Executives' Blaming External Factors and Market Reactions: Evidence from Earnings Conference Calls

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Abstract

We investigate how market participants react to corporate executives' strategically blaming the economy or industries for poor firm performance. In the quarters subsequent to earnings conference calls, we find that the "blame sentences", which capture executives' blaming tactics, predict negative and non-reverting abnormal returns, negative earnings surprises, and analyst recommendation downgrades. These blaming tactics also reduce the sensitivity of executives' turnover to their past performance. Our findings imply that executives strategically inject into the blame sentences the negative value-relevant information which market participants can digest by combining distinct categories of information (e.g., firm-specific vs economy-wide), leading to delayed market reactions to the blame sentences.

1 Introduction

It has been widely documented that people have tendencies to internalize successes and externalize failures (Bradley (1978), Miller (1978), and Baumeister (1982)). Do corporate executives also exhibit similar tendencies when explaining their firms' performance? If so, how different market participants react to these tendencies? In this paper, we attempt to answer these important questions by analyzing quarterly earnings conference call transcripts using an innovative textual analysis approach.

We develop a novel and simple sentence-based textual analysis methodology to extract the statements from earnings conference calls that assign blame to external factors (e.g., the economy or industries). For each conference call, we measure executives' tendency to attribute firms' poor performance to these external factors by the percentage of sentences that have negative descriptions of the economy or industries out of total number of sentences (referred to as the "blame measure" hereafter). We then isolate the effects of the *excessive* and *strategic* usage of the blame statements by corporate executives in quarterly earnings conference calls by controlling for industry×time fixed effects in our empirical tests.[1]

First, we uncover that our blame measure is significantly and negatively associated with two proxies for past firm performance, i.e., past 12-month cumulative returns and most recent earnings forecast errors. This result indicates that better performance by a firm reduces the need for executives to attribute its negative performance to external factors. In contrast, we find that those two proxies for past firm performance are not associated with the percentage of sentences with positive descriptions of the economy or industries (out of total number of sentences). These results are consistent with the idea that corporate executives strategically externalize the poor performance, but not the good performance, of their firms, and provide useful validation for our blame measure.

[1] In our validation analysis in Section 4.1, we find that there can be a mechanical and non-strategically-motivated "baseline" correlation between executives' negative descriptions of the economy or industries and the change in economic or industry conditions. In this paper, we primarily focus on executives' strategically blaming the external factors in the excess of this baseline correlation and investigate its economic implications.

Then, we document how different market participants react to executives' blaming tactics. We find that our blame measure predicts negative and non-reverting abnormal returns in the subsequent quarter after earnings conference calls. This result implies that investors underreact to the negative value-related information in the blame sentences since they need to process and combine distinct categories of information (e.g., firm-specific vs economy-wide) together to digest the implications of the blame sentences, and thus consume more cognitive resources.[2] We uncover that the economic magnitude of this "blame effect" is significant. Trading strategies which take long positions in firms without a blame sentence and take short positions in firms with high percentages of blame sentences generate annualized risk-adjusted returns of up to 6.8% under the four factor pricing model of Fama and French (1993) and Carhart (1997). These alphas survive after additionally controlling for the post earnings announcement drift and adjusting for industry-level returns, indicating that the blame effect is driven largely by firm-specific shocks. In addition, we also find that our blame measure predicts negative earnings surprises and analysts' recommendation downgrades in the quarter subsequent to earnings conference calls. These results support the idea that security analysts also underreact to the negative value-related information contained in the blame statements like investors. Taken together, all these results strongly and consistently indicate that market participants who have limited cognitive resources take longer time to digest the negative value-related information in the blame statements, which is strategically injected by executives when their firms perform poorly, because they contain the information that belongs to multiple categories.

Finally, we uncover that the blame measure is strongly associated with employment outcomes for corporate executives. Specifically, we present strong evidence that executives' strategically blaming external factors for poor firm performance is significantly associated

[2]This explanation for the return predictability by the blame measure is in similar spirits to Peng and Xiong (2006) and Cohen and Lou (2012). The model of Peng and Xiong (2006) predicts that investors who have limited attention tend to learn categorically, leading them to focus more on one category over the other. Cohen and Lou (2012) argue that the information dissemination about conglomerates is slower than that about standalones due to their more complicated internal structure, inducing a return predictability.

with a reduced sensitivity of executives' performance-turnover relation. This result implies that executives have incentives to inject the negative multi-categorical information, which induces delayed reactions by market participants, into their voluntary disclosures in the form of sentences blaming the external factors.

Several aspects of our findings are inconsistent with potential alternative explanations. First, our blame measure predicts negative abnormal returns in the subsequent quarter after earnings conference calls, and they do not revert afterward. This return pattern is against an interpretation that stock prices might initially overreact to executives' blaming tactics and then revert back to the fundamental values of firms. Second, we find that a similarly defined textual measure that captures positive descriptions of the economy or industries possesses no return predictability. This asymmetry in return predictability is difficult to explain with a standard risk-based explanation based on exposure to the economy or industries. Finally, our blame measure also predicts negative earnings surprises and analysts' recommendation downgrades in the quarter subsequent to earnings conference calls. These results further contrast with a risk-based explanation.

This paper makes significant contributions to several strands of existing literature. First, we contribute to an extensive literature on managers' strategic disclosure of information by showing that executives strategically inject the negative value-relevant information, which market participants can digest by combining different categories of contents, into disclosures when firms perform poorly. This form of strategic disclosure of information is novel in the literature but it is consistent with the theoretical predictions by Acharya et al. (2011) and Grenadier et al. (2014).[3] It is worthwhile to emphasize that executives' blaming tactics are likely to increase the amount of value-relevant information released to public, thus potentially being useful for investors, if digested timely and properly. Therefore, these tactics are distinct

[3]Acharya et al. (2011) develop a model with a prediction that a bad market news triggers firms' negative news releases and generates the clustering of negative announcements across firms. Grenadier et al. (2014) develop a real-options model with a prediction that managers strategically time the abandonment of bad projects until a common shock hits in an effort to protect their reputations.

from traditional "obfuscation" attempts made by executives to hide bad news about firms,[4] e.g., by injecting value irrelevant complex language or jargon into disclosures (Li (2008)), by spinning positive news through investor relations firms (Solomon (2012)), by employing excessive positive tone (Huang et al. (2013)), by holding evasive shareholder meetings (Li and Yermack (2014)), or by playing favorites for the bullish analysts (Cohen et al. (2020)). All these obfuscation-motivated tactics are likely to decrease the amount of valuable information released to investors and to reduce the efficiency in price discovery.

Second, our paper contributes to another extensive literature that explores how investors' bounded rationality affects asset prices. We find strong evidence that investors with limited cognitive resources take longer time to process different categories of information together than information in a single category, thus leading to their delayed reactions.[5] The underlying economic mechanism for our blame effect is distinct from but also consistent with that in Cohen and Lou (2012). Other studies in this literature have shown that investors' bounded rationality, especially the level of inattention, plays a critical role in determining the speed of information dissemination and the efficiency of price discovery in different economic settings.[6]

Third, we contribute to an existing literature on executives' performance and turnover relation by showing that executives' strategically shifting blame to external factors for poor firm performance is strongly associated with a lower probability of their being fired, which is a novel factor that can influence the outcomes of executive labor markets. Earlier studies have shown that executives' turnover is negatively associated with stock returns (Kaplan and Minton (2006)). Jenter and Kanaan (2006) show that negative industry shocks can lead to executives' turnover although the turnover sensitivity to industry shocks is lower than

[4]Kothari et al. (2009) present evidence that managers, on average, delay the disclosure of bad news to investors relative to good news.

[5]Existing studies in the literature on investors' categorical thinking have shown that investors with limited attention categorize the information and this behavior affects their asset allocations and asset prices. See, e.g., Barberis and Shleifer (2003), Peng and Xiong (2006), Jame and Tong (2014), Huang (2019), and Huang et al. (2019).

[6]For example, an incomplete list of recent papers include Cohen and Frazzini (2008), Menzly and Ozbas (2010), Noh (2014), Huang (2015), Chen et al. (2016), Cen et al. (2017), Parsons et al. (2018), Hoberg and Phillips (2018), and Scherbina and Schlusche (2020).

that to idiosyncratic shocks. Duchin and Schmidt (2013) also show that executives are less likely to be fired for poor merger and acquisition decisions when their peers are also riding on merger waves.

