The Blame Game

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Abstract

I propose a textual analysis-based measure to detect when corporate executives blame bad performance on external factors such as industry or the economy (BLAME measure). Using this methodology to analyze quarterly earnings announcement conference call transcripts, I find that: (1) executives are more likely to blame these external factors when their companies experience bad performance, but are unwilling to credit the external factors when they perform well; (2) a high BLAME measure predicts low returns subsequent to the conference call date after controlling for the tone of the transcripts and other known predictive variables. The hedged portfolio that takes long positions in companies with low BLAME measure and short positions in companies with high BLAME measure generates abnormal returns up to 6.8% per year; (3) the BLAME measure negatively predicts earnings surprises and analyst recommendation revisions in the subsequent quarter, indicating underreaction to firm-specific negative information; (4) a high BLAME measure reduces executive turnover-performance, implying that blaming external factors reduces the punishment on executives who underperformed. Overall, the evidence suggests that investors underreact to negative information when managers attribute negative performance to external factors.

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1 Introduction

This paper studies how self-serving attribution behaviors of corporate executives affect shareholders. In neoclassical economics, corporate executives are often modeled as corporate value maximizers. However, empirical literature shows that agency problems and behavioral characteristics could lead to diverging choices of corporate strategies (Bertrand and Schoar, 2011). One important behavioral characteristics that has been documented repeatedly in the psychology literature is the self-serving attribution bias, meaning that people tend to attribute success to internal factors and to blame failure on external factors (e.g., Tetlock and Levi (1982)). In this study, I analyze these self-serving attribution behaviors of corporate executives using an innovative textual analysis technique. I find that these behaviors lead to delayed responses to negative information.

There are several reasons to believe that these executive self-serving attribution behaviors may be value relevant for investors. First, the self-serving attribution behavior is believed to be a manifestation of self-presentation concern (Baumeister, 1982). People with self-presentation concerns tend to present a glossier image of their performance than the reality, which may mislead investors about the real value of the firm. In addition, psychology research indicates that self-serving attribution behaviors can be associated with impression management (e.g., Bradley (1978), Miller (1978)). For example, executives may direct the focus from potentially persistent problem within the company to relatively transient shocks to economy or industry. These behaviors may maintain confidence of shareholders towards the ability and plans of the management and lead to underreaction to negative information.

Second, research in psychology and management has indicated that biases in attribution may indicate negative managerial ability. This research predicts that attribution biases are likely to create impediments for problem solving at the firm. For example, past research shows that self-serving attribution bias may lead to failed course of action (Staw and Ross, 1978), because the decision maker is unable to correctly identify the causes of problems.

In addition, psychologists also find that attribution biases decrease people's effectiveness in decision making (Janis, 1989, Janis and Mann, 1977). Finally, it is also shown that stake holders tend to commit less resources to executives when they are perceived to be attributing failures (Schwenk, 1990). Overall, existing literature suggests that self-serving attribution behaviors should relate to worse financial performance in the upcoming months.

As a result, if investors do not pay attention to the signs of self-serving attribution behaviors (e.g., Hirshleifer et al. (2009), Dellavigna and Pollet (2009)), stock returns are likely to experience sustained underperformance after executives' self-serving attribution behaviors.

An additional effect of attributing negative performance externally is that it may sway shareholders' and board members' decision to retain or replace the executives. Executives who tend to play the blame game in conference calls can also use similar excuses to appease the board members. Previous literature shows that executives are punished less when the bad performance is a result of external factors (e.g., Gibbons and Murphy (1990), Jenter and Kanaan (2006)). If the board members are convinced by their excuses, the executives are more likely to be allowed to stay and their salaries are less likely to be reduced following their bad performance than those who do not play the blame game. Thus, attribution behaviors may affect the turnover performance sensitivity.

Although executives' self-serving attribution behaviors are important for shareholders, there is limited existing research in this field. One reason for the lack of research is the difficulty in identifying these attribution behaviors. Existing literature largely avoids direct identification of these self-serving attribution behaviors in a large sample setting. In this paper, I infer attribution behaviors directly using transcripts from conference calls. Direct evidence can be established on how attribution bias affects corporate values.

Executives blaming negative impacts that are beyond their control is a sign of their attribution bias. In the corporate world, firms' fortunes are often tied to factors that cannot be managed by the executives. For example, the macroeconomic and industry fluctuations can impact results of individual firms. Few firms can avoid these negative shocks. As a result, macroeconomic performance and the factors related to the industry performance can be obvious scapegoats for corporate performances. For example, a company is experiencing headwinds in its operating results. The executives of the company have a choice of how to explain their performances. They can choose to discuss their companies' results in detail or they can simply attribute the bad performance to reasons such as luck. Whereas the impact of economic and industrial trends inevitably swing corporate performances up and down, these discussions are unlikely to be helpful for investors, since these factors impact all firms in the market or in the sector. Therefore, these discussions are likely to be signs of biases in attribution.

I use a sentence-based textual analysis to identify the sentences used to blame economy and industries in earnings conference calls. I first look for key words about industry and economy in the sentences of conference calls. Then, I count the number of positive and negative words in the same sentence. If there are more negative words than positive words in that sentence, it is considered as a sentence with a negative description of industry or the economy (or BLAME sentence). The overall tendency to attribute bad performance to external factors is measured by the percentage of BLAME sentences in the conference call (I will refer to this measure as BLAME measure hereafter). The BLAME measure is significantly negatively correlated with performance measures, such as returns and SUE, indicating that better performance reduces the need to attribute negative performances. However, in the placebo test, I do not find companies' past performance significantly correlates with the fraction of sentences with positive description about industry or the economy, consistent with the idea that blaming external factors is an impression management tactic of corporate executives. Consistent with investors underreacting to firm-specific negative news, I document that companies with high BLAME measures subsequently underperform those with low BLAME measures by up to 7% annually after risk-adjustment. Analyst recommendations in the quarter following the conference call support the hypothesis of underreaction in stock prices to BLAME measure.

In addition to returns, I also find that the BLAME measure changes CEO employment outcome. I show that blaming external factors reduces the sensitivity of executive turnover. These results indicate that blaming the industry and economy may shift the focus of board members away from the missteps of corporate executives and towards the factors beyond managers' controls. Thus, these managers are less likely to be punished through turnover.

This paper makes contributions on several fronts. First, this study documents a new executive behavioral bias and shows that this behavioral bias impacts the wealth of shareholders with a significant economic magnitude. Past research has documented a number of behavioral biases among corporate executives. The most prominent biases among them are overconfidence, optimism and hubris. These behavioral biases influence corporate operating and financial strategies significantly (Roll, 1986, Malmendier and Tate, 2005, 2008).[1] While self-serving attribution bias is closely related to overconfidence, this paper shows that it affects shareholder wealth in a very distinct way. A number of existing papers examine how managers' attribution bias or attribution behaviors affect their investment decisions and reporting behaviors. For example, Billett and Qian (2008) and Doukas and Petmezas (2007) investigate how self-attribution bias affects merger and acquisition decisions. Both papers argue that managers' overconfidence manifested in merger and acquisition activities is driven by self-attribution bias. Similar to this paper, Li (2010b) use a textual analysis method to extract terms for self-references such as "I" and "we" as a proxy for self-serving attribution. The paper finds self-attribution bias is positively related to firms' investment behaviors. In addition, Baginski et al. (2004) examine the attribution behavior of 900 earnings forecasts statements by manual classifications. There are several key difference between this paper and the aforementioned study. The Baginski et al. (2004) focus on the explanations of earnings forecasts, which is largely forward-looking. This paper explores earnings

[1] Other influential studies in corporate finance include Roll (1986), which associates value destruction in M&A with hubris, Baker et al. (2012) which document that reference prices affect the offer price for target company in mergers and acquisitions, Heaton (2002), which models pecking order of financing based on executives' optimism, and Aktas et al. (2010), which infer narcissism from CEO speeches and find that CEOs with narcissism tend to influence takeover decisions.

conference calls and the statements are related both to the companies' past performances and future expectations. Thus, this is a more general setting for managers' attribution behaviors. More importantly, the previous study's focus is on the determinants of attribution behaviors. This paper emphasizes the consequences of attribution activities in the earnings conference calls, including investors' underreaction to negative news and reduced sensitivity in turnover-performance. Furthermore, this paper provides a consistent argument that can jointly explains empirical observations in the attribution behaviors and its effect in stock returns and executive performance incentives. To my best knowledge, this is the first time to document that executive behavioral characteristics that is associated with future stock return.

