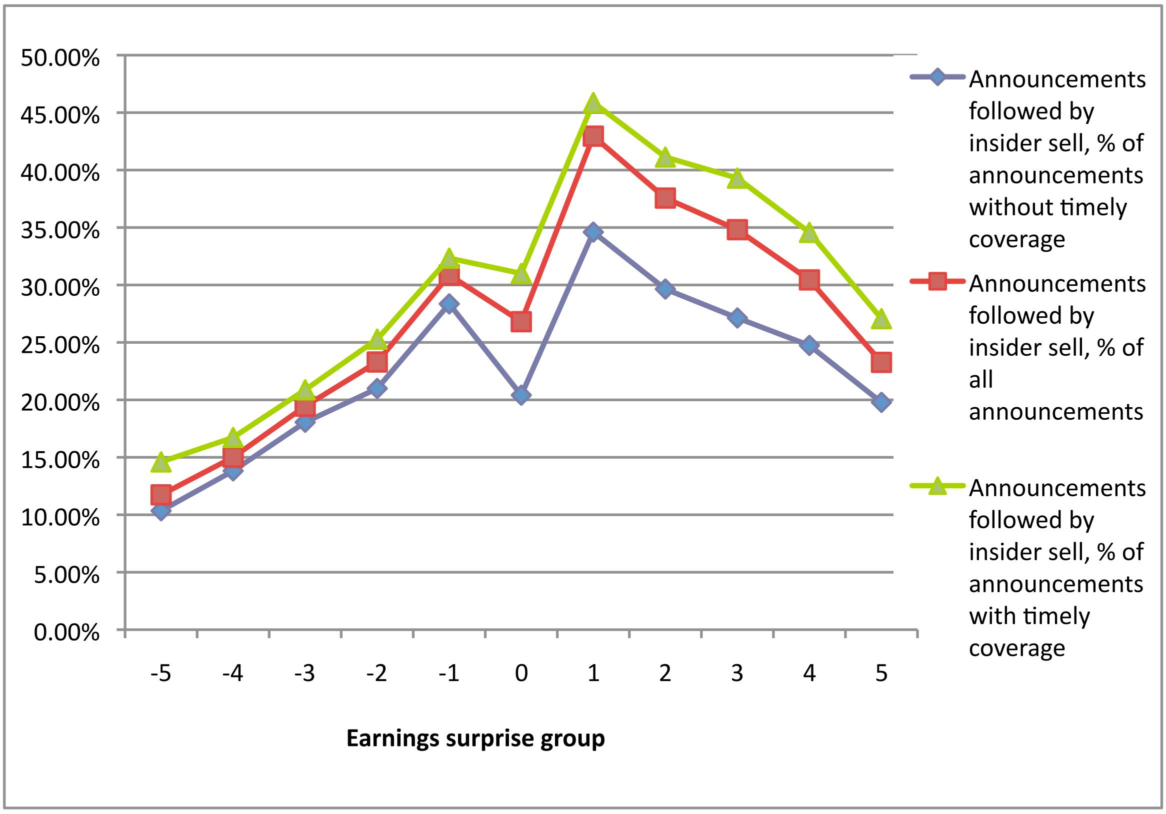

Figure 3.1: Insiders' sale after earnings announcement

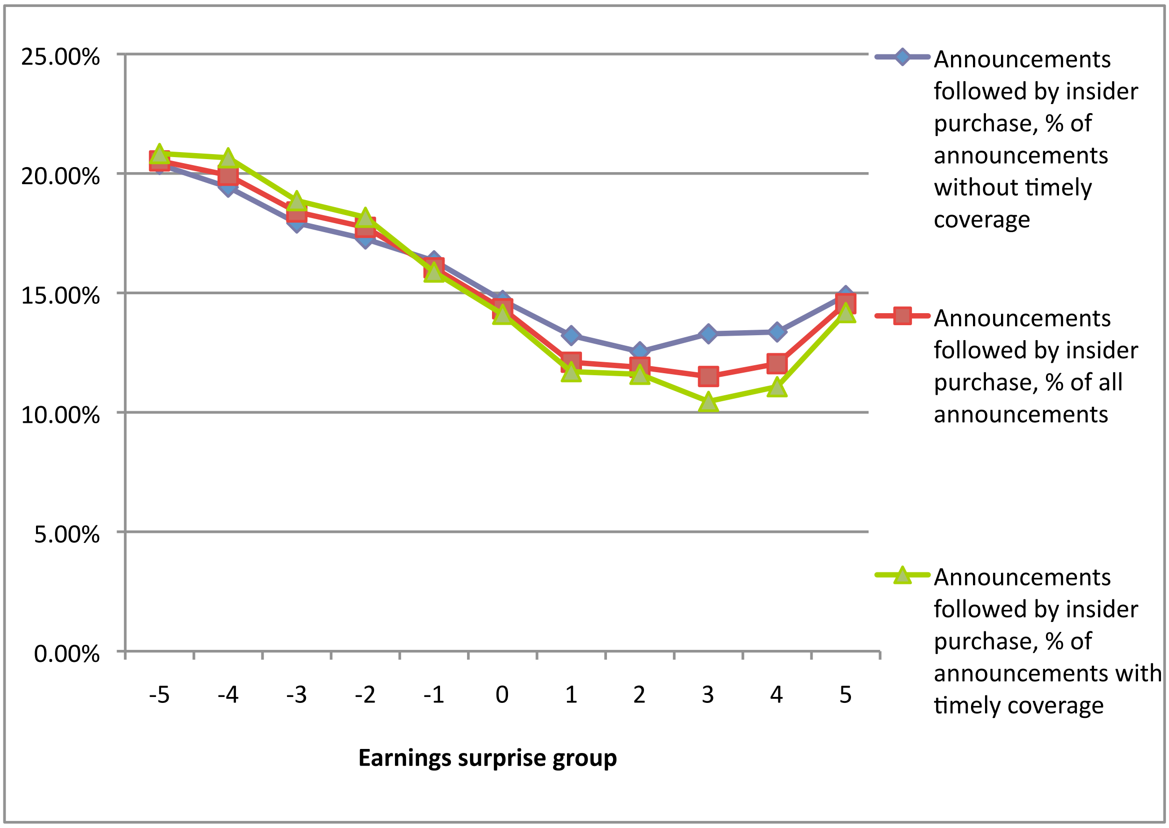

Figure 3.2: Insiders' purchase after earnings announcement

Table 3.1: INSIDER SALES AND ANALYSTS RESPONSIVENESS BY EARNINGS SURPRISE GROUPS

Panel A presents summary statistics for earnings announcements and insider trades in the two consecutive weeks.
Panel B provides information on number of earnings announcements followed by insider sale or insider purchase, classified by earnings surprise groups. The quantity of observations is expressed as percentage of the announcements with or without timely coverage. Group 0 corresponds to earnings surprise equal to 0. Groups 1 to 5 correspond to quintiles of positive surprises. Groups -1 to -5 correspond to quintiles of negative surprises. (-5 - largest in absolute value negative surprise; 5 - largest positive surprise)

Panel A

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
Earnings_surprise	-0.124	38.87	-14893.62	107.143	162835
First_day_response	2.952	4.108	0	37	162835
First_week_response	1.868	2.707	0	33	162835
Day_response_ratio	0.356	0.331	0	1	153337
Week_response_ratio	0.278	0.305	0	1	153337