Finally, we make a novel methodological contribution to a burgeoning literature on textual analysis by demonstrating that our sentence-based approach has an ability to capture novel informational contents that can be missed by traditional bag-of-words approaches (Tetlock et al. (2008), Loughran and McDonald (2011), and Jegadeesh and Wu (2013)).[7] Our results indicate that analyzing and understanding words in the context of sentences can provide additional insight on financial texts.[8] It is a recent trend in multiple strands of literature to deviate from bag-of-words approaches, which rely on unigrams predominantly. For example, Li (2010a) uses a naive Bayesian machine learning approach to analyze the textual sentiment in forward-looking statements. Hoberg and Maksimovic (2015) use combinations of adjacent words to identify financially constrained firms. Cookson et al. (2021) present evidence that bigrams and trigrams can be important in capturing firms' usage of imprecise language in their 10-K disclosures and in understanding how market participants react to it.[9]

The remainder of the paper proceeds as follows. We develop testable hypotheses in Section 2. In Section 3, we introduce the source of the data and discuss the construction of our blame measure and other variables used in our empirical analyses. Section 4 presents and discusses the empirical test results of our hypotheses. In Section 5, we conclude the paper.

[7]More broadly, the results in our paper add to a large literature on the analysis of textual and linguistic information in financial markets. Earlier papers have documented that the textual tone in news articles contains the information about firm fundamentals (Tetlock et al. (2008) and Engelberg (2008)), and even noninformative tonal component can also affect asset prices (Tetlock (2011) and Engelberg and Parsons (2011)). In addition, Hanley and Hoberg (2010) show that the higher the proportion of informative contents in initial public offering (IPO) prospectuses, the less the IPO underpricing is.

[8]We find strong evidence that the information contained in the blame sentences and that in a list of negative words are distinct and thus market participants react to them differently. Specifically, the return predictability by our blame measure survives after controlling for the overall linguistic tone measure of conference call transcripts, which counts the number of negative words based on Loughran and McDonald (2011). In contrast, this linguistic tone measure is not predictive of future return.

[9]Other examples in this recent trend are Hassan et al. (2019) and Hassan et al. (2020) who develop textual measures of firm-level political risk and epidemic disease-related risk, respectively.

2 Hypothesis Development

Extensive evidence shows that people tend to attribute their success to their own efforts and their failures to external factors (e.g., Bradley (1978), Miller (1978), and Baumeister (1982)). Several studies provide different explanations for the potential roots of these behaviors. For example, Baumeister (1982) and Staw et al. (1983) argue that these behaviors are motivated by self-presentation purposes. In other words, people intentionally blame away their mistakes in order to defend themselves. Others view these behaviors as indicative of a behavioral bias (so-called self-serving attribution bias), which may be linked to managers' overconfidence in corporate settings (e.g., Billett and Qian (2008) and Li (2010b)). These theories of blaming behavior lead to a set of predictions in the setting of executives' information disclosure.

First, motivated by Kothari et al. (2009) and Grenadier et al. (2014), we hypothesize that corporate executives are more likely to attribute their firms' poor performance to external factors such as the economy or industries (than good performance) in quarterly earnings conference calls. If so, we should be able to find empirical evidence that our blame measure, which has a negative description of the economy or industries, is negatively associated with proxies for firms' past performance such as past cumulative returns and earnings forecast errors. Like the other side of the same coin, we also hypothesize that corporate executives are less likely to attribute firms' good performance to those external factors (than poor performance). Accordingly, we expect to find that the two proxies for firms' past performance have no significant association with a textual measure, which is defined similarly to the blame measure, to quantify a positive description of the economy or industries.

Second, we hypothesize that executives' blaming tactics are likely to be associated with negative price reactions by investors since they are likely to dump a lump of accumulated bad news into the blame statements when there is an opportunity to blame external factors. This prediction is motivated by Kothari et al. (2009), presenting evidence that managers accumulate and withhold bad news up to a certain threshold, and Acharya et al. (2011), showing that bad market news triggers clustering of negative announcements across firms. In addition, investors may not digest the value-relevant information contained in the blame statements immediately since they need to infer or extract value-related implications from the negative situations that the economy or their industries face. This process requires investors to combine different categories of information (e.g., firm-specific vs economy-wide) together and is likely to make them consume more cognitive resources.[10] As a result, investors who have limited cognitive resources are unable to incorporate the value-relevant information in the blame statements into stock prices fully and immediately. We hypothesize that higher blame measures predict lower and non-reverting abnormal returns in the quarter subsequent to conference calls. In the same spirit, other market participants, who share similar bounded rationality, may also react slowly to the information contents of the blame statements. For firms whose disclosures contain more blame statements, we accordingly hypothesize that security analysts are likely to be surprised by those firms' poor earnings in the following quarter and to downgrade their recommendations gradually after earnings conference calls. These hypotheses compose of our main set of predictions on how different market participants react to executives' strategically blaming external factors.

Finally, executives' blaming tactics can be related to their turnover. It has been well documented that poor firm performance leads to a higher probability of executive turnover (e.g., Murphy and Zimmerman (1993)). Jenter and Kanaan (2006) and Duchin and Schmidt (2013) find that boards of directors become more benevolent to executives either when poor firm performance is driven by industry-wide shocks or when industry peers are in a similar situation.[11] If a board of directors externalizes the main causes of poor performance following an executive's blame statement, it could be less likely to punish the executive. Therefore, we hypothesize that executives' blaming tactics are negatively associated with the sensitivity of their performance-turnover relation, which can serve as a major incentive for them to blame

[10] This idea is consistent with Barberis and Shleifer (2003), Peng and Xiong (2006), and Huang (2019).

[11] Bertrand and Mullainathan (2011) find that CEO compensation is sometimes affected by the performance of the entire industry.

the economy or industries for poor firm performance.

3 Data, Methodology, and Variable Construction

The quarterly earnings conference call transcript data used in our analyses come from two main sources: StreetEvents of Thomson One and Call Street of FactSet and they are collected manually. Our sample period starts from January, 2003 and ends at December, 2012. Both data sources together provide about 90,000 raw transcripts of earnings conference calls. After merging the conference call transcript data with CRSP, Compustat, and I/B/E/S, the sample size reduces to around 70,000 earnings conference call transcripts. For our sample, we remove observations with stock prices less than $2 in the month preceding each earnings conference call to mitigate concerns that might be caused by the bid-ask bounce following Jegadeesh and Wu (2013).

Many studies employ bag-of-words approaches to decipher the information in financial texts (e.g., Tetlock et al. (2008) and Loughran and McDonald (2011)). Some other studies consider multiple words in proximity to gain a better understanding of financial texts. One example is Hoberg and Maksimovic (2015) who search for the keywords from two different lists within 12 words from each other in order to determine whether a firm is financially constrained.[12] In our study, we use sentences as the basic unit for our analyses. One clear advantage of using sentences over the bag-of-words method is that sentences in principle express complete thoughts. As a result, our sentence-based methodology provides a more natural way to separate one group of related words from another group without needing to specify an artificial maximum distance between two proximate words. In addition, our methodology is easy to implement and does not require additional information other than a pre-determined financial dictionary such as the one proposed by Loughran and McDonald

[12]In addition, Hoberg and Moon (2015) consider paragraphs as a unit in their analyses and Cookson et al. (2021) employ not only unigrams but also bigrams and trigrams to contruct their linguistic imprecision measure.

(2011). Our approach also provides more context to the words in financial texts.

We parse the texts from the raw transcripts of earnings conference calls in the following way. We first split a given text into sentences by identifying punctuation, such as a period, a question mark, a semicolon, or an exclamation point, at the end of a sentence. For each sentence, we then search for words related to the economy or industries. Specifically, we employ the following procedure to identify words and phrases related to the economy or industries. We first add the basic terms "economy" and "industry," as well as their plural forms "economies" and "industries," to the initial word list. Further, we randomly sample 200 sentences containing "economic" or "industrial" from all earnings conference call transcripts. We check these sampled sentences to examine whether they describe the state of the economy or industries and to filter out phrases which are unrelated to the conditions of the economy or industries. We discover that none of the phrases that lead with "industrial" captures the conditions of industries, and thus the word is excluded from our final word list. Based on this exercise, we include "economic growth" and "economic condition," as well as their plural forms, as additional search terms in our final word list.[13] Then, each sentence identified as a description of the economy or industries is classified by the program into positive, negative, or neutral sentence based on the lists of positive and negative words proposed by Loughran and McDonald (2011). If more positive words appears in a sentence than negative ones, the sentence is classified as being positive about the economy or industries. If more negative words appear in a sentence than positive ones, the sentence is classified as having a negative description of the economy or industries (referred to as a "blame sentence").[14] Otherwise,

[13]Our test results on the return predictability by the blame measure are robust to a choice of these keywords or phrases. E.g., constructing the blame measure based on the two basic terms "industry" and "economy," as well as their plural forms, we find that the test results are consistent with those in Tables 4 and 5. We also consider other similar words, such as sector and segment, as indicators for mention of industry. By reading a random sample of conference call transcripts, we find that the words "sector" and "segment" most often refer to sector or segment within a company. Therefore, we decide not to include these two words in our final word list.

[14]We hired two research assistants and each of them independently examined a random sample of 200 sentences identified by the program as blame sentences. We find that the program correctly identified 170 and 161 out of these 200 sentences, respectively, which translates into an 82.75% accuracy rate on average.

the sentence is classified as being neutral about the economy or industries. In this paper, we primarily focus on the negative descriptions of the economy or industries, i.e., blame sentences, to capture executives' strategic blaming tactics reflected in earnings conference calls, and to examine how market participants react to the blame sentences.