Second, this study is broadly related to the literature on the information environment and the information content of corporate disclosure. Existing literature shows that changes in information environment may significantly change investor response. For example, Solomon (2012) finds that companies who hire an IR firm exhibit more ability to spin news and cause a delay in the incorporation of bad news. Cohen et al. (2013) find that analysts can cast their conference calls by calling friendly analysts. Li and Yermack (2014) document that evasive annual shareholder meetings predict low stock return. Other papers also find non-numerical information from earnings announcement conference calls informative. Hollander et al. (2010) find that silence during the conference call contains information. Matsumoto et al. (2011) find that the Q&A part of the conference calls is more informative than management discussions. Mayew and Venkatachalam (2012) find that tonal information from managers' voices contains information about firms' future performances. More closely related to this paper, Larcker and Zakolyukina (2010) find certain words in conference calls can be used to detect accounting misstatements. This paper builds on the existing research and shows that earnings conference calls also contain meaningful information about executive behavioral characteristics.

Third, this paper is also related to a set of papers that examine the executive turnover performance. Past literature documents that CEO turnover is significantly negatively related to stock returns (e.g., Kaplan and Minton (2006), Jenter and Kanaan (2006)). Moreover, Jenter and Kanaan (2006) document that negative industry shocks can lead to turnover. However, turnover sensitivity to industry shocks is lower than the sensitivity to companies' idiosyncratic performances. This paper adds to the literature and shows that the executives' explanations matter for the turnover decisions. Attributing negative performance can alleviate the pressure on executives by lowering turnover performance sensitivity. These results also complement the previous research on executives getting paid based on their luck (e.g., Bertrand and Mullainathan (2011)). While Bertrand and Mullainathan (2011) show that executives are sometimes paid for the sheer luck, this paper indicates that managers may also avoid blame by shifting the responsibility to external factors.

Finally, this paper also makes a methodological contribution.[2] Previous literature often uses pure dictionary method (e.g., Loughran and Mcdonald (2011), Jegadeesh and Wu (2013)) to capture the information from the texts. Li (2010a) show that using Naive Bayesian method to analyze words in the forward-looking sentences can extract useful information. This paper shows that sentence-based analyses, combining with a correctly specified dictionary, can provide additional information beyond pure word counts. While word count methodology has proved to be useful in capturing additional information to numerical information, simple word counts may miss important information from the context of sentences. This paper demonstrates that analyzing words in the context of sentences can provide insights into their context. For example, the sentence-based analysis helps provide information such as executive personal characteristics.

The rest of the paper will proceed as follows. Section 2 describes the source of the data

[2]Broadly speaking, the results from this paper add to a large literature related to textual and linguistic information in the financial markets. A number of papers document that tonal information in news articles contains information about firm fundamentals (eg Tetlock et al. (2008), Engelberg (2008)). In addition, it has also been shown that noninformative tonal information may also be incorporated into the asset prices (e.g., Tetlock (2011), Engelberg and Parsons (2011)). Finally, managers are able to manipulate the tone in the business press to affect the prices in the broad market.

and the construction of the BLAME measure in detail. The main results will be discussed in detail in section 3. Section 4 discusses the hypotheses about what cause the self-serving attribution bias. Section 5 concludes the paper.

2 Data and Methodology

The texts from conference call transcripts are used to analyze self-attribution biases in this study. Executives hold earnings conference calls to discuss the financial performances of the company in the fiscal quarter. Substantial amount of textual information is disclosed during the conference call. Past literature clearly indicates that the textual information in conference calls contains value relevant information in addition to the accounting information released by firms. Conference calls also offer opportunities for analysts and investors to interact with the management. In general, conference calls offer a valuable venue for managers to explain the companies' performances in detail to investors. Because of the rich linguistic information in the conference call, the language of disclosure may well shape the perceptions of the performance of the company.

One advantage of using conference calls to capture executive behavioral characteristics over using written materials such as letters to shareholders or annual reports (previous management literature such as Staw et al. (1983) and Clapham and Schwenk (1991)) is that written materials are often written by a committee rather than an individual. Therefore, the written materials are less accurate in capturing individual behavioral characteristics. Moreover, because of executives need to answer questions from the participating analysts, they are more likely to offer spontaneously reaction to the question. These spontaneous remarks are more likely to reveal executives' thinking processes.

The quarterly earnings conference call transcript data used in this study comes from two sources. I first download the available conference call transcripts from StreetEvents of Thomson One from 2003 to 2012. I supplement the missing observations with the data from Call Street, a unit of Factset. Combining these two sources, I obtain about 90,000 raw transcripts. After merging with CRSP, Compustat and IBES, the sample size reduces to around 70,000. I also delete the observations whose stock price is below 5 dollars in the month preceding the earnings announcement.

I parse the texts from these transcripts in the following way: I first split the text into sentences, by identifying the punctuation indicating the end of sentences, such as periods, question marks, semicolons and exclamations. For each sentence, I look for words related to economy and industry. Specifically, I look for "economy," "economic condition," "economic conditions," and "economic growth" for economic related descriptions and "industry" and "industries" as indicators for industry related descriptions.[3] The sentences identified as descriptions related to economy and industry performances are classified into positive, negative and neutral description sentences. I use the Loughran and Mcdonald (2011) financial dictionary to identify positive and negative words in the previously identified sentences. If there are more positive words than negative words in the sentence, it is classified as a positive sentence. Meanwhile, if there are more negative words than positive words, the sentence is classified as a negative sentence. Otherwise, the sentence is classified as neutral. In this paper, I focus on negative description of industry or economy to capture the attribution behaviors. To better understand the negative sentences captured using this methodology, I have selected a number of these sentences in table 1. In the first two sentences, managers attribute negative performance to the economy. In the third example, executive attribute negative performances to industry. The program first captures the key words related to industry or economy (in bold letters). The program then identifies positive words (non-existent in the sentences displayed in these examples) and negative words (in red color). Since there are more negative words in these sentences than positive words, these sentences

[3] I also consider other similar words, such as sector and segment as indicator for mentions of industry. By reading a random sample of conference call transcripts, the words "sector" and "segment" are most often referring to sector or segment within a company. Therefore, using these two words as indicator for mention of the overall industry condition will likely generate noisy results.

are classified as sentences with a negative description of industry or the economy (referred as BLAME sentences). Although this paper does not focus on the positive description of industry or economy, I have also examined a number of positive description sentences. The positive description sentences are a much noisier collection of sentences, since many executives proclaim that their companies are "industry-leading" or "better than the industry average." There are three sentences with positive descriptions of the economy and the industry exhibited in table 1. We can see that the last positive industry description sentence is really about the firm performance. The number of sentences with positive description of industry or economy (N(POSITIVE)), neutral description (N(NEUTRAL)) and negative description (N(BLAME)) are reported in the panel B of table 2. I find that there are more positive/neutral description sentences of industry or economy than negative descriptions, indicating a relatively high hurdle for sentences to qualify as a negative description sentence on industry or the economy. Overall, the number of BLAME sentences are not many. One may question whether managers can change investors' view of their companies with such few sentences. I argue that these sentences only serve as a proxy for the tendency to attribute failures. Thus, one should only view these BLAME sentences as red flags of attribution biases.