Total_analysts	7.579	5.991	1	44	153337
Share_sold	40.31	37.27	0.00	100	73813
$CAR_{IS}[-1;5]$	-0.26	8.20	-113.26	308.58	73726

Panel B

Earnings surprise group	All announcements	Announcements with forecast revision in [0;1]	Announcements followed by IS, % of announcements without timely coverage	Announcements followed by IS, % of all announcements	Announcements followed by IS, % of announcements with timely coverage	Announcements followed by IP, % of announcements without timely coverage	Announcements followed by IP, % of all announcements	Announcements followed by IP, % of announcements with timely coverage
-5	4,628	1,507	10.35%	11.73%	14.60%	20.38%	20.53%	20.84%
-4	4,632	1,883	13.82%	15.00%	16.73%	19.43%	19.93%	20.66%
-3	4,633	2,290	18.05%	19.45%	20.87%	17.93%	18.39%	18.86%
-2	4,632	2,488	20.99%	23.29%	25.28%	17.26%	17.75%	18.17%
-1	4,636	2,929	28.35%	30.87%	32.33%	16.34%	16.05%	15.88%
0	8,902	5,374	20.41%	26.80%	31.00%	14.68%	14.33%	14.10%
1	12,673	9,381	34.60%	42.95%	45.88%	13.21%	12.10%	11.70%
2	12,678	8,738	29.64%	37.56%	41.13%	12.54%	11.89%	11.59%
3	12,677	8,003	27.13%	34.81%	39.30%	13.29%	11.50%	10.46%
4	12,678	7,350	24.74%	30.44%	34.57%	13.36%	12.04%	11.07%
5	12,681	6,059	19.78%	23.26%	27.07%	14.89%	14.55%	14.18%