To provide a better understanding of the contents that our blame sentences capture, we present a couple of example sentences extracted from earnings conference call transcripts in the top half of Table 1. Our keywords related to the economy or industries are presented in bold, while negative words and positive words are marked in red and green, respectively. Although we are not focusing on positive descriptions of the economy or industries, we also present a couple of their example sentences in the bottom half of Table 1 as a comparison. In Panel B of Table 2, we present the average numbers of sentences with positive, negative, and neutral descriptions of the economy or industries, respectively, denoted as N(POSITIVE), N(NEGATIVE), and N(NEUTRAL). We also report the average number of all sentences in an earnings conference call transcript, denoted as N(SENTENCE). We uncover that on average there are more sentences with positive or neutral descriptions of the economy or industries than sentences with negative descriptions, indicating that there is a relatively high hurdle for a sentence to be qualified as a blame sentence.[15] Overall, the number of blame sentences is relatively low.

For each earnings conference call, we calculate our blame measure as the percentage of the blame sentences out of all sentences as follows and call it BLAME:

$$\text{BLAME} = \frac{\text{N(NEGATIVE)}}{\text{N(SENTENCE)}}. \tag{1}$$

Similarly, we construct the POSIE measure as the percentage of the sentences that contain

[15] This is consistent with that on average corporate executives tend to use more positive words in their disclosures.

positive descriptions of the economic or industry conditions out of all sentences:

$$\text{POSIE} = \frac{\text{N(POSITIVE)}}{\text{N(SENTENCE)}}. \tag{2}$$

For our sample, in Panel C of Table 2, we find that the pairwise correlation of BLAME and POSIE is significantly positive at 0.32. Thus firms that employ the blame sentences more frequently are also more likely to use the positive descriptions of the economy or industries in their earnings conference calls. In addition, to ensure that BLAME captures the unique and distinct information from the negative tone of the overall text, we construct a proxy for the negative tone of each earnings conference call transcript as follows and call it NEG (in percentage):[16]

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

which is based on the list of negative words by Loughran and McDonald (2011). We expect that NEG is positively correlated with BLAME by their constructions. In Panel C of Table 2, we indeed find that the pairwise correlation of NEG and BLAME is significantly positive at 0.29, while that of NEG and POSIE is negative and insignificant. Tetlock et al. (2008) and Loughran and McDonald (2011) find that NEG captures more information than a similarly defined proxy for the positive tone of the overall text. Following these two studies, in our subsequent analyses, we employ NEG as the main variable that controls for the overall textual tone of earnings conference call transcripts. However, we also find that our blame effect is robust to controlling for a composite tone measure, calculated as the difference in number between negative words and positive words, scaled by the total number of words in each earnings conference call transcript.[17]

[16] We also build up a sentence-based negative tone measure. This measure is calculated as the total number of negative sentences dividend by the total number of sentences in each earnings conference call transcript. The negative sentences are the ones with more negative words than positive words. The test results presented in this paper are robust to controlling for this alternative measure of negative tone instead of NEG.

[17] When limiting the search for the blame sentences to paragraphs containing company performance-related information (such as earnings, revenues, sales, margin, and so on), we also find that our blame effect remains robust.

Next, we combine our textual variables built up above with common financial, accounting, and analyst-related variables based on CRSP, Compustat, and I/B/E/S databases. The list of these non-textual variables include the pre-conference-call earnings forecast error (FE), book-to-market ratio (BM),[18] market equity (ME) defined as price times the total number of shares from the end of the previous year, past 12-month cumulative return (MOMENTUM), accrual (ACCRUAL) defined as the accrued earnings divided by total assets,[19] annualized volatility of daily returns (VOLATILITY) in the preceding month, percentage of institutional ownership (INSTOWN) in the preceding quarter, number of analysts following (NUMEST) from the latest forecast period, and average daily share turnover (TURNOVER) in the preceding month before each earnings conference call.[20] All variables are pre-conference-call quantities based on the information available as of each earnings conference call date. Among them, we define the pre-conference-call earnings FE in detail as follows: For stock i in quarter t,

$$\mathrm{FE}_{i,t} = \frac{\mathrm{E}_{i,t} - \mathrm{F}_{i,t}}{\mathrm{P}_{i,t}}, \tag{3}$$

where $\mathrm{E}_{i,t}$ denotes the quarterly realized earnings for firm i, $\mathrm{F}_{i,t}$ represents the most recent consensus (mean) of earnings forecasts across analysts following stock i available before each realized earnings, and $\mathrm{P}_{i,t}$ is the stock price at the end of the I/B/E/S statistical period when the consensus of analysts' earnings forecasts is calculated. The consensus of analysts' earnings forecasts is formed on the closest I/B/E/S statistical period end date prior to each realized earnings. We then winsorize FE at the 1st and 99th percentiles of its distribution to eliminate potential outliers. In Panels A and C of Table 2, we present the summary statistics and pairwise correlations for a list of variables used in the subsequent analyses.

[18] BM is defined as the logarithm of the book-to-market ratio from the end of the previous year. To avoid a potential forward-looking bias, we require a six-month gap between the end of the previous year and each earnings conference call date.

[19] I.e., ACCRUAL = (IBCY-OANCFY)/ATQ based on Compustat. The information on ACCRUAL is taken from the quarter associated with each earnings conference call.

[20] We define VOLATILITY as the variance of daily returns in the preceding month before each earnings conference call. We define INSTOWN based on the 13-F data as the number of shares held by institutions divided by total number of shares outstanding at the end of the previous quarter before each conference call.

Finally, we decompose a firm's past return performance into its systematic and firm-specific components. Specifically, we first run the following daily time-series regression over period T (either a quarter or a year depending on test): For stock i on day d,

$$\mathrm{RETRF}_{i,d} = \alpha_i + \beta_{\mathrm{MKT},i}\mathrm{MKT}_d + \beta_{\mathrm{IND},i}\mathrm{IND}_{I,d} + \epsilon_{i,d}, \tag{4}$$

where $\mathrm{RETRF}_{i,d}$ is the daily return of stock i in the excess of risk-free rate, MKT_d is the daily market return from Ken French's library, and $\mathrm{IND}_{I,d}$ is the equal-weighted daily return of the industry to which firm i belongs based on the SIC-3 industry classifications. For each stock i, with the parameters estimated from equation (4), we then define the systematic and firm-specific components of past returns over period T, respectively, as:

$$\begin{aligned} \mathrm{SRET}_{i,T} &= \sum_{d\in T}\hat{\beta}_{\mathrm{MKT},i}\mathrm{MKT}_d + \sum_{d\in T}\hat{\beta}_{\mathrm{IND},i}\mathrm{IND}_{I,d}, \\ \mathrm{FRET}_{i,T} &= \hat{\alpha}_i, \end{aligned} \tag{5}$$

where, e.g., $\hat{\beta}_{\mathrm{MKT},i}$ is the estimate of $\beta_{\mathrm{MKT},i}$ and $\sum_{d\in T}\hat{\epsilon}_{i,d} = 0$ since $\hat{\epsilon}_{i,d}$ represents residuals from equation (4). Based on this SRET (FRET), we also construct a negative-performance-based indicator variable, SRETDUM (FRETDUM), that equals one when SRET (FRET) is negative, and equals zero otherwise. These SRETDUM and FRETDUM provide binary measures for each firm's poor systematic and idiosyncratic returns over period T, respectively.

4 Reactions to Executives' Blaming External Factors

4.1 Validation

We here investigate how BLAME and POSIE, which were constructed by our sentence-based textual methodology introduced in Section 3, are correlated with other variables. This analysis provides useful validation not only for our sentence-based textual approach but also for our blame measure intended to capture executives' strategic blaming tactics before examining the reactions by different market participants to the blame sentences in the subsequent analyses.

As an initial investigation, we explore the time-series variability of two aggregate variables based on BLAME to examine whether they are correlated with macroeconomic fluctuations. We present the time-series plots of the cross-stock mean of BLAME, the percentage of firms with positive values of BLAME (out of all available firms), and the contemporaneous growth in gross domestic product (GDP) in Figure 1. The economic performance captured by the GDP growth seems to be negatively associated with the blame measure on average, which is the most clear in 2008 and 2009 during the Great Recession.[21] This observation suggests that executives naturally tend to discuss the negative performance of the economy or industries more frequently when the economic growth is lower, and thus there can be a mechanical and non-strategically-motivated baseline link between BLAME and the change in the economic or industry conditions. Accordingly, in all of our subsequent tests, we include industry×time fixed effects in panel regressions as an attempt to isolate the effects of executives' *excessive* and *strategic blaming* over this baseline behavior.[22]

Next, we examine the hypothesis that measures related to past firm performance are negatively associated with BLAME, but are not associated with POSIE, by exploring the determinants of BLAME and POSIE. Specifically, we run the following panel regression: For stock i in quarter t,

$$\text{BLAME}_{i,t} = \alpha + \gamma' \mathbf{X}_{i,t} + \epsilon_{i,t}, \tag{6}$$

where $\mathbf{X}_{i,t}$ is a column vector with explanatory variables which potentially affect our blame measure and which will be also employed as control variables in our tests of market reactions to BLAME below, and γ is another column vector with the corresponding slope coefficients.