For each conference call, I calculate BLAME measure (Negative Description of Industry and Economy) in the following formula to capture the frequency of negative descriptions of industry and economic conditions:

$$BLAME = \frac{\text{N(BLAME Sentences)}}{\text{Number of Sentences}}.$$

In addition, I construct a measure for the fraction of sentences that with positive description about industry or economy as a placebo variable. Positive descriptions sentences are similar to BLAME sentences, except that they have more positive words than negative words in an industry or economy-related sentence. I construct a POSIE measure calculated as total number of positive sentences related to industry or economy. I also calculate the overall number of positive and negative words from the conference call. I intend to use the BLAME measure to proxy the tendency of attributing negative performance to external factors. To insure the BLAME measure captures the information independent of the tone of the overall text, I control the tone of the overall conference call using the following negativity measure[4]:

$$NEG = \frac{\text{Number of Negative Words}}{\text{Number of Words}}.$$

The parsed data is then merged with CRSP, Compustat and IBES to obtain the common financial measures such as market equity, book-to-market ratio, past return and Standardized Unexpected Earnings. The cumulative abnormal return (CAR) is calculated using the Fama-French 3-factor model (Fama and French, 1993). The beta of the factor loadings are estimated using the daily returns in the interval of [-180,-15] relative to the date of the conference call. Standardized unexpected earnings or SUE is calculated as

$$SUE_{i,t} = \frac{E_{i,t} - FE_{i,t}}{P_{i,t}},$$

where E represents realized quarterly earnings, FE represents the consensus analyst forecast earnings and P is the stock price at the end of the IBES statistical period when consensus analyst earnings forecasts are calculated. The consensus analyst forecast expectation is formed on the closest IBES statistical period end date prior to the conference call. SUE is winsorized between -0.1 and 0.1. The key dependent variable is cumulative abnormal return or CAR. CAR is calculated using a 3-factor model, where the loadings on the Fama-French factors are estimated by returns from the prior 180 days to 10 days relative to the earnings announcement date. The results presented in the rest of paper are robust if market adjusted returns (calculated as firm returns minus market returns) are used as cumulative abnormal

[4]I have also examined a sentence-based tone measure. The measure is calculated as the total number of negative sentences dividend by the number of sentences in the conference call transcript, and negative sentences are the ones with more negative words than positive words. The results presented in this paper are robust when I use the alternative tone measure as a control.

returns. Volatility is the estimated daily volatility one year prior to the conference call date. Share turnover is the monthly turnover in the month before the conference call date. Institutional ownership is formed based on the 13F data at the end of the quarter prior to the conference call. Executive employment information is obtained from Execcomp. Executive turnover date is based on the date that CEO steps down.

3 Results

3.1 Determinants of Executives' Blame Behaviors

Before proceeding to analyze the impact on returns, I first investigate the determinants of the BLAME measure (negative description of industry or the economy). I explore the time series variability of the BLAME measure to examine whether it is correlated with the macroeconomic fluctuations. I plot the BLAME measure (scaled up by 100), percentage firms with non-zero BLAME and the contemporaneous GDP growth data in figure 1. The plot clearly indicates that economic performance is negatively associated with BLAME measure. This trend is most clear during the period of the economic downturn around 2008-2010. This observation reflects that executives are more likely to discuss negative economy or industry performance when economic growth is slower.

The second test explores the cross-sectional variation of the BLAME measure. I hypothesize that several factors are positively associated with BLAME. First, firms that performed poorly are likely to be associated with higher BLAME measures. A firm with good performance has little incentive to discuss the negative impact of external factors, since they do not need to find any scapegoat for their performance. Second, firms of systemic importance are more likely to mention negative industry or economic factors, since the performance of these firms is more likely to be associated with higher economic performance and less likely to be associated with idiosyncratic performances. Third, firms with less external monitoring are more likely to be associated higher BLAME measures. These firms with less monitoring may play the blame game more often to shape a better self-image.

I run a tobit regression (dependent variable censored at 0) to explore what drives BLAME. To control for time series variations, I control for year-quarter dummies in the regression. The results are reported in table 3[5]. In addition to results, I also report the predicted signs for the coefficients. I find that consistent with the first hypotheses, firms with worse performance in either financial or accounting metrics tend to have higher BLAME measures. Specifically, I find that SUE is negatively associated with the BLAME measure, indicating that firms with lower earnings tend to mention negative effects of the economy and the industry more frequently. Similarly, lag returns are negatively associated with the BLAME measure, indicating that better stock performance reduces the need to blame the industry and the economy. The percentage of negative words, which can serve as a rough proxy for other negative information revealed linguistically, has a significant positive correlation with BLAME measure. Furthermore, valuation is negatively related to the BLAME measure, indicated by the positive coefficient from book-to-market ratio.

Second, larger firms are associated with higher BLAME measures. This relationship is clearly indicated by the significantly positive coefficient of log market equity. This indicates that larger firms are more likely to encounter negative industry and economic shocks. In addition, I use the R^2 (see Roll (1988) for a discussion of the information content of R^2) from the following market and industry time series model to estimate the company's total exposure to industry and the economy factors:

$$\begin{aligned} RETRF_{i,t} =& \alpha_i + \beta^{(1)}_{MKT,i} MKT_{t-1} + \beta^{(2)}_{MKT,i} MKT_t + \beta^{(3)}_{MKT,i} MKT_{t+1} + \\ & \beta^{(1)}_{IND,i} IND_{t-1} + \beta^{(2)}_{IND,i} IND_t + \beta^{(3)}_{IND,i} IND_{t+1} + \epsilon_{i,t} \end{aligned}$$

[5] An additional OLS regression with CEO fixed effects is reported in the appendix table A1. The idea is that some CEOs are habitually more likely to blame than others. Because of the fixed effect specification, tobit model cannot be used. The executive information is taken from Execcomp. The merged sample is roughly 2/3 the size of the original sample in the tobit regression. The result from the OLS regression is largely consistent with the tobit regression reported in the table 3.

where $RETRF$ is the difference between return and risk free rate, MKT is market return minus risk free rate and IND is value weighted industry return minus risk free rate. The industry return is defined using Fama-French 48 industry classification (Fama and French, 1997). The lead and lag industry and market returns are included to account for nonsynchronous trading (e.g., Dimson (1979)). The R^2 (estimated using daily return data with 1-year lag) estimated using the above model is significantly positively associated with the BLAME measure, indicating higher likelihood to mention industry and economy performance when a firm's exposure to macroeconomic performances is higher. This could also indicate that it is more convincing for executives of firms with higher exposure to systematic risk to blame industry and economy performance.

Third, analyst coverage is negatively associated with BLAME. High analyst coverage is associated with higher external monitoring as documented in the prior literature (Moyer et al., 1989). Analysts also confront the management about the bad performances from time to time. The negative coefficient of analyst coverage in this regression indicates intense external monitoring reduces the frequency of blaming external factors. Surprisingly, institutional ownership is positively associated the BLAME measure, though with less economic significance. Perhaps institutional investors do not usually field questions into the conference call, so they are less likely to be able to confront with the management during the conference call.