Table 3.2: Summary of market reaction to insider sales by analysts responsiveness to the earnings announcements
This tables presents summary statistics for the market reaction to insider trades following after earnings announcements. Panel A classifies the insider trades by analysts' reaction during a day after the earnings announcement.
Panel B classifies the insider trades by analysts' reaction during a week after the earnings announcement, but after the first day.
Panel C classifies the insider trades by total analysts' reaction during a week after the earnings announcement.
$First\_day\_response$ is the number of analysts revising their forecasts on earnings announcement day or on the next day;
$First\_week\_response$ is the number of analysts revising their forecasts in the first week after earnings announcement, but not on the earnings announcement day or the next day;
$Total\_response$ is the number of analysts revising their forecasts in the first week after earnings announcement,
$CAR_{IS}[-1;5]$ is cumulative abnormal return in the [-1;5] window where day 0 is the day of the insider sale.

Panel A: summary for $CAR_{IS}[-1;5]$ by response to EA in [-1;1] window					
$First\_day\_response$	0	1	[2;3]	[4;7]	[8;37]
Mean	-0.0029	-0.0038	-0.0041	-0.0027	0.0004
Median	-0.0023	-0.0032	-0.0024	-0.0014	0.0012
Standard deviation	0.0874	0.0934	0.0831	0.0755	0.0687
Min	-1.1326	-0.9844	-0.7243	-1.0965	-0.6982
Max	0.9538	3.0858	0.7071	0.7841	0.6733
Number of observations	22063	9680	13651	15243	13089
Panel B: summary for $CAR_{IS}[-1;5]$ by response to EA in [2;5] window					
$First\_week\_response$	0	1	2	3	[4;33]
Mean	-0.0046	-0.0022	-0.0020	-0.0022	-0.0002
Median	-0.0033	-0.0015	-0.0001	-0.0016	0.0005
Standard deviation	0.0875	0.0797	0.0799	0.0805	0.0764
Min	-0.9854	-1.1326	-1.0965	-0.7558	-0.9843
Max	3.0858	0.7841	0.5694	0.9538	0.6733
Number of observations	25327	17869	10537	6276	13717
Panel C: summary for $CAR_{IS}[-1;5]$ by total response to EA					
$Total\_response$	[0;1]	[2;3]	[4;6]	[7;10]	[11;41]
Mean	-0.0051	-0.0046	-0.0017	-0.0023	0.0013
Median	-0.0043	-0.0033	-0.0009	-0.0011	0.0022
Standard deviation	0.0972	0.0858	0.0771	0.0750	0.0698
Min	-1.1326	-0.8360	-0.9274	-1.0965	-0.5303
Max	3.0858	0.9538	0.7841	0.5982	0.6733
Number of observations	15446	15021	17111	13631	12517

Table 3.3: INSIDER SALES SIZE AND ANALYSTS RESPONSIVENESS TO THE EARNINGS ANNOUNCEMENTS

This table presents the summary on market reaction, classified by the size of transaction (percentage over total capitalization) and analysts' reaction during a week after the earnings announcement. Each cell contains average cumulative abnormal return for the corresponding quintile of analysts' reaction and quintile of share sold.

$CAR_{IS}[-1;5]$ is cumulative abnormal return (expressed in percentage) in the [-1;5] window where day 0 is the day of the insider sale.