[21] The quarterly correlations of the GDP growth with the cross-stock mean of BLAME and the percentage of firms with positive values of BLAME are −0.57 and −0.56, respectively. Excluding 2007 to 2009, these correlations reduce to 0.03 and −0.01, respectively.

[22] Our industry×time fixed effects are based on the SIC-3 industry classifications. All test results for our blame effect are robust to using an alternative industry classification, such as the Fama-French 48 industry classification and the FNIC 500 classification from Hoberg and Phillips (2010, 2016).

The explanatory variables include the pre-conference-call earnings forecast error (FE), book-to-market ratio (BM), market equity (ME) in logarithm, past 12-month cumulative return (MOMENTUM), accrual (ACCRUAL) defined as the accrued earnings divided by total assets, negative tonal measure (NEG), annualized volatility of daily returns (VOLATILITY), percentage of institutional ownership (INSTOWN), logarithm of one plus number of analysts following (LNUMEST), and average daily share turnover (TURNOVER). We construct all these explanatory variables based on the information available to executives as of the time of each earnings conference call and provide their detailed definitions in Section 3. For ease of interpretation, each of explanatory variables is standardized to have the mean of zero and the standard deviation of one. To ensure that our test results are not driven by time-varying industry-wide dynamics, we also control for industry×quarter fixed effects based on the SIC-3 classifications when estimating equation (6). Following Petersen (2009), we calculate the clustered standard errors by industry to control for potential serial correlations in BLAME.

We present the test results of equation (6) in Table 3. In Columns (1) and (2), we find that the evidence strongly supports our hypothesis: firms with worse performance in either financial or accounting metrics tend to employ more blame statements in their earnings conference calls. Specifically, FE is significantly and negatively associated with BLAME, indicating that firms with lower earnings surprises before conference calls tend to have the negative descriptions of the economy or industries more frequently during the conference calls. Similarly, MOMENTUM is also significantly and negatively associated with BLAME, indicating that lower past returns tend to increase executives' blaming the economy or industries during earning conference calls. The percentage of negative words (NEG), which can serve as a proxy for the other negative information revealed linguistically through the conference call, has a positive and highly significant coefficient as expected.[23] The valuation is strongly negatively related to the blame measure, as indicated by the positive and significant coefficient of BM. Interestingly, in Columns (1) and (2), we find that the values of R-squared

[23]In Columns (1) and (2), our findings are robust to including or excluding NEG in equation (6).

stay fairly similar at 34% and 31%, respectively, with and without controlling for NEG. This is consistent with the pairwise correlation of BLAME and NEG being at 0.29 (see Panel C of Table 2). These results imply that BLAME captures unique informational contents from earnings conference calls, and it is distinct from NEG which counts the number of negative words. These results also demonstrate that our sentence-based approach indeed captures novel information that can be missed by traditional bag-of-words approaches.

We repeat the same regression analysis with POSIE as the dependent variable in equation (6), which is the percentage of positive sentences about the economy or industries (out of all sentences) for each earnings conference call. From Columns (3) and (4), we find no significant association between any of the two past firm performance metrics (FE and MOMENTUM) and POSIE. This implies that executives do not attribute firms' good performance to the external factors like the economy or industries, which is a sharp contrast with their blaming tactics when firms perform poorly. Taken together, the main findings in Table 3 support the hypothesis that corporate executives tend to externalize their poor performance, but are reluctant to associate their good performance to the economy or industries.

In Table 3, we also examine how other explanatory variables influence BLAME. Larger firms are associated with higher values of BLAME, indicated by the significant and positive coefficient of ME (in logarithm). The security analyst coverage captured by LNUMEST is significantly and negatively associated with BLAME. Moyer et al. (1989) argues that higher analyst coverage is associated with a higher level of external monitoring. Security analysts also confront a firm's management about its poor performance from time to time. Thus, the negative coefficient of LNUMEST indicates that intense external monitoring reduces the frequency of corporate executives' blaming the economy or industries. To the extent that investors' trading activities capture a firm's visibility, as advocated by Gervais et al. (2001), Kaniel et al. (2012), and Israeli et al. (2020), the significant and negative coefficient of TURNOVER implies that the visibility also reduces managers' tendency to blame.

4.2 Immediate Return Reaction

We now investigate how investors react to corporate executives' strategic blaming tactics on the earnings conference call period by running the following panel regression: For stock i in quarter t,

$$\text{CAR}[-1,1]_{i,t} = \alpha + \beta\text{BLAME}_{i,t} + \gamma'\mathbf{X}_{i,t} + \epsilon_{i,t}, \tag{7}$$

where $\text{CAR}[-1,1]_{i,t}$ is the cumulative abnormal return over the three-trading-day period from one-day before and one-day after each earnings conference call day, which is obtained by controlling for the contributions of the three factors under Fama and French (1993).[24] $\mathbf{X}_{i,t}$ is a column vector that contains a set of control variables based on equation (6) and γ is another column vector with the corresponding slope coefficients. For ease of interpretation, each of explanatory variables is standardized to have the mean of zero and the standard deviation of one. To ensure that our test results are not driven by time-varying industry-wide dynamics, we control for industry×quarter fixed effects in equation (7). Additionally, to control for the cross-stock correlation in $\text{CAR}[-1,1]$, we calculate the clustered standard errors by quarter following Petersen (2009).[25]

We provide the test results of equation (7) in Table 4, where the slope coefficients are presented in percentage. In Column (1), the univariate regression indicates that our blame measure is negatively associated with the abnormal return on the earnings conference call period and its slope coefficient is highly significant at the 1% level. It also implies that one standard deviation increase in BLAME (=0.33%) leads to 38 basis points (bps) decrease in the abnormal return on the earnings conference call period. When adding a set of control variables, including NEG, into Column (2), we find that the slope coefficient of our blame measure is negative and significant at the 5% level although its magnitude is reduced to 13

[24]Their factor loadings are estimated using daily returns over the interval of [-180,-15] relative to the date of each earnings conference call. Our test results in Sections 4.2 and 4.3 are robust when we calculate the abnormal return on a given day as the difference in return between stock i and the market portfolio.

[25]The test results are robust when we calculate the double-clustered standard errors by quarter and by industry (or firm).

bps compared to the univariate regression. This immediate and negative market reaction to BLAME implies that the blame sentences in earnings conference calls contain negative value-relevant information about firms, which is distinct from the information in NEG,[26] and investors understand and incorporate a part of it into stock prices. In addition, we find that the slope coefficient of NEG is negative and highly significant at the 1% level. Interestingly, the magnitude of its slope coefficient at 99 bps is about eight times larger than that of BLAME at 13 bps. This difference in magnitude implies that investors react to the information in NEG much more strongly and immediately than the information in BLAME. When replacing BLAME with POSIE for equation (7), we find in Column (4) that the slope coefficient of POSIE is positive but insignificant in the presence of controls. Thus there is no immediate return reaction to the positive descriptions of the economy or industries, implying that no value-relevant information is revealed through them.

Overall, these test results support our hypothesis that managers opportunistically bundle accumulated negative information into the blame statements in earnings conference calls, generating the negative and immediate return reactions.

4.3 Delayed Return Reaction

If investors do not fully understand the value-relevant implications of the blame sentences during the earnings conference call period, they would react to the negative information in BLAME slowly and thus it could negatively predict the subsequent returns after earnings conference calls. This is likely when the two conditions are met: 1) the informational contents of BLAME and NEG are distinct, and 2) investors consume more cognitive resources to digest the information in BLAME than that in NEG while they suffer from the limited cognitive resources. In Section 4.2, we already had supportive evidence for the first condition. The second condition could be also met in our setting if investors need to infer value-relevant

[26] We repeat the test in equation (7) by replacing BLAME with the "residual" blame measure, BLAME_R, which we obtain from the regression of BLAME on NEG and an intercept. From this modified regression, we also find that the slope coefficient of BLAME_R is negative and significant.

implications for their firms from the negative situations that the economy or industries are facing, which requires them to process and combine distinct categories of contents together.