I repeat the same exercise with the POSIE measure as the dependent variable (fraction of positive sentences about industry or economy). I do not find significant evidence that past returns are associated positive descriptions of economy and the industry, which indicates that corporate executives do not attribute success to industry when their performance excels. This asymmetry may suggest that attributing negative performance to the industry is an impression management tactics used by the corporate executives when the companies underperform.

In the second specification, I use a regression discontinuity approach to detect whether there is a dramatic increase in BLAME at the cutoff point of meeting the analyst forecast revision if the companies slightly miss the analysts' consensus earnings estimates. The specification of the regressions discontinuity design is similar to the one proposed in Imbens and Lemieux (2008). The outcome variable (dependent variable) is BLAME and the assignment variable (independent variable) is SUE. Results are reported in the panel B of table 3. The need to play the blame game reduces significantly if the market expectations are met. Consistent with this hypothesis, I find that there is a significant difference in the mean at the cutoff point $SUE = 0$ and the coefficient of the jump is negative. In the placebo test, I do not find there is substantially more positive description about economy or the industry when companies experience good performance. In untabulated results, I repeat the same analysis for percentage negative words (NEG) as a placebo test. The null hypothesis that there is a cutoff at $SUE = 0$ cannot be rejected at conventional threshold. This suggests that this discontinuity is not driven by the behaviors of the assignment variable SUE or negative word counts. Summarizing the results from these regression discontinuity tests, BLAME seems to capture the tendency to present an optimistic picture when the performance falls short of expectations.

3.2 Predicting Post Conference Call Returns

The key test to confirm whether the "blame game" can be associated with delayed reaction to negative information is to examine whether BLAME can predict future returns. If the BLAME measure captures the tendency of companies' impression management of their performances during the conference call, market participants are likely to underreact to bad news. As a result, the stock is likely to experience negative performance after the earnings announcement. I first test this hypothesis using a Fama-Macbeth regression (Fama and MacBeth, 1973) specified as follows:

$$CAR[2,60]_{i,t} = \alpha + \beta BLAME_{i,t} + \gamma X_{i,t} + \epsilon_{i,t}$$

where $CAR[2, 60]$ is the cumulative abnormal return calculated using the Fama-French 3 factor model. The standard errors are adjusted for serial correlations following Newey and West (1987). Because the earnings announcements are made on a quarterly basis, I group all earnings announcements made in one quarter as a cross-section. The predictive horizon is over the following 60 trading days after the earnings announcement. This trading horizon roughly covers 3 months. Past research used this predictive horizon in post earnings announcement drift, as information from earnings announcements is largely realized over this time horizon (Dellavigna and Pollet, 2009, Hirshleifer et al., 2009). These results are reported in table 4. The BLAME measure is the only independent variable in the first specification. The coefficient of the BLAME measure is negative with statistical significance below the 1% level. The economic magnitude implied by this regression is substantial. One standard deviation change in the BLAME measure corresponds to roughly 50 basis points change in return in the following 60 trading days[6].

In the second regression, I add a set of control variables to ensure the results from the univariate regression is not driven by confounding effects of known predictive variables. These variables include book-to-market ratio, lag 6-month return, return volatility, standardized unexpected earnings, number of analysts, turnover and institutional ownership. In addition, I control overall negativity in the conference call transcript using NEG, percentage of negative words. Price et al. (2012) find that the conference call tone predicts future returns. Although the economic magnitude decreased, the BLAME measure still predicts the post earnings announcement returns with high statistical significance. Notably, the NEG measure is negatively correlated with post earnings announcement return, but the coefficient is statistically insignificant.[7] Hence, the results from the BLAME measure are independent of

[6]In the untabulated results, I also use positive industry and economy description as the independent variables. I find that while positive industry description is positively correlated with contemporaneous returns, but does not significantly predict future returns, consistent with the idea that the predictability is generated uniquely by the negative description.

[7]This results differ from Price et al. (2012). First, this paper investigates a larger sample, so this results is likely to be more accurate than the previous study. Second, Price et al. (2012) use OLS regression when predicting returns, while this study uses Fama-Macbeth regression. I find that NEG predicts future return

the negativity measure. In addition, BLAME measure captures further predictability under controlling the widely observed post earnings announcement drift (e.g., Bernard and Thomas (1989)), since controlling for SUE does not weaken the BLAME measure significantly. In terms of economic magnitude, the BLAME measure can generate return predictability comparable to the standardized unexpected earnings.

Next, I assess how much investors can profit from the information of BLAME measure by forming a calendar time portfolio following Lyon et al. (1999). I first take long positions in all the companies with a BLAME of 0. The short leg consists of companies with BLAME measure above 20% from the previous quarter, so that no forward-looking bias is driving the return results. All stocks are held in the portfolio for 60 trading days after the date of the conference call. The returns are equal weighted and at least 10 stocks are required in each portfolio. Then both Fama-French 3 factor models (Fama and French, 1993) and Carhart 4 factor models (e.g., (Carhart, 1997, Jegadeesh and Titman, 1993)) are calculated to assess the α from the hedged portfolio. The results are reported in table 5. The results indicate that the hedged portfolio can generate substantial abnormal return. For example, the 3-factor alpha is 59 basis points per month or 7% per year. The four factor model alpha is 57 basis points or 6.8% per year. Both alphas are statistically significant at the 1% level. Thus, the information from the BLAME measure is highly valuable for investors.

To ensure that these results are not driven by post-earnings announcement drift, I form portfolios based on double sort. Specifically, I independently assign stocks into portfolios based on BLAME and SUE measures. Classification of high BLAME and low BLAME measures is the same as the single sort. High BLAME measure stocks are those with BLAME measures in the top 20% and low BLAME measure are those stocks with BLAME measures equal to 0. The break points for SUE are the top and bottom 30%. I first test the economic magnitude of BLAME portfolios for both low and high SUE stocks. In both cases, BLAME-

significantly using the OLS specification, but not the Fama-Macbeth specification. This may imply that NEG does not have great power in predicting stock returns in the cross sectional setting.

sorted portfolios generate significant four factor alphas. However, the alpha of the BLAME sorted portfolios is much lower than in the low SUE stocks than in high SUE stocks. This indicates that the attribution to industry or the economy is more harmful for investors when the company experiences bad earnings. To compare the economic magnitude of BLAME measure and the post earnings announcement drift, I also exhibit the abnormal performance of taking long positions in high SUE and short position in low SUE firms. Across high BLAME and low BLAME measures, the SUE exhibit robust abnormal returns. These returns are slightly higher the returns in the portfolios sorted based on BLAME. These results are consistent with the findings of Fama-Macbeth regression.

In summary, both Fama-Macbeth regression and the calendar-time portfolio tests provide evidence that the BLAME measure significantly predicts negative return after the date of conference call. These results indicate that a high BLAME measure is associated with investors' delay in incorporating negative news about the firm.