$CAR_{IS}[-1;5]$

Quintile of share sold	1	2	3	4	5	
Total response quintile						**Total**
1	-0.303	-0.470	-0.485	-0.741	-0.468	**-0.514**
2	-0.309	-0.092	-0.474	-0.082	-1.055	**-0.440**
3	-0.275	-0.190	-0.124	-0.081	-0.600	**-0.258**
4	-0.217	-0.152	-0.103	-0.354	-0.946	**-0.334**
5	0.242	0.271	0.274	-0.272	-0.548	**0.087**
Total	**-0.064**	**-0.098**	**-0.146**	**-0.322**	**-0.671**	

Table 3.4: Market reaction to insiders' sales following the earnings announcement
This table presents the results of OLS regressions. The dependent variable is CAR_{IS}, cumulative abnormal return in the event window around insider sale.

$$CAR_{ISijt} = \alpha + \beta_1 First\_day\_response_{it} + \beta_2 First\_week\_response_{it} + \beta_3 Total\_analysts_{i(t+1)} + \beta_4 \times Cap\_decile_{it} + \beta_5 Share\_sold + \sum_{n=1}^{10} \gamma_n \times Surprise\ group_{it}$$

$First\_day\_response$ is the number of analysts revising their forecasts on earnings announcement day or on the next day; $First\_week\_response$ is the number of analysts revising their forecasts in the first week after earnings announcement, but not on the earnings announcement day or the next day; $Total\_analysts$ is the number of analysts covering the firm in the quarter $t+1$; Cap_decile is the capitalization decile (computed on annual basis); $Share\_sold$ is the percentage of shares sold among shares outstanding.
CAR_{IS} and $Share\_sold$ are expressed in percentages.
To control for post-earnings announcement drift, I include into the model dummies for earnings surprise group.
By the stars I denote the significance levels of less than 5%, 1% and 0.1%.

	CAR_{IS}[-1;1]	CAR_{IS}[2;5]	CAR_{IS}[-1;5]
$First\_day\_response$	0.056***	0.072***	0.129***
$First\_week\_response$	0.066***	0.092***	0.158***
$Share\_sold$	-0.001*	-0.004***	-0.005***
$First\_day\_response \times Share\_sold$	-0.000	-0.000	-0.000
$First\_week\_response \times Share\_sold$	-0.000	-0.000	-0.000
$Total\_analysts$	-0.028**	-0.052***	-0.080***
Cap_decile	-0.005	-0.004	-0.009
group 1	-0.096	-0.271**	-0.367**
group 2	-0.000	-0.180*	-0.180
group 3	0.354***	-0.132	0.222
group 4	0.608***	0.147	0.755***
group 5	0.796***	0.224*	1.020***
group(-1)	-0.218	0.117	-0.101
group(-2)	-0.306*	-0.272*	-0.577**
group(-3)	-0.367*	0.200	-0.167
group(-4)	-0.242	0.045	-0.197
group(-5)	-1.956***	-0.102	-2.057***
Constant	0.046	-0.202	-0.157
N	70947	70946	70946
Adj. R2	0.006	0.003	0.007

Table 3.5: MARKET REACTION TO INSIDERS' SALES FOLLOWING THE EARNINGS ANNOUNCEMENT: FIXED-EFFECT MODELS.
This table presents the results of the same OLS regressions as Table 3.4, but controlling for firm fixed effects.
The dependent variable is CAR_{IS}, cumulative abnormal return in the event window around insider sale.
CAR_{IS} and $Share\_sold$ are expressed in percentages.
Stars denote the significance levels of less than 5%, 1% and 0.1%.

	CAR_{IS}[-1;1]	CAR_{IS}[2;5]	CAR_{IS}[-1;5]
$First\_day\_response$	0.060***	0.065***	0.125***
$First\_week\_response$	0.067***	0.080***	0.147***
$Share\_sold$	0.003**	-0.003***	-0.000
$First\_day\_response \times Share\_sold$	-0.020	0.007	-0.012
$First\_week\_response \times Share\_sold$	-0.052*	-0.005	-0.057
$Total\_analysts$	-0.024*	-0.028**	-0.052***
Cap_decile	-0.008	-0.078***	-0.086***
group 1	-0.059	-0.343***	-0.403**
group 2	0.142	-0.163	-0.021
group 3	0.475***	-0.130	0.345*
group 4	1.026***	0.230*	1.255***
group 5	1.381***	0.624***	2.005***
group (-1)	-0.123	0.024	-0.099
group (-2)	-0.059	-0.260	-0.320
group (-3)	-0.106	0.238	0.132
group (-4)	0.080	-0.019	0.061
group (-5)	-0.574*	0.061	-0.513
Constant	-0.371*	0.022	-0.349
Firm fixed effects	***	***	***
N	70946	70946	70946
Overall R2	0.0043	0.0018	0.0048