We now investigate how investors react to corporate executives' strategic blaming tactics after the earnings conference call period by running the following regression: For stock i in quarter t,

$$\text{CAR}[2,60]_{i,t} = \alpha + \beta \text{BLAME}_{i,t} + \gamma' \mathbf{X}_{i,t} + \epsilon_{i,t}, \tag{8}$$

where $\text{CAR}[2,60]_{i,t}$ is the cumulative abnormal return over the 60-trading-day period, which is approximately the same as three calendar months, after the earnings conference call period. Past studies such as Dellavigna and Pollet (2009) and Hirshleifer et al. (2009) employ the same predictive horizon in analyzing the post-earnings announcement drift (PEAD) since the information from earnings announcements is largely realized over this time horizon. The abnormal return is obtained by controlling for the contributions of the three risk factors under Fama and French (1993). $\mathbf{X}_{i,t}$ is a column vector that contains a set of control variables based on equation (6) and γ is another column vector with the corresponding slope coefficients. For ease of interpretation, each of explanatory variables is standardized to have the mean of zero and the standard deviation of one. To make sure that our test results are not driven by time-varying industry-wide dynamics, we control for industry$\times$quarter fixed effects in estimating equation (8). In addition, to control for the cross-stock correlation in $\text{CAR}[2,60]$, we calculate the clustered standard errors by quarter.

We provide the test results of equation (8) in Table 5, where the slope coefficients are presented in percentage. In Column (1), the univariate regression shows that the coefficient of our blame measure is negative and significant at the 1% level. The economic magnitude implied by this coefficient is substantial. On average, one standard deviation increase in BLAME (= 0.33%) leads to about 35 bps decrease in abnormal return over the subsequent 60-trading-day period after earnings conference calls. In Column (2), we add a set of control variables including NEG into equation (8) to ensure that the test result from the univariate regression is not driven by potential confounding effects of known return predictors. We find that our blame measure can still predict negatively and significantly the post-conference-call abnormal return although its economic magnitude decreases. Although NEG is negatively correlated with the future abnormal return, its coefficient becomes statistically insignificant in any conventional level, indicating that NEG is not predictive of the subsequent abnormal return after earnings conference calls. Combining the results in Tables 4 and 5, we conclude that average investors understand about 30% ($=\frac{13.4}{13.4+30.7}$) of the value-related information in BLAME immediately, while they digest the remaining 70% ($=\frac{30.7}{13.4+30.7}$) of the information gradually over the next 60-trading-day period after conference calls. In contrast, investors tend to understand the negative information contained in NEG almost immediately during the earnings conference call period. These results confirm that the information in BLAME is distinct from the one in NEG (as in Table 3), thus leading investors to react to these two textual measures differently. In addition, we present evidence that our blame measure possesses additional return predictability beyond the widely observed PEAD (e.g., Bernard and Thomas (1989)) since controlling for FE does not weaken the blame effect significantly.[27] In Column (4), when replacing BLAME with POSIE for equation (8), the slope coefficient of POSIE is statistically indistinguishable from zero in the presence of controls. Together, these findings are supportive for the idea that executives strategically inject the negative value-relevant information into the blame sentences in earnings conference calls, while the sentences with positive descriptions of the economy or industries contain no such information.

Further, we investigate whether our blame measure can predict the abnormal return in a longer horizon. Specifically, in equation (8), we replace CAR[2,60] with CAR[61,252], which is the cumulative abnormal return defined over a period between 61 and 252 trading days (approximately one calendar year) after each earnings conference call. We present the test results of this regression in Appendix Table A2. We find no indication of a return reversal

[27] In Appendix Table A1, we also repeat our tests in equation (8) by replacing FE with EADCAR[-1,1], which is calculated over the earning announcement period, as an alternative proxy for the PEAD following Frazzini (2006). Our test results are robust to this alternative specification.

that the blame measure is positively correlated with future abnormal returns over this longer horizon. The coefficient of BLAME is negative but statistically indistinguishable from zero at any conventional significance level. This evidence implies that the negative predictability of CAR[2,60] by our blame measure is unlikely driven by an overreaction to BLAME. Also it is worthwhile to emphasize that this pattern of abnormal returns subsequent to conference calls is inconsistent with a risk-based explanation since BLAME should have been positively correlated with the expected return if it is a proxy for a firm's exposure to latent systematic risk factors.[28]

Next, to evaluate its economic magnitude on a deeper level, we investigate how much profit investors can make from the blame effect by forming calendar time portfolios following Lyon et al. (1999). Specifically, in the beginning of each quarter, we first set the cutoff point for the long-side portfolio at 0, and the cutoff point for the short-side portfolio at the top 20% of the distribution of BLAME observations obtained from the previous quarter. Then, in the quarter, a blame measure is calculated for each earnings conference call. If the blame measure equals 0, the firm is added to the long-side portfolio for the trading day $d+2$ relative to the earnings conference call day d. If the blame measure is higher than the short-side cutoff, the firm is added to the short-side portfolio for the trading day $d+2$ relative to the earnings conference call day d. We hold the same firm within each portfolio for 60 trading days since its inclusion on the trading day $d+2$, require at least ten stocks included for each portfolio, and then calculate equal-weighted return across stocks.[29] Finally, we calculate the risk-adjusted return, i.e., alpha, of the long-short portfolio under the four-factor asset pricing model combining Fama and French (1993) and Carhart (1997). We provide this result in Panel A of Table 6, which indicates that the hedged portfolio generates substantial risk-adjusted returns. E.g., we obtain an alpha of 59 bps per month (=7% per year) under the

[28]In Section 4.4 below, we analyze the relations of our blame measure with the future earnings surprise and change in stock recommendations made by security analysts. These additional analyses are useful to further disentangle our information-based explanation and a risk-based explanation.

[29]When employing value-weighted portfolio returns, we find that the magnitudes of risk-adjusted returns are slightly lower than those reported in Tables 6 and 7, but they are significant at the 5% level.

three-factor model, and an alpha of 57 bps per month (=6.8% per year) under the four factor model, respectively. Both alphas are statistically significant at the 1% level. Therefore, we find that the investment signals obtained from the blame sentences in earnings conference calls are highly valuable to investors and the performance of an associated trading strategy is not explained by the exposure to four prominent risk factors.

To make sure that our results on alphas are not driven by a nonlinear relation between BLAME and a proxy for the PEAD, we repeat our analysis by forming portfolios based on an independent double sort on BLAME and FE. Similar to the previous one-way sort in Panel A, the high BLAME group includes stocks whose blame measures belong to the top 20%, while the low BLAME group includes stocks whose blame measures are 0. For each quarter, the two breakpoints for FE are the top and bottom 30% of the distribution of realized FEs from the previous quarter. We separately examine the economic magnitude of the BLAME-sorted long-short portfolio for each of low and high FE groups in Panel B of Table 6. In both cases, we find that the BLAME-sorted hedging portfolios generate positive and significant four-factor alphas. However, the alpha of the BLAME-sorted hedging portfolio from the high FE group is much lower than the same alpha from the low FE group. These results imply that the blame effect becomes much stronger among firms with poor earnings performance, which is consistent with the idea that executives tend to use more blame statements strategically when firms suffer from worse earnings performance.

Figure 2 presents the cumulative abnormal returns for the BLAME-sorted portfolios in the event window ranging from -120 to 120 trading days around the earnings conference call day. These results indicate that firms in the high BLAME group (in red dashed line) have experienced strong poor returns for 120 trading days before the earnings conference call day and then continue to perform poorly for 120 trading days afterward. This is the main driving force for the performance of the BLAME-sorted long-short portfolio (in cyan dash-dotted line). In contrast, firms in the low BLAME group (in blue solid line) have much less change in cumulative abnormal return over the same event window. This asymmetry between the high and low BLAME groups is another confirmation that our blame effect is not a manifestation of the PEAD since the only past poor performance largely continues after earnings conference calls, while the past good performance does not.

A potential alternative explanation for the performance of the BLAME-sorted long-short portfolios is as follows. Our blame measure might capture the negative information about the future performance of industries which a firm belongs to, and investors might underreact mainly to this industry-wide information. To investigate this possibility, we now construct industry-adjusted calendar time portfolios. Specifically, we calculate the following daily industry-adjusted return by subtracting the daily value-weighted return of the matched SIC-3 industry portfolio (IND): For each stock i on day d,

$$\mathrm{RET}_{ADJ,i,d} = \mathrm{RETRF}_{i,d} - \mathrm{IND}_{I,d}. \tag{9}$$

We then employ these daily industry-adjusted stock returns to construct the BLAME-sorted long-short portfolio by following the same procedure discussed above. If the risk-adjusted returns obtained from the previous calendar time portfolio approach is driven mainly by investors' underreaction to the industry-wide negative information revealed by executives, this adjustment by industry-level returns should eliminate the risk-adjusted returns identified above or substantially reduce their magnitudes. We provide the test results for the industry-adjusted calendar time portfolios in Table 7. We find that the risk-adjusted returns remain positive and highly significant at the 1% level under the three-factor and four-factor asset pricing models. The three-factor alpha is 5.4% per year, and the four-factor alpha is 5.3% per year. These economic magnitudes of alphas are slightly lower than those in Table 6 without the industry-level adjustment, which indicates that a small portion of the blame effect is potentially due to the negative industry-wide information. However, the overall evidence is much more supportive for the idea that our blame measure reflects the negative and largely firm-specific information.