3.3 Industry-Adjusted Portfolio

An alternative explanation for the previous cross-sectional and industry regression is that the BLAME measure contains information about future performance of industry or the economy and investors are underreacting to those warnings. First, if BLAME measure contains information about the overall economy and the stock market fails to react to this information, we still should not expect to find any cross-sectional predictability, since it should impact all firms in the economy. In the appendix table A2, I also show that the predictability does not concentrate in the companies with strong comovement with the market or the industry, since the interaction term between firms' time-series R^2 and its BLAME measure does not generate a significant coefficient in the predictability regression. As a result, it is unlikely that the predictability generated from BLAME measure is a result of underreaction to industry-wide negative information. Second, to address the possibility that the BLAME measure contains negative information about the industry of the firm, I form an industry-adjusted calendar time portfolio. Specifically, I calculate industry-adjusted return for each stock by subtracting matched Fama-French 48 industry return (IND) from the daily stock return:

$$RET_{i,t}^{ADJ} = RETRF_{i,t} - IND_t^{IND}.$$

These industry-adjusted returns are then used to form the calendar-time time portfolio using the procedure described in the previous paragraph. If the abnormal return observed in the previous calendar time portfolio is a result of underreaction to industry-wide negative information revealed by executives, the industry adjustment should eliminate the observed abnormal returns. Therefore, adjusting industry return should eliminate the abnormal returns in the calendar time portfolio not adjusted for return. The results of the industry-adjusted calendar time portfolio is reported in table 6. The portfolio indicates a significant α for both 3-factor and 4-factor models. The 3-factor alpha is 5.5% in annual term and the four factor alpha is 5.4%. Both alphas are significant at the 1% level. These economic magnitudes are slightly lower than the unadjusted portfolio, which may indicate BLAME also contains certain negative information about the industry. The overall evidence, however, is that BLAME measure contains information independent of overall industry performance.

3.4 Predicting Future Earnings

Next, I examine whether BLAME measure predicts future earnings. BLAME measure can be associated with future earnings in two ways. First, if high BLAME measure is a result of self presentation concern. The reported earnings can be inflated for presentation purpose, which then leads to subsequent reversals. Second, if high BLAME measure is driven by cognitive bias, the executives tend to be worse problem solvers. Therefore, it may take more time for them to address the problems present at the company and it will take longer for earnings to recover. Both possibilities predict a negative association between BLAME measure and future earnings. I test this hypothesis using the following Fama-Macbeth regression:

$$SUE = \alpha + \beta BLAME + \gamma X + \epsilon,$$

where SUE is standardized unexpected earnings and X is a vector of control variables.

The results from this set of regressions are reported in table 7. Consistent with the hypothesis, I find that BLAME significantly predicts next quarter SUE with p-value below 5%, indicating that analysts do not completely incorporate the negative information.

3.5 Evidence from Analyst Recommendations

In this section, I further explore whether stock prices underreact to negative information using changes in analyst recommendations. I look at whether the analysts recognize the displacement of stock prices after the earnings announcement by examining whether analysts change their recommendation after earnings announcement date. Specifically, I examine the first recommendation change to capture the initial reaction from analysts within 90 days after the earnings conference call. I use the Fama-Macbeth regression, similar to the specification in Jegadeesh et al. (2004). As indicated in the results reported in table 8, I find that the BLAME measure significantly predict this recommendation change measure with a negative sign, indicating that analysts gradually incorporate the information from the BLAME measure, as they realize that the stock prices of the firms with high BLAME are overvalued. Control variables do not reduce the significance level of the predictability results.

The evidence from the analyst recommendations are consistent with the idea that the broad market underreacts to the negative information when companies attribute negative performance to industry or economy. Analysts pick up the negative information subsequent to the earnings conference calls in the course of the next 90 days after the conference call. Thus, they tend to downgrade these firms in the following quarter for companies with high

BLAME measures.

3.6 Contemporaneous Stock Returns

After looking at post earnings announcement returns, I analyze the announcement return at the date of the conference call. It is difficult to predict the sign of coefficient for the BLAME measure. On one hand, if high BLAME measure implies executives withholding some negative information, BLAME measure should be positively related to the conference call abnormal return. On the other hand, high BLAME measure means that there is negative information to assign blame, since it would be unnecessary to assign blame if there is no negative news. If this negative information is not captured by the control variables, then BLAME could be associated with negative contemporaneous return. Thus, I leave the verdict to the data.

The research setting is similar to the long-term return following the conference call. The dependent variable is the three-day cumulative abnormal returns from day -1 to day 1 relative to the earnings announcement date, adjusted using the Fama-French three factor model. The main independent variable of interest is BLAME. I run Fama-Macbeth style return regressions. Overall, I find that the BLAME measure is significantly associated with negative CAR, both with and without controls. In terms of economic magnitude, the coefficient in the regression with control variables is roughly one third that of the regression without control variables. Therefore, the lion share of negative information captured by the BLAME measure is correlated with the control variables. However, it is obvious that control variables do not capture all the negative information correlated with BLAME measure. These results, again, indicate that the BLAME measure is associated with negative firm-specific performance.

3.7 Executive Turnover

Results from the previous sections indicate that managers tend to attribute bad performances to external factors such as industry and economy. When the executives play the blame game, investors tend to underreact to the negative information. In this section, I provide evidence that the attribution behaviors significantly change the probability of executive turnover. Extensive research has documented that bad CEO performance (e.g., low stock returns) lead to higher executive turnover (e.g., Murphy and Zimmerman (1993)) and lower executive compensations (e.g., Gibbons and Murphy (1990)). Jenter and Kanaan (2006) document that bad industry performance also leads to executive turnover, but to a lesser extent. Similarly, Bertrand and Mullainathan (2011) document that CEO compensations are sometimes affected by the performance of the whole industry. The authors also find that this result is asymmetric: CEOs tend to be rewarded for good luck, but not blamed for bad luck. Thus, if executives can associate their performance with bad economic or industry environment, they are less likely to be held responsible for the bad performances. If executives attribute negative performance when they talk about their results in front of shareholders, they are also likely to use the same excuses when they face the board of directors. This possibility has been suggested in several previous contexts. For example, Duchin and Schmidt (2013) show that when executives make value-destructive mergers during merger waves, they are less likely to be fired than those who make bad merger decisions during the normal time, since the executives can argue that their peers all make similar decisions. In other words, the executives can blame the industry environment for the bad decisions that they made and board members tend to be more lenient on their bad decisions when these excuses are present. Nevertheless, this hypothesis has never been tested directly. I will empirically examine whether negative performances can reduce the pressure on the executives from the board members directly using the BLAME measure.

The specification in the form of Jenter and Kanaan (2006) is adopted to test whether attribution behaviors affect executive turnover performance sensitivity. I conduct a Probit regression. Similar to Jenter and Kanaan (2006), the dependent variable is CEO turnover in the next year. I also control ROA as additional control for firm performance. CEO age is also added as a control, as more CEO turnover may be observed when a CEO gets closer to retirement age. Similar to the intuition from the prior literature, lag one year return and ROA are negatively associated with CEO turnover. The proxy for attribution behavior is BLAMEDUM, a dummy variable that indicates whether there is attribution behavior during that year. I use this dummy variable as opposed to BLAME measure mainly because it is easier to interpret the economic magnitude of the interaction term. The statistical significance of the results reported in this table does not change significantly if the raw BLAME measure is used. The two variables of interests are BLAMEDUM and BLAMEDUM*LAGRET. BLAMEDUM itself is negatively correlated with executive turnover. However, this relationship is not statistically significant. The interaction variable BLAMEDUM*LAGRET is highly significant and positive. The positive coefficient indicates lower turnover performance sensitivity. The marginal effect of this coefficient is roughly one-third that of the coefficient of LAGRET, indicating a much lower likelihood for turnover if the performance is unsatisfactory.

Jenter and Kanaan (2006) show that executives are blamed less for the results from the negative performance of the industry. To make sure that this result is not driven by the possibility that the firms with high BLAME measure are in the industry with a negative shock, I separate the returns into two separate components: INDRET (the Fama-French 48 industry portfolio returns) and EXRET (difference between company returns and industry returns). The coefficient for the interaction term is still positive and highly significant. Thus, the reduced sensitivity is not a result of bad industry performance.