Table 3.6: LIKELIHOOD OF INSIDERS' SALE AFTER AN EARNINGS ANNOUNCEMENT
This table presents the results of logit regressions. The dependent variable is *Insider Sale*, a dummy variables equal 1 if an insider sale happens in two weeks following an earnings announcement, 0 otherwise.

$$P(Insider\ Sale_{it} = 1) = \Phi(c + \alpha_1 \times Response\ dummy_{it} + \alpha_2 \times First\_day\_response_{it} + \alpha_3 \times First\_week\_response_{it} + \beta \times Cap\_decile_{it} + \gamma \times CAR_E\_decile_{it} + \sum_{n=1}^{10} \delta_n \times Surprise\ group_{it} + \sum_{n=1}^{10} \mu_n \times Surprise\ group_{it} \times Response\ dummy_{it})$$

Response dummy is equal to one if at least one analyst revises his forecast on earnings announcement day or on next day; *First_day_response* is the number of analysts who revise forecast on earnings announcement day or on next day; *First_week_response* is the number of analysts who revise forecast on earnings announcement during a week after announcement, but later than a next day; *Cap_decile* is a decile (computed for each year) of firm's capitalization; CAR_{EA}*_decile* is a decile of cumulative abnormal return in the window [0;1] around earnings announcement; *Surprise group* takes value from -5 to -1 for negative surprises and 1 to 5 for positive surprises. By the stars I denote the significance levels of less than 5%, 1% and 0.1%.

CAR_{EA}_decile	0.079***	0.078***	0.078***	0.079***
Cap_decile	0.091***	0.079***	0.079***	0.049***
group 1	0.580***	0.559***	0.606***	0.624***
group 2	0.395***	0.378***	0.401***	0.407***
group 3	0.314***	0.308***	0.328***	0.319***
group 4	0.144***	0.147***	0.190***	0.177***
group 5	-0.173***	-0.149***	-0.066	-0.082
group (-1)	0.159***	0.163***	0.353***	0.359***
group (-2)	-0.137**	-0.116**	0.034	0.029
group (-3)	-0.320***	-0.292***	-0.106	-0.111
group (-4)	-0.571***	-0.522***	-0.387***	-0.403***
group (-5)	-0.794***	-0.730***	-0.660***	-0.682***
$Response\_dummy$		0.320***	0.420***	0.246***
$First\_day\_response$				0.053***
$First\_week\_response$				0.038***
$group1 \times Response\ dummy$			-0.074	-0.119
$group2 \times Response\ dummy$			-0.040	-0.080
$group3 \times Response\ dummy$			-0.030	-0.052
$group4 \times Response\ dummy$			-0.063	-0.069
$group5 \times Response\ dummy$			-0.131	-0.114
$group(-1) \times Response\ dummy$			-0.285***	-0.309***
$group(-2) \times Response\ dummy$			-0.243**	-0.240**
$group(-3) \times Response\ dummy$			-0.321***	-0.296**
$group(-4) \times Response\ dummy$			-0.252*	-0.218*
$group(-5) \times Response\ dummy$			-0.114	-0.076
Constant	-1.974***	-2.098***	-2.158***	-2.083***
N	93418	93418	93418	93418
Pseudo R2	0.0475	0.0510	0.0513	0.0570

Table 3.7: LIKELIHOOD OF INSIDERS' SALE AFTER AN EARNINGS ANNOUNCEMENT: MARGINAL EFFECTS

This table presents the marginal effects for the estimations from Table 3.6.

dy/dx

	model 1	model2	model 3	model 4
CAR_{EA}_decile	0.0162	0.0160	0.0159	0.0162
Cap_decile	0.0187	0.0162	0.0161	0.0100
group 1*	0.1284	0.1232	0.1344	0.1386
group 2*	0.0855	0.0816	0.0869	0.0882
group 3*	0.0675	0.0659	0.0704	0.0684
group 4*	0.0301	0.0307	0.0400	0.0372
group 5*	-0.0345	-0.0299	-0.0134	-0.0166
group (-1)*	0.0335	0.0344	0.0768	0.0781
group (-2)*	–0.0273	-0.0231	0.0071	0.0061
group (-3)*	-0.0614	-0.0563	-0.0212	-0.0223
group (-4)*	-0.1035	-0.0956	-0.0731	-0.0758
group (-5)*	-0.1364	-0.1271	-0.1168	-0.1200
$Response\_dummy$*		0.0647	0.0843	0.0497
$First\_day\_response$				0.0108
$First\_week\_response$				0.0078
$group1 \times Response\ dummy$*			-0.0150	-0.0238
$group2 \times Response\ dummy$*			-0.0080	-0.0162
$group3 \times Response\ dummy$*			-0.0062	-0.0106
$group4 \times Response\ dummy$*			-0.0127	-0.0140
$group5 \times Response\ dummy$*			-0.0262	-0.0227
$group(-1) \times Response\ dummy$*			-0.0549	-0.0592
$group(-2) \times Response\ dummy$*			-0.0472	-0.0466
$group(-3) \times Response\ dummy$*			-0.0613	-0.0568
$group(-4) \times Response\ dummy$*			-0.0488	-0.0426
$group(-5) \times Response\ dummy$*			-0.0227	-0.0153