Taken together, all test results in this subsection provide strong evidence that our blame measure predicts the negative abnormal return significantly in the period subsequent to earnings conference calls. These results imply that on average investors tend to underreact to the negative firm-specific information captured by the blame measure due to their limited cognitive resources.[30]

4.4 Security Analysts' Reactions

We now investigate how security analysts react to corporate executives' strategic blaming tactics reflected on earnings conference call transcripts based on the two different outcomes of their activities: forecasts of future earnings and stock recommendations. Compared to the two return-based tests in Sections 4.2 and 4.3, these analyses based on security analysts' earnings forecasts and recommendations can provide unique and additional insights on a potential underlying economic mechanism that drives the blame effect. Specifically, to the extent that security analysts are not involved in actual trading of stocks that they follow, the tests with future earnings surprises and changes in stock recommendation can provide us convincing reasons to disentangle our information-based explanation and a risk-based explanation for the blame effect.

We first examine whether security analysts understand and incorporate the value-relevant information in the blame sentences into their earnings forecasts in a timely manner. If the blame measure is predictive of future earning surprises, it suggests that security analysts do not immediately understand the information in the blame sentences, thus being unable to incorporate it into their projections of firms' future earnings. We test this hypothesis using the following regression: For stock i in quarter t,

$$\mathrm{SUE}_{i,t} = \alpha + \beta \mathrm{BLAME}_{i,t} + \gamma' \mathbf{X}_{i,t} + \varepsilon_{i,t}, \tag{10}$$

[30] These are consistent with the theoretical prediction by Peng and Xiong (2006) that investors with limited attention tend to focus more on market or sector-wide information than firm-specific information. They call this behavior investors' category-learning.

where $\text{SUE}_{i,t}$ is the *future* standardized unexpected earnings (SUE), which is defined similarly to FE in equation (3) but for the next quarter after each earnings conference call and is scaled up by 10,000, $\mathbf{X}_{i,t}$ is a column vector that contains the same set of control variables (except the pre-conference-call FE) as in equations (7) and (8), and γ is another column vector with the corresponding slope coefficients. For ease of interpretation, each of explanatory variables is standardized to have the mean of zero and the standard deviation of one. To make sure that our test results are not driven by time-varying industry-wide dynamics, we control for industry×quarter fixed effects when estimating equation (10). To control for the potential cross-stock correlation in SUE, we also calculate the clustered standard errors by quarter.

We present the test results in Table 8. From the univariate and multivariate regressions, we find that our blame measure predicts the earnings surprise in the next quarter negatively and significantly at the 5% level. This result indicates that like investors, on average, security analysts do not immediately understand the negative value-relevant implications of the blame sentences, and as a result, they are slow in incorporating this negative information into their forecasts of firms' future earnings. This supports our information-based explanation for the blame effect, and also implies that investors and security analysts share a common bounded rationality that slows down them to digest the information in the blame statements.

We next investigate whether security analysts digest the value-relevant information in the blame sentences and incorporate it into their recommending stocks in a timely manner. Specifically, for stock i in quarter t, we first define the change in analyst recommendation consensus (mean), i.e., $\text{MEANRECCHG}_{i,t}$, as the difference between the consensus over the 60-trading-day period, starting from two days after each earnings conference call, and the consensus over the two-trading-day period, including the conference call day and the next day. We then replace SUE with MEANRECCHG and re-estimate equation (10) with this new dependent variable. As reported in Table 9, we find strong evidence that our blame measure negatively predicts the change in the consensus recommendation subsequent to earnings conference calls. This result implies that security analysts gradually understand the negative value-relevant information that corporate executives inject into the blame sentences, as they realize that the stock prices of firms with high blame measures are overvalued. This evidence is consistent with the predictability by our blame measure of the abnormal returns and earnings surprises in the subsequent periods after earnings conference calls.

Taken together, the test results based on security analyst reactions to executives' strategic blaming tactics corroborate our information-based explanation for the blame effect.

4.5 Blame Effect and Decomposition of Past Performance

One interesting picture that emerges from Table 3 and Figure 2 is a potential economic link between firms' poor past performance and the blame effect. Since corporate executives are more likely to employ negative descriptions of the economy or industries strategically when their firms experience poor performance (as shown in Table 3), we are also likely to observe a stronger blame effect in those times (as suggested by Figure 2). We here investigate this economic link by using the past 90-day returns up to the earnings conference call date as a firm's past performance, and obtain more insights on the blame effect by decomposing the past return performance into its firm-specific and systematic components.

First, we test whether the predictability of future abnormal returns by our blame measure becomes stronger when firms suffer from either poor firm-specific or systematic performance in the quarter leading up to each conference call date. We conduct the test by adding two dummy variables related to past firm-specific and systematic returns, i.e., FRETDUM and SRETDUM, respectively, and their interaction terms with BLAME into equation (8). Based on equation (5), FRETDUM is an indicator variable that equals one if the firm-specific return (FRET) over the past 90-day period is negative, while SRETDUM is an indicator variable that equals one if the systematic return (SRET) over the same 90-day period is negative. In Column (1) of Table 10, we find that the slope coefficient of the firm-specific interaction term (FRETDUM$\times$BLAME) is negative, while that of the systematic interaction term (SRETDUM$\times$BLAME) is positive, although both of them are insignificant.

This evidence suggests that the blame effect may become stronger when firms experienced poor idiosyncratic performance in the past.

Next, we examine whether the predictability of future earnings surprises by the blame measure is stronger when firms suffer from poor firm-specific or systematic performance over the past 90-day period. We repeat the estimation of equation (10) after adding FRETDUM and SRETDUM and their interaction terms with BLAME, whose results are presented in Column (2) of Table 10. We find that the coefficient for FRETDUM×BLAME is negative and highly significant at the 1% level, while that for SRETDUM×BLAME is negative but statistically indistinguishable from zero. We also find that after including those interaction terms, the coefficient for BLAME itself becomes positive although insignificant, indicating that the negative SUE predictability by our blame measure in Section 4.4 is mainly driven by firms with past poor idiosyncratic returns. Together, these results imply that the poor firm-specific performance in the past is a much more important economic channel through which the blame effect arises than the poor systematic performance in the past.

Lastly, we also examine when our blame measure predicts the recommendation revisions by security analysts most strongly. We repeat the same analysis with the change in analyst recommendation consensus (MEANRECCHG) in Section 4.4 after adding FRETDUM and SRETDUM and their interaction terms with BLAME into the regression. We present this result in Column (3) of Table 10. We find that the coefficient of FRETDUM×BLAME is negative and significant at the 5% level and its magnitude is comparable to that of BLAME, implying that the predictability of the future change in analyst recommendation consensus by the blame measure is about two times stronger when firms suffer from poor idiosyncratic past returns. Meanwhile, the coefficient of SRETDUM×BLAME is positive and insignificant. These test results are consistent with Columns (1) and (2) of Table 10.

In summary, we find evidence that our blame measure has higher predictive power for the future returns, earnings surprises, and analyst recommendation revisions when firms experienced poor idiosyncratic, but not systematic, performance in the past.

4.6 Executives' Blaming Tactics and Turnover

We here examine how corporate executives' strategic blaming is associated with their turnover. Specifically, we hypothesize that executives' blaming tactics can lower a chance of being fired when their firms perform poorly. If so, this can serve as a major incentive for executives to blame poor firm performance on external factors like the economy or industries.

To test our hypothesis, we estimate an yearly probit regression as in Jenter and Kanaan (2006), where we employ as the dependent variable the forced CEO turnover in the following year $y+1$ after executives blame in a quarter of year y. We define the forced CEO turnover as an indicator variable, which equals one if the CEO is fired under 65 in year $y+1$, and equals zero otherwise.[31] Our list of main explanatory variables in the regression is as follows. BLAMEDUM is an indicator variable for BLAME in year y, which equals one if BLAME has a positive value for any quarter in year y, and equals zero otherwise. We employ this blame indicator variable (BLAMEDUM) instead of the continuous blame measure (BLAME) since it provides a more straightforward interpretation of the economic magnitudes of its interaction terms.[32] LAGRET is the cumulative return in year y. As in equation (5), SRET and FRET are, respectively, calculated as the systematic and firm-specific components of LAGRET in year y. We also include the interaction terms of LAGRET, or SRET and FRET with BLAMEDUM to examine the impact of executives' strategic blaming on the sensitivities of the forced CEO turnover to different components of past firm performance. Further, we add into the regression some control variables that have been known in the literature to affect the sensitivity of executive performance-turnover relation, e.g., return on assets (ROA), CEO age, and a retirement-related indicator variable (RETIRE), which equals one if the CEO age is equal to or greater than 60, and equals zero otherwise. For ease of interpretation, each of explanatory variables (except indicators and interaction terms) is standardized to have the

[31] We obtain the executive employment information from the ExecComp database and define the CEO turnover date as the date that the CEO steps down from his or her position.

[32] We find that the statistical significance and signs of the test results reported in Table 11 do not change when using BLAME instead of BLAMEDUM (unreported for brevity).

mean of zero and the standard deviation of one. We add yearly dummies into the probit regression as additional controls and calculate the clustered standard errors by industry. Ai and Norton (2003) point out that the interaction terms in nonlinear models like ours need to be interpreted with caution. Therefore, we adopt the methodology suggested by Ai and Norton (2003) and Norton et al. (2004) to estimate the adjusted average interaction effects and their statistical significance.