Taken together, attributing negative performance to external factors helps bad performing managers by reducing turnover performance sensitivity and the effect is the strongest when the firm's bad performance is not a result of industry shock.

4 Conclusion

Self-serving attribution bias is a widely documented behavioral bias. However, there is limited prior study on how it affects participants in the financial market. This paper uses textual analysis to capture the tendency to attribute failures to external factors. To my best knowledge, this is the first paper in the finance literature that provides direct evidence of executives' self-serving attribution bias. I find that managers attribute negative performances externally to industry and economy. These behaviors lead to underperformance of stock prices after the conference call. Further evidence from analyst recommendations is consistent with the idea that investors underreact to negative information when executives attribute negative performances. Using industry-adjusted calendar time portfolio, I show that these attribution activities do contain significant negative information about the industry. Thus, the underperformance is driven primarily by firm-specific negative information. Furthermore, executives who attribute negative performance to external factors are less likely to be fired in the next year, indicating that these executives are successful at lobbying board members by attributing bad performance externally. Thus, self-serving attribution bias affects both asset prices and corporate decisions. In summary, this study shows that behavioral characteristics of corporate executives have significant impact to shareholders.

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Appendix

Table 1: Examples of Positive and Negative Description of Industry and the Economy

This table exhibits examples of positive and negative descriptions of industry and the economy. The first three examples are negative descriptions and are considered as executives playing the blame game. The first two involves executives blaming economy conditions. The third one demonstrates when executives blame the industry. The fourth example is a positive sentence about the economy. The last two examples are positive descriptions of industry captured by the program. Negative words are colored with red, positive words are colored with green and key words for economy and industry are marked with bold letters. Words in the square brackets are from the preceding sentence.

Blaming the economy	
Watts Water Technologies 2009Q2	Sales into Eastern Europe has remained depressed due to poor **economy** conditions, customer credit risk remain a major issue in Eastern Europe.
Fuel Systems Solutions 2009Q2	[We continue to experience softness in our aftermarket business.] We believe this reflects mainly continued weakness in the global **economy**.
Blaming the industry	
Navigator 2011Q4	We view this as an acceptable outcome given the magnitude of the loss to the global insurance **industry**.
Positive Economy Sentence	
Microsoft 2010Q1	We should start to see that improve going forward as we see the **economy** recover.
Positive Industry Sentences	
Honeywell 2006Q4	I think it's in a good space, the **industry** is doing well, and we see it both with UOP and process solutions that that industry should continue to do well and I think it's a good part of Honeywell.
BEAM 2012Q1	Notably, that includes strong growth for our **industry**-leading bourbon portfolio, which starts with sustained growth for our core Jim Beam White product and accelerates up the price ladder, delivering favorable mix.

Table 2: Summary Statistics

This table reports summary statistics for variables used in the paper. Panel A reports the summary statistics of relevant variables from the return regressions. Panel B reports the number of positive, negative and neutral industry and economy description sentences and total number of sentences in the conference call texts. CAR[2,60] and CAR[-1,1] are cumulative abnormal returns from trading day 2 to 60 and -1 to 1 relative to the date of the conference call. The cumulative abnormal return is calculated using Fama-French 3 factor model. BLAME is percentage sentences attributing negative performance to industry or economy. POSIE is percentage of sentences attributing positive performance to industry or economy. Accrual is the accrued earnings divided by total assets ((IBCY-OANCFY)/ AT). NEG is the percentage negative words in the text. NUMEST is the number of analysts covering the firm. SUE is standardized unexpected earnings. BM is log book-to-market ratio. MOM is the lag 12 month cumulative return. INSTOWN is institutional ownership. VOLATILITY is the annualized daily volatility calculated using the data from the month preceding the conference call. TURN is the average share turnover in the month preceding the conference call. RSQ is the R-squared estimated using market and industry factors. N(POSIE), N(BLAME) and N(NEUIE) are number of sentences with positive, negative and neutral description on industry or economy. N(SENTENCE) is the total number of sentences from conference calls.

Panel A: Variables in regresion analyses

Variable	**Mean**	**Median**	**Std Dev**	**Q1**	**Q3**
CAR[2,60]	0.316	0.011	20.528	-9.296	9.422
CAR[-1,1]	0.347	0.249	10.115	-4.447	5.239
BLAME	0.201	0.000	0.329	0.000	0.293
POSIE	0.316	0.195	0.421	0.000	0.467
ACCRUAL	0.972	0.977	0.478	0.946	1.001
ME	4996017	863327	19108962	312097	2666794
NEG	1.092	1.046	0.315	0.872	1.262
NUMEST	8.524	7	6.515	4	12
SUE	-0.042	0.052	1.577	-0.103	0.243
BM	-0.790	-0.740	0.852	-1.264	-0.263
MOM	6.392	6.531	40.782	-11.215	23.629
TURN	0.211	0.155	0.220	0.092	0.260
INSTOWN	0.721	0.771	0.206	0.606	0.879
VOLATILITY	0.297	0.194	0.490	0.107	0.355
RSQ	0.417	0.410	0.243	0.215	0.602

Panel B: Conference call descriptive statistics

Variable	**Mean**	**Median**	**Std Dev**	**Q1**	**Q3**
N(POSITIVE)	1.505	1	2.004	0	2
N(BLAME)	0.953	0	1.546	0	1
N(NEUTRAL)	2.281	1	2.784	0	3
N(SENTENCE)	480.723	477	164.361	373	576

Table 3: Determinants of BLAME Measure

This table explores the determinants of BLAME measure. I also report the results for POSIE (Positive Description of Industry and Economy) as placebo tests. Panel A reports the relevant variables from the revision analyses. Panel A reports a tobit regression (censored at lower bound 0) with year-quarter dummies. The standard errors (reported in parenthesis) is clustered by quarter. Panel B reports the result from the Regression Discontinuity test. The outcome variable is BLAME and the assignment variable is SUE. BLAME is percentage sentences attributing negative performance to industry or economy. Accrual is the accrued earnings divided by total assets ((IBCY-OANCFY)/ AT). NEG is the percentage negative words in the text. NUMEST is the number of analysts covering the firm. SUE is standardized unexpected earnings. BM is log book-to-market ratio. MOM is the lag 12 month cumulative return. INSTOWN is institutional ownership. VOLATILITY is the annualized daily volatility calculated using the data from the month preceding the conference call. TURN is the average share turnover in the month preceding the conference call. RSQ is the r-squared estimated using market and industry factors. The first column reports the predicted sign. The second column predicts the results from the regression. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Panel A: Tobit Regression			
VARIABLES	Predicted Sign (BLAME)	BLAME	POSIE
SUE	-	-0.122***	-0.0308
		(0.0208)	(0.0303)
BM	+	0.446***	0.371***
		(0.0400)	(0.0297)
Log(ME)	+	0.526***	0.477***
		(0.0334)	(0.0417)
RET	-	-0.174***	0.00963
		(0.0422)	(0.0481)
ACCRUAL	+	0.128***	0.128***
		(0.0298)	(0.0266)
NEG	+	1.358***	-0.0509
		(0.0711)	(0.0386)
VOLATILITY	?	-0.188***	-0.265***
		(0.0668)	(0.0547)
INSTOWN	-	0.0518**	0.00746
		(0.0222)	(0.0290)
NUMEST	-	-0.154***	-0.00901
		(0.0410)	(0.0271)
TURN	?	-0.0915***	-0.0150
		(0.0304)	(0.0403)
RSQ	+	0.165***	-0.156***
		(0.0364)	(0.0362)
R-squared		0.037	0.0078
Panel B: Regression Discontinuity Design			
Discontinuity at	-	-0.212***	0.0771
SUE = 0		(0.0731)	(0.0973)
Observations		64,950	64,950