(*) dy/dx is for discrete change of dummy variable from 0 to 1

Bibliography

Altman, Edward I., 1968, Financial ratios, discriminant analysis and the prediction of corporate bankruptcy, *The Journal of Finance* 23, 589–609.

Angwin, J., and M. Peers, 2001, Cold calls: AOL may be snubbing Merill, *The Wall Street Journal*.

Bagnoli, M., S. Levine, and S.G. Watts, 2002, Analyst estimate revision clusters and corporate events, *Annals of Finance 1* Part 1.

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

Beaver, William, 1962, Market prices, financial ratios, and the prediction of failure, *Journal of Accounting Research* 6, 179–192.

——— , 1966, Financial ratios as predictors of failure, empirical research in accounting selected studies, *Supplement to Journal of Accounting Research* pp. 71–127.

Bettis, J. Carr, Jeffrey L. Coles, and Michael L. Lemmon, 2000, Corporate policies restricting trading by insiders, *Journal of Financial Economics* 57, 191–220.

Bowen, L., A. Devis, and D. Matsumoto, 2002, Do conference calls affect analysts forecasts?, *The Accounting Review* 77, 285–316.

Brown, Lawrence, and Marcus Caylor, 2005, A temporal analysis of thresholds: Propensities and valuation consequences, *The Accounting Review* 80, 423–440.

Chen, S., and D. Matsumoto, 2006, Favorable versus unfavorable recommendations: The impact on analyst access to management-provided information, *Journal of Accounting Research* 44, 657–689.

Clement, M.B., 1999, Analyst forecast accuracy: Do ability, resources and portfolio complexity matter, *Journal of Accounting and Economics* pp. 285–303.

——— , and S.Y. Tse, 2005, Financial analyst characteristics and herding behavior in forecasting, *The Journal of Finance* LX, 307–341.

Davis, Piger, and Sedor, 2008, Beyond the numbers: Managers' use of optimistic and pessimistic tone in earnings press releases, AAA 2008 Financial Accounting and Reporting Section (FARS) Paper.

Degeorge, Francois, Jayendu Patel, and Richard Zeckhauser, 1999, Earnings management to exceed thresholds, *Journal of Business* 72, 1–33.

Dellavigna, Stefano, and Joshua M. Pollet, 2009, Investor inattention and friday earnings announcements, *Journal of Finance* LXIV, 709–749.

Demers, Elizabeth, and Clara Vega, 2008, Soft information in earnings announcements: News or noise?, INSEAD.

Elstrom, Peter, 2001, On the firing line at Qwest, *Business Week* p. p.72.

Engelberg, Joseph, 2009, Costly information processing: Evidence from earnings announcements, Northwestern University.

Fama, and Jensen, 1983, Agency problems and residual claims, *Journal of Law and Economics* 26, 327–349.

Fehr, E., and S. Gachter, 2000, Fairness and retaliation: The economics of reciprocity, *The Journal of Economic Prospectives* 14, 159–181.

Francis, J., and D. Philbrick, 1993a, Analysts' decisions as products of a multi-task environment., *Journal of Accounting Research* pp. 216–230.

Francis, Jennifer, and Donna Philbrick, 1993b, Analysts' decisions as products of a multi-task environment, *Journal of Accounting Research* 31, 216–230.

Harway, I. Norman, and Howard P. Iker, 1969, A computer approach towards the analysis of content, *Behavioral science* 10, 173–182.

Hilary, Gilles, and John Shon, 2007, Sell recommendations, market sentiment, and analyst credibility, *working paper*.