We present the test results in Table 11. First, we establish that LAGRET is negatively and significantly associated with the forced CEO turnover in the following year, indicating that the better the firm performs, the less likely that executive will be forced out in the future. One standard deviation decrease in LAGRET leads to 5.20% increase in the probability of CEO turnover. We then find that the slope coefficient of BLAMEDUM×LAGRET is positive and significant in the 5% level and its average interaction effect based on Ai and Norton (2003) is also positive and highly significant in the 1% level. These results indicate that executives are much less likely to be punished if they blame the economic or industry conditions when their firms underperform. Conditioning on executives' blaming external factors (BLAMEDUM = 1), one standard deviation decrease in LAGRET leads to 2.75%(= 5.20%−2.45%) increase in the probability of CEO turnover. This is about 50% reduction in the probability of the forced CEO turnover compared to when executives do not blame (BLAMEDUM = 0).

Jenter and Kanaan (2006) present evidence that executives are less harshly punished for poor industry performance than for poor firm-specific performance. To ensure that our finding is not driven by the possibility that firms with high values of the blame measure belong to industries that experience negative shocks, we decompose LAGRET into its systematic (SRET) and firm-specific (FRET) components.[33] We then separately interact each of these two components with BLAMEDUM and include these variables in the places of LAGRET

[33] Jenter and Kanaan (2006) use a cross-sectional regression for their decomposition. One advantage of our time-series decomposition in equations (4) and (5) is that it allows differential exposures to the market and industry-wide returns.

and its blame interaction term for the probit regression. In the last two columns of Table 11, we first establish that both SRET and FRET are negatively and significantly associated with the forced CEO turnover in the following year. One standard deviation decreases in SRET and FRET lead to, respectively, 3.73% and 4.15% increases in the probability of CEO turnover. We then find that the coefficient for BLAMEDUM×FRET is positive and significant in the 5% level, while that for BLAMEDUM×SRET is insignificant. Conditioning on executives' blaming external factors (BLAMEDUM = 1), one standard deviation decrease in FRET leads to 2.21%(= 4.15%−1.94%) increase in the probability of CEO turnover. This again means about 50% reduction in the probability of the forced CEO turnover compared to when executives do not blame (BLAMEDUM = 0). We conclude that the reduced sensitivity of executives' performance-turnover relation due to their blaming external factors is driven by the idiosyncratic component of past returns.

In summary, we find that executives' strategically attributing negative firm performance to the economy or industries helps them reduce the sensitivity of their performance-turnover relation. We also find that this effect is much stronger when firms' poor past performance is driven by negative idiosyncratic shocks than by negative economy- or industry-wide shocks.

5 Conclusion

We develop a novel sentence-based textual methodology to quantify executives' attributing poor firm performance to the economy or industries in quarterly earnings conference calls. Using our "blame measure", we first find that executives strategically blame the economy or industries when their firms underperform and that the blame sentences contain the negative and firm-specific value-relevant information. When investigating how market participants react to executives' blaming tactics, we find that investors tend to underreact to the negative information in the blame measure since they need to process and combine different categories of information contents together, enabling it to predict cumulative abnormal returns in the subsequent quarter after earnings conference calls. We also uncover that security analysts are similarly slow in digesting the information in the blame measure, leading to the predictability of earnings surprises and recommendation downgrades in the subsequent quarter by the blame measure. Furthermore, we find evidence that executives who attribute poor firm performance to those external factors are less likely to be fired in the following year, which incentivises them to blame the economy or industries.

References

Viral V. Acharya, Peter DeMarzo, and Ilan Kremer. Endogenous Information Flows and the Clustering of Announcements. *The American Economic Review*, 101(7):2955–2979, 2011.

Chunrong Ai and Edward C Norton. Interaction terms in logit and probit models. *Economics letters*, 80(1): 123–129, 2003.

Nicholas Barberis and Andrei Shleifer. Style investing. *Journal of Financial Economics*, 68(2):161–199, May 2003.

Roy F. Baumeister. A self-presentational view of social phenomena. *Psychological Bulletin*, 91(1):3–26, 1982. ISSN 1939-1455(Electronic);0033-2909(Print).

Victor L. Bernard and Jacob K. Thomas. Post-earnings-announcement drift: Delayed price response or risk premium? *Journal of Accounting Research*, 27:1–36, January 1989. ISSN 00218456. doi: 10.2307/2491062. ArticleType: research-article / Issue Title: Current Studies on The Information Content of Accounting Earnings / Full publication date: 1989 / Copyright © 1989 Accounting Research Center, Booth School of Business, University of Chicago.

Marianne Bertrand and Sendhil Mullainathan. Are CEOS rewarded for luck? the ones without principals are*. *Quarterly Journal of Economics*, 116(3):901–932, March 2011. ISSN 0033-5533. doi: i:10.1162/00335530152466269⟨/p⟩.

Matthew T. Billett and Yiming Qian. Are overconfident CEOs born or made? evidence of self-attribution bias from frequent acquirers. *Management Science*, 54(6):1037–1051, June 2008. ISSN 0025-1909, 1526-5501. doi: 10.1287/mnsc.1070.0830.

Gifford W. Bradley. Self-serving biases in the attribution process: A reexamination of the fact or fiction question. *Journal of Personality and Social Psychology*, 36(1):56–71, 1978. ISSN 1939-1315(Electronic);0022-3514(Print). doi: 10.1037/0022-3514.36.1.56.

Mark M. Carhart. On persistence in mutual fund performance. *The Journal of Finance*, 52(1):57–82, March 1997. ISSN 0022-1082. doi: 10.2307/2329556. ArticleType: research-article / Full publication date: Mar., 1997 / Copyright © 1997 American Finance Association.

Ling Cen, Michael G. Hertzel, and Christoph Schiller. Speed Matters: Limited Attention and Supply-Chain Information Diffusion. SSRN Scholarly Paper ID 2925460, Social Science Research Network, November 2017.

Long Chen, Gaiyan Zhang, and Weina Zhang. Return predictability in the corporate bond market along the supply chain. *Journal of Financial Markets*, 29:66–86, June 2016.

Lauren Cohen and Andrea Frazzini. Economic Links and Predictable Returns. *The Journal of Finance*, 63 (4):1977–2011, 2008.

Lauren Cohen and Dong Lou. Complicated firms. *Journal of Financial Economics*, 104(2):383–400, May 2012.

Lauren Cohen, Dong Lou, and Christopher J. Malloy. Casting Conference Calls. *Management Science*, 66 (11):5015–5039, April 2020. Publisher: INFORMS.

J. Anthony Cookson, S. Katie Moon, and Joonki Noh. Imprecise and Informative: Lessons from Market Reactions to Imprecise Disclosure. January 2021. URL `https://papers.ssrn.com/abstract=3152460`.

Stefano Dellavigna and Joshua M Pollet. Investor inattention and friday earnings announcements. *The Journal of Finance*, 64(2):709–749, March 2009. ISSN 1540-6261. doi: 10.1111/j.1540-6261.2009.01447.x.

Ran Duchin and Breno Schmidt. Riding the merger wave: Uncertainty, reduced monitoring, and bad acquisitions. *Journal of Financial Economics*, 107(1):69–88, January 2013. ISSN 0304-405X. doi: 10.1016/j.jfineco.2012.07.003.

Joseph Engelberg. Costly information processing: Evidence from earnings announcements. *SSRN eLibrary*, 2008. URL `http://ssrn.com/paper=1107998`.

Joseph E. Engelberg and Christopher A. Parsons. The causal impact of media in financial markets. *The Journal of Finance*, 66(1):67–97, 2011. ISSN 1540-6261. doi: 10.1111/j.1540-6261.2010.01626.x.

Eugene F. Fama and Kenneth R. French. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1):3–56, February 1993. ISSN 0304-405X. doi: 10.1016/0304-405X(93)90023-5.

Andrea Frazzini. The disposition effect and underreaction to news. *The Journal of Finance*, 61(4):2017–2046, 2006.

Simon Gervais, Ron Kaniel, and Dan H. Mingelgrin. The High-Volume Return Premium. *The Journal of Finance*, 56(3):877–919, 2001.

Steven R. Grenadier, Andrey Malenko, and Ilya A. Strebulaev. Investment busts, reputation, and the temptation to blend in with the crowd. *Journal of Financial Economics*, 111(1):137–157, January 2014.

Kathleen Weiss Hanley and Gerard Hoberg. The information content of ipo prospectuses. *Review of Financial Studies*, 23(7):2821–2864, 2010.

Tarek A Hassan, Stephan Hollander, Laurence van Lent, and Ahmed Tahoun. Firm-Level Political Risk: Measurement and Effects*. *The Quarterly Journal of Economics*, 134(4):2135–2202, November 2019.