Table 4: Predicting Post Conference Call Returns

This table reports results from return predictability regressions. The dependent variable is the cumulative abnormal return (adjusted using Fama-French 3 factor model) from trading day 2 to trading day 60 following the conference call. BLAME is percentage sentences attributing negative performance to industry or economy. Accrual is the accrued earnings divided by total assets ((IBCY-OANCFY)/ AT). NEG is the percentage negative words in the text. LNUMEST is the log of one plus number of analysts covering the firm. SUE is standardized unexpected earnings. BM is log book-to-market ratio. MOM is the lag 12 month cumulative return. INSTOWN is institutional ownership. VOLATILITY is the annualized daily volatility calculated using the data from the month preceding the conference call. TURN is the average share turnover in the month preceding the conference call. RSQ is the R-squared estimated using market and industry factors. The third regression regresses CAR[2,60] on two components of BLAME. P(BLAME) is the predicted values from cross-sectional regression with BLAME as dependent variable and Log(ME), RSQ as independent variables. R(BLAME) is the residual from the same regression. Newey-West adjusted standard errors are reported in parenthesis. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

VARIABLES	CAR[2,60]	CAR[2,60]
BLAME	-0.500***	-0.432***
	(0.125)	(0.103)
SUE		0.634***
		(0.205)
BM		-0.0869
		(0.118)
Log(ME)		-0.0625
		(0.161)
MOM		-0.134
		(0.287)
ACCRUAL		-1.075***
		(0.173)
NEG		-0.108
		(0.140)
VOLATILITY		-0.379
		(0.687)
INSTOWN		-0.0253
		(0.107)
LNUMEST		-0.449**
		(0.203)
TURN		0.0988
		(0.195)
R-squared	0.003	0.049
Number of groups	40	40

Table 5: Calendar Time Portfolios

This table presents various estimates of abnormal returns from portfolios sorted based on BLAME measure. The hold periods for these portfolios are trading day 2 to 60 after the date of conference calls. Panel A reports the hedged portfolio that takes long position in companies with BLAME equals to 0 and short positions in companies with BLAME greater than 80 percentile based on the previous quarter. Panel B reports the portfolio returns based on sorting independently on SUE and BLAME. Low SUE stocks are those with SUE below 30 percentile and high SUE stocks are those with SUE higher than 70 percentile. The intercepts reflect monthly returns. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Panel A: Portfolio sorted by BLAME				
ALPHA	MKTRF	SMB	HML	UMD
Excess Return				
0.518***				
(0.193)				
3-Factor Model				
0.590***	-0.024***	0.010	-0.241***	
(0.181)	(0.007)	(0.015)	(0.016)	
4-Factor Model				
0.570***	0.003	-0.014	-0.153***	0.128***
(0.174)	(0.007)	(0.014)	(0.016)	(0.009)

Panel B: Portfolio sorted by SUE and BLAME				
ALPHA	MKTRF	SMB	HML	UMD
Low BLAME High SUE - High BLAME High SUE				
0.341*	-0.036***	-0.070***	-0.038***	0.107***
(0.185)	(0.008)	(0.015)	(0.018)	(0.010)
Low BLAME Low SUE - High BLAME Low SUE				
0.616***	0.009	-0.044***	-0.117***	0.098***
(0.198)	(0.008)	(0.016)	(0.019)	(0.011)
Low BLAME High SUE - High BLAME High SUE				
0.440***	0.040***	-0.038***	0.062***	0.228***
(0.176)	(0.007)	(0.014)	(0.016)	(0.009)
High BLAME High SUE - High BLAME Low SUE				
0.792***	0.084***	-0.013	-0.017	0.219***
(0.220)	(0.009)	(0.017)	(0.020)	(0.011)

Table 6: Industry Adjusted Calendar Time Portfolio

This table presents various estimates of abnormal returns from industry adjusted portfolios sorted based on BLAME measure. The hold periods for these portfolios are trading day 2 to 60 after the date of conference calls. The hedged portfolio that takes long position in companies with BLAME equals to 0 and short positions in companies with BLAME greater than 80 percentile based on the previous quarter. The individual stock returns are adjusted by subtracting the matched value weighted Fama-French 48 industry returns. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

ALPHA	MKTRF	SMB	HML	UMD
		Excess Return		
0.408**				
(0.165)				
		3-Factor Model		
0.460***	-0.030***	0.007	-0.133***	
(0.159)	(0.006)	(0.013)	(0.014)	
		4-Factor Model		
0.449***	0.014**	-0.008	-0.080***	0.078***
(0.157)	(0.006)	(0.013)	(0.015)	(0.008)

Table 7: Predicting Future Earnings

This table examines whether BLAME is associated with lower earnings in the following quarter. The dependent variable is standardized unexpected earnings (scaled up by 10000). BLAME is percentage sentences attributing negative performance to industry or economy. Accrual is the accrued earnings divided by total assets ((IBCY-OANCFY)/ AT). LNUMEST is the log of one plus number of analysts covering the firm. BM is log book-to-market ratio. MOM is the lag 12 month cumulative return. INSTOWN is institutional ownership. VOLATILITY is the annualized daily volatility calculated using the data from the month preceding the conference call. TURN is the average share turnover in the month preceding the conference call. The specification of this regression is Fama-Macbeth regression. Newey-West standard errors are reported in the parentheses. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

VARIABLES	SUE	SUE
BLAME	-4.219***	-3.810***
	(0.940)	(0.810)
NEG		-5.628***
		1.017
BM		-4.879***
		(1.798)
Log(ME)		1.772*
		(0.894)
MOM		7.381***
		(1.095)
ACCRUAL		-1.564
		(1.289)
INSTOWN		6.437***
		(1.535)
TURN		-3.876***
		(1.377)
R-squared	0.002	0.02
Number of groups	39	39

Table 8: Recommendation Changes

This table reports Fama-Macbeth regressions with mean recommendation change as dependent variable. The independent variable is the difference between consensus analyst recommencation at the end of the 3-month period after conference call and the consensus recommendation right after the conference call. Newey-West standard errors are reported in parenthesis. BLAME is percentage sentences attributing negative performance to industry or economy. NEG is the percentage negative words in the text. SUE is standardized unexpected earnings. BM is log book-to-market ratio. MOM is the lag 12 month cumulative return. INSTOWN is institutional ownership. TURN is the average share turnover in the month preceding the conference call. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

VARIABLES	MEANRECCHG	MEANRECCHG
BLAME	-0.0205**	-0.0236***
	(0.00772)	(0.00727)
NEG		-0.0168*
		(0.00874)
SUE		0.0265**
		(0.0101)
Log(ME)		0.0561***
		(0.00979)
BM		0.0340***
		(0.0102)
MOM		0.0572**
		(0.0229)
TURN		-0.00330
		(0.00708)
INSTOWN		0.00984
		(0.0237)
R-squared	0.001	0.0137
Number of groups	40	40