Hirshleifer, Lim, and Teoh, forthcoming, Driven to distraction: Extraneous events and underreaction to earnings news, *Journal of Finance*.

Hong, Harrison, and Jefrey D. Kubik, 2003a, Analyzing the analysts: Career concerns and biased earnings forecasts, *The Journal of Finance* LVIII, 313–351.

Hong, Harrison, and Jeffrey D. Kubik, 2003b, Analyzing the analysts: Career concerns and biased earnings forecasts, *The Journal of Finance* 58, 313–352.

Kasznik, Ron, and Maureen F. McNichols, 2002, Does meeting earnings expectations matter? evidence from analyst forecast revisions and share prices., *Journal of Accounting Research* 40, 727–759.

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.

Kelly, Bryan T., and Alexander Ljungqvist, 2007, The value of research, EFA 2008 Athens Meetings Paper.

Kelly, K., 2003, One analyst learns Candor doesn't pay, *The Wall Street Journal.*

Kothari, 2001, Capital markets research in accounting, *Journal of Accounting and Economics* 31, 105–231.

Lang, M., and R. Lundholm, 1996, Corporate disclosure policy and analyst behaviour, *The Accounting Review* 74, 467–492.

Li, Feng, 2006, Do stock market investors understand the risk sentiment of corporate annual reports?, previously titled "The implications of annual report's risk sentiment for future earnings and stock returns".

Ljungqvist, A., C. Malloy, and F. Marston, 2008, Rewriting history, NYU, Virginia, and Harvard working paper.

Loughran, Tim, and Bill McDonald, forthcoming, When is a liability not a liability? textual analysis, dictionaries, and 10-ks, *Journal of Finance.*

Matsumoto, Dawn A., 2002, Management's incentives to avoid negative earnings surprises, *The Accounting Review* 77, 483–515.

Mayew, William J., and Mohan Venkatachalam, 2009, The power of voice: Managerial affective states and future firm performance, Duke University.

Michaely, R., and K. L. Womack, 1999, Conflict of interest and the credibility of underwriter analyst recommendations, *The Review of Financial Studies* 12, 653–686.

Mikhail, M., B. Walther, and R.Willis, 2004, Do security analysts exhibit persistent differences in stock picking ability?, *Journal of Financial Economics* pp. 67–91.

Myers, and Majluf, 1984, Corporate financing and investment decisions when firms have information that investors do not have, *Journal of Financial Economics* pp. 187–221.

Ober, Scot, Jensen J. Zhao, Rod Davis, and Melody W. Alexander, 1999, Telling it like it is: The use of certainty in public business discourse, *Journal of business communication* 36, 280–300.

Reingold, Dan, 2007, *Confessions of a Wall Street analyst* (Collins).

Ross, Stephen, 1977, The determination of financial structure: the incentive- signalling approach, *Bell Journal of Economics* pp. 23–39.

Schauer, Frederick, and Richard Zeckhauser, 2009, Paltering, in *Deception: From Ancient Empires to Internet Dating* . pp. 38–54 (Brooke Harrington, Stanford University Press).

Siconolfi, M., 1995, Incredible 'Buys': Many companies press analysts to steer clear of negative ratings - stock research is taynted as naysayers are banned, undermined and berated - small investors in the dark, *The Wall Street Journal*.

Solomon, D., and R. Frank, 2003, You don't like our stock? you are off the list - SEC sets new front on conflicts by taking aim at companies that retaliate against analysts., *The Wall Street Journal*.

Tennyson, Mack B., Robert W. Ingram, and Michael T. Dugan, 1990, Assessing the information content of narrative disclosures in explaining bankruptcy, *Journal of Business Finance and Accounting* 17, 391–410.

Tetlock, Paul, 2007, Giving content to investor sentiment: The role of media in the stock market, *The Journal of Finance* 62, 1139–1168.

Tetlock, Paul C., Maytal Saar-Tsechansky, and Sofus Macskassy, 2008, More than words: Quantifying language to measure firms' fundamentals, *Journal of Finance* 63, 1437–1467 9th Annual Texas Finance Festival.

Womack, K.L., 1996, Do brokerage analysts' recommendations have investment value?, *Journal of Finance* pp. 137–167.

Zhang, Yuan, 2008, Analyst responsiveness and the post-earnings-announcement drift, *Journal of Accounting and Economics* 46, 201–215.