Tarek Alexander Hassan, Stephan Hollander, Laurence van Lent, Markus Schwedeler, and Ahmed Tahoun. Firm-Level Exposure to Epidemic Diseases: COVID-19, SARS, and H1N1. SSRN Scholarly Paper ID 3566530, Social Science Research Network, June 2020.

David Hirshleifer, Sonya Seongyeon Lim, and Siew Hong Teoh. Driven to distraction: Extraneous events and underreaction to earnings news. *The Journal of Finance*, 64(5):2289–2325, October 2009. ISSN 1540-6261. doi: 10.1111/j.1540-6261.2009.01501.x.

Gerard Hoberg and Vojislav Maksimovic. Redefining financial constraints: a text-based analysis. *Review of Financial Studies*, 28(5):1312–1352, 2015.

Gerard Hoberg and S Katie Moon. Offshore activities and financial vs operational hedging. *Robert H. Smith School Research Paper No. RHS*, 2456323, 2015.

Gerard Hoberg and Gordon Phillips. Product market synergies and competition in mergers and acquisitions: A text-based analysis. *Review of Financial Studies*, 23(10):3773–3811, 2010.

Gerard Hoberg and Gordon Phillips. Text-based network industries and endogenous product differentiation. *Journal of Political Economy*, 124(5):1423–1465, 2016.

Gerard Hoberg and Gordon M. Phillips. Text-Based Industry Momentum. *Journal of Financial and Quantitative Analysis*, 53(6):2355–2388, December 2018.

Shiyang Huang, Yulin Huang, and Tse-Chun Lin. Attention allocation and return co-movement: Evidence from repeated natural experiments. *Journal of Financial Economics*, 132(2):369–383, May 2019.

Xing Huang. Thinking Outside the Borders: Investors' Underreaction to Foreign Operations Information. *The Review of Financial Studies*, 28(11):3109–3152, November 2015.

Xing Huang. Mark Twain's Cat: Investment experience, categorical thinking, and stock selection. *Journal of Financial Economics*, 131(2):404–432, February 2019.

Xuan Huang, Siew Hong Teoh, and Yinglei Zhang. Tone management. *The Accounting Review*, 89(3): 1083–1113, 2013.

Doron Israeli, Ron Kaniel, and Suhas A. Sridharan. The Real Side of the High-Volume Return Premium. SSRN Scholarly Paper ID 2909494, Social Science Research Network, Rochester, NY, October 2020.

Russell Jame and Qing Tong. Industry-based style investing. *Journal of Financial Markets*, 19:110–130, June 2014.

Narasimhan Jegadeesh and Di Wu. Word power: A new approach for content analysis. *Journal of Financial Economics*, 110(3):712–729, December 2013. ISSN 0304-405X. doi: 10.1016/j.jfineco.2013.08.018.

Dirk Jenter and Fadi Kanaan. CEO turnover and relative performance evaluation. Working Paper 12068, National Bureau of Economic Research, March 2006. URL `http://www.nber.org/papers/w12068`.

Ron Kaniel, Arzu Ozoguz, and Laura Starks. The high volume return premium: Cross-country evidence. *Journal of Financial Economics*, 103(2):255–279, February 2012.

Steven N. Kaplan and Bernadette Minton. How has CEO turnover changed? increasingly performance sensitive boards and increasingly uneasy CEOs. Working Paper 12465, National Bureau of Economic Research, August 2006. URL `http://www.nber.org/papers/w12465`.

S. P. Kothari, Susan Shu, and Peter D. Wysocki. Do Managers Withhold Bad News? *Journal of Accounting Research*, 47(1):241–276, 2009.

Feng Li. Annual report readability, current earnings, and earnings persistence. *Journal of Accounting and Economics*, 45(2):221–247, August 2008.

Feng Li. The information content of forward-looking statements in corporate Filings—A naïve bayesian machine learning approach. *Journal of Accounting Research*, 48(5):1049–1102, 2010a. ISSN 1475-679X. doi: 10.1111/j.1475-679X.2010.00382.x.

Feng Li. Managers' self-serving attribution bias and corporate financial policies. *University of Michigan: working paper*, 2010b. URL `http://www.mccombs.utexas.edu/~/media/Files/MSB/Departments/Accounting/Workshop%20Papers/Li_Feng.pdf`.

Yuanzhi Li and David Yermack. Evasive shareholder meetings. SSRN Scholarly Paper ID 2409627, Social Science Research Network, Rochester, NY, March 2014. URL `http://papers.ssrn.com/abstract=2409627`.

Tim Loughran and Bill McDonald. When is a liability not a liability? textual analysis, dictionaries, and 10-ks. *The Journal of Finance*, 66(1):35–65, 2011. ISSN 1540-6261. doi: 10.1111/j.1540-6261.2010.01625.x.

John D. Lyon, Brad M. Barber, and Chih-Ling Tsai. Improved methods for tests of long-run abnormal stock returns. *The Journal of Finance*, 54(1):165–201, 1999. ISSN 1540-6261. doi: 10.1111/0022-1082.00101.

Lior Menzly and Oguzhan Ozbas. Market Segmentation and Cross-predictability of Returns. *The Journal of Finance*, 65(4):1555–1580, 2010.

Dale T. Miller. What constitutes a self-serving attributional bias? a reply to bradley. *Journal of Personality and Social Psychology*, 36(11):1221–1223, 1978. ISSN 1939-1315(Electronic);0022-3514(Print). doi: 10.1037/0022-3514.36.11.1221.

R. Charles Moyer, Robert E. Chatfield, and Phillip M. Sisneros. Security analyst monitoring activity: Agency costs and information demands. *Journal of Financial and Quantitative Analysis*, 24(04):503–512, 1989. doi: 10.2307/2330982.

Kevin J Murphy and Jerold L Zimmerman. Financial performance surrounding CEO turnover. *Journal of Accounting and Economics*, 16(1–3):273–315, January 1993. ISSN 0165-4101. doi: 10.1016/0165-4101(93)90014-7.

Joonki Noh. Industry Networks and the Speed of Information Flow. SSRN Scholarly Paper ID 2531450, Social Science Research Network, Rochester, NY, November 2014. URL `https://papers.ssrn.com/abstract=2531450`.

Edward C Norton, Hua Wang, and Chunrong Ai. Computing interaction effects and standard errors in logit and probit models. *Stata Journal*, 4:154–167, 2004.

Christopher A. Parsons, Riccardo Sabbatucci, and Sheridan Titman. Geographic Lead-Lag Effects. SSRN Scholarly Paper ID 2780139, Social Science Research Network, Rochester, NY, September 2018.

Lin Peng and Wei Xiong. Investor attention, overconfidence and category learning. *Journal of Financial Economics*, 80(3):563–602, June 2006.

Mitchell A Petersen. Estimating standard errors in finance panel data sets: Comparing approaches. *Review of financial studies*, 22(1):435–480, 2009.

Anna Scherbina and Bernd Schlusche. Follow the Leader: Using the Stock Market to Uncover Information Flows between Firms*. *Review of Finance*, 24(1):189–225, February 2020.

David H. Solomon. Selective publicity and stock prices. *The Journal of Finance*, 67(2):599–638, 2012. ISSN 1540-6261. doi: 10.1111/j.1540-6261.2012.01726.x.

Barry M. Staw, Pamela I. McKechnie, and Sheila M. Puffer. The justification of organizational performance. *Administrative Science Quarterly*, 28(4):582–600, December 1983. ISSN 0001-8392. doi: 10.2307/2393010.

Paul C. Tetlock. All the news that's fit to reprint: Do investors react to stale information? *Review of Financial Studies*, 24(5):1481–1512, May 2011. ISSN 0893-9454, 1465-7368. doi: 10.1093/rfs/hhq141.

Paul C Tetlock, Maytal Saar-tsechansky, and Sofus Macskassy. More than words: Quantifying language to measure firms' fundamentals. *The Journal of Finance*, 63(3):1437–1467, June 2008. ISSN 1540-6261. doi: 10.1111/j.1540-6261.2008.01362.x.

Table 1: Sentences with Positive and Negative Descriptions of the Economy or Industries

This table provides example sentences that contain positive and negative descriptions of the economy or industries from quarterly earnings conference call transcripts. The first set of three examples includes negative descriptions of the economy or industries in the top half of the table. Specifically, the first two examples involve executives' assigning blame for poor firm performance to economic conditions, while the third one involves executives' blaming poor firm performance on the industries. Then, the second set of three examples includes positive descriptions of the economy or industries in the bottom half of the table. Specifically, the fourth example is a positive sentence about the economy. The last two examples have positive descriptions of the industries. In those example sentences, negative words are in red; positive words are in green; and our keywords for the economy or industries are in bold. Words in square brackets are borrowed from their preceding sentence for better understanding of each of the example sentences.

Blaming the Economy	
Watts Water Technologies, 2009:Q2	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, 2009:Q2	[We continue to experience softness in our aftermarket business.] We believe this reflects mainly continued weakness in the global **economy**