Table 9: Contemporaneous Returns

This table reports results from contemporaneous returns regressions. The dependent variable is the cumulative abnormal return (adjusted using Fama-French 3 factor model) from trading day -1 to trading day 1 relative to the conference call. BLAME is percentage sentences attributing negative performance to industry or economy. Accrual is the accrued earnings divided by total assets ((IBCY-OANCFY)/ AT). NEG is the percentage negative words in the text. LNUMEST is the log of one plus number of analysts covering the firm. SUE is standardized unexpected earnings. BM is log book-to-market ratio. MOM is the lag 12 month cumulative return. INSTOWN is institutional ownership. VOLATILITY is the annualized daily volatility calculated using the data from the month preceding the conference call. TURN is the average share turnover in the month preceding the conference call. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	CAR[-1,1]	CAR[-1,1]
BLAME	-0.363***	-0.105**
	(0.0429)	(0.0404)
SUE		2.049***
		(0.0930)
BM		0.131**
		(0.0614)
Log(ME)		-0.0219
		(0.0803)
MOM		-0.305***
		(0.0845)
ACCRUAL		-0.264***
		(0.0604)
NEG		-1.009***
		(0.0725)
VOLATILITY		-0.622***
		(0.219)
INSTOWN		0.0536
		(0.0554)
LNUMEST		-0.132**
		(0.0609)
TURN		-0.0466
		(0.0811)
R-squared	0.002	0.074
Number of groups	40	40

Table 10: CEO Turnover

This table reports results from logit regression. The dependent variable is CEO turnover. The independent variables are BLAMEDUM (equals to 1 if BLAME is greater than 1 for one of the quarters in year t). LAGRET is identical to momentum, which is defined as past 12 month returns. INDRET is the matched Fama-French 48 industry returns. EXRET is the difference between LAGRET and INDRET. ROA is return on assets. CEO Age is the age of CEO reported on Execcomp. RETIRE is a dummy variable indicating that CEO is in the range of retirement age (equal or above 60). Additionally, year dummies are added as controls, but not reported in the table. Standard errors are clustered by Fama-French 48 industries. The odd columns besides the coefficient columns report the marginal effects from the coefficient estimates. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

VARIABLES	CEO TURNOVER	Margins	CEO TURNOVER	Margins
BLAMEDUM	-0.0126	-0.00104	-0.00609	-0.000988
	(0.0315)	(0.00262)	(0.0158)	(0.00256)
BLAMEDUM * LAGRET	0.0852***	0.00707***	0.0426***	0.00691***
	(0.0319)	(0.00261)	(0.0151)	(0.00242)
LAGRET	-0.245***	-0.0203***		
	(0.0288)	(0.00273)		
INDRET			-0.0995***	-0.0161***
			(0.0127)	(0.00226)
EXRET			-0.101***	-0.0164***
			(0.0307)	(0.00528)
ROA	-0.0753***	-0.00625***	-0.0393***	-0.00637***
	(0.0246)	(0.00212)	(0.0133)	(0.00223)
CEO Age	0.210***	0.0174***	0.113***	0.0183***
	(0.0480)	(0.00380)	(0.0253)	(0.00392)
RETIRE	0.321***	0.0267***	0.162***	0.0263***
	(0.0766)	(0.00625)	(0.0381)	(0.00612)
Pseudo R-Squared	0.0272		0.0273	
Observations	11,730	11,730	11,730	11,730

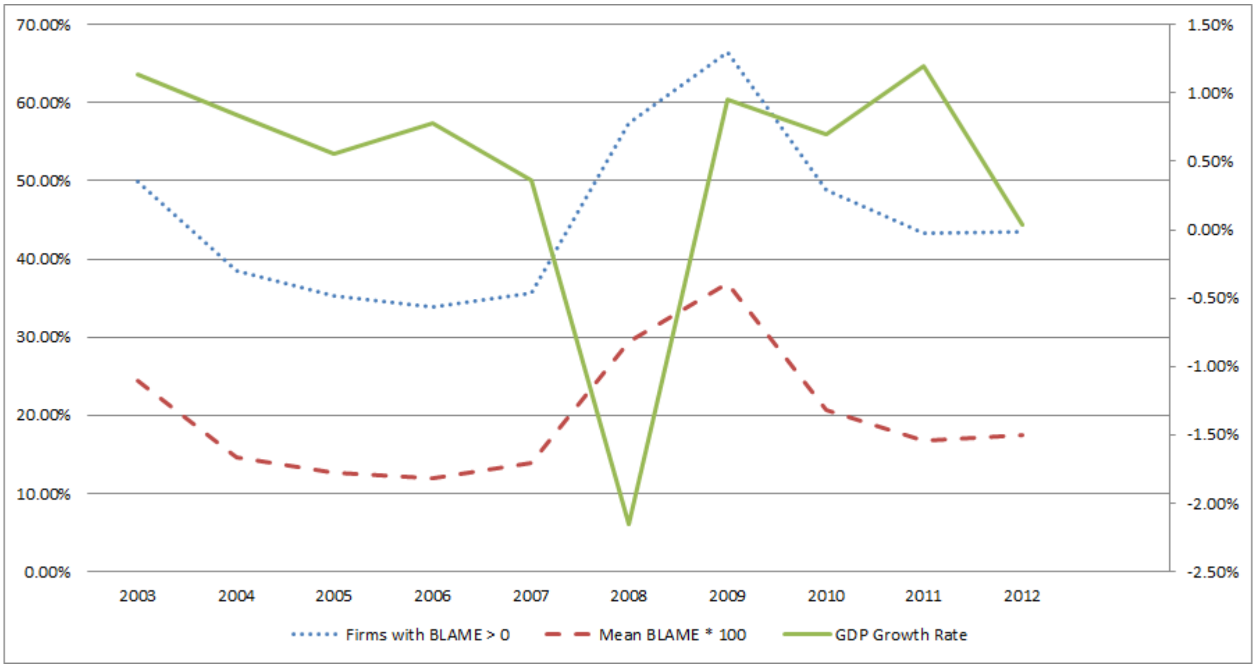

Figure 1: Time Series of BLAME

Table A1: Determinants of BLAME Measure

This table explores the determinants of BLAME measure. The table reports OLS regression with year-quarter dummies and CEO fixed effects. The standard errors (reported in parenthesis) is clustered by quarter. BLAME is percentage sentences attributing negative performance to industry or economy. Accrual is the accrued earnings divided by total assets ((IBCY-OANCFY)/ AT). NEG is the percentage negative words in the text. LNUMEST is the log of one plus number of analysts covering the firm. SUE is standardized unexpected earnings. BM is log book-to-market ratio. MOM is the lag 12 month cumulative return. INSTOWN is institutional ownership. VOLATILITY is the annualized daily volatility calculated using the data from the month preceding the conference call. TURN is the average share turnover in the month preceding the conference call. RSQ is the R-squared estimated using market and industry factors. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

VARIABLES	BLAME
SUE	-0.0294*
	(0.0147)
BM	-0.0200
	(0.0482)
Log(ME)	0.0932
	(0.0992)
RET	-0.113***
	(0.0194)
ACCRUAL	0.0158
	(0.0153)
NEG	0.727***
	(0.0527)
VOLATILITY	-0.00356
	(0.0173)
INSTOWN	-0.0389***
	(0.0142)
NUMEST	0.0300
	(0.0352)
TURN	-0.0413**
	(0.0200)
RSQ	-0.0809
	(0.113)
Constant	2.231***
	(0.0570)
R-squared	0.341
Observations	41,084

Table A2: Comovement with Market and Industry Factors and Returns

This table reports results from return predictability regressions. The dependent variable is the cumulative return from trading day 2 to trading day 60 following the conference call. BLAME is percentage sentences attributing negative performance to industry or economy. RSQ is the R-squared estimated using market and industry factors. Newey West adjusted standard errors are reported in parenthesis. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

VARIABLES	CAR[2,60]
BLAME	-0.660***
	(0.145)
RSQ	-0.168
	(0.163)
BLAME * RSQ	0.138
	(0.0884)
Number of groups	40
R-squared	0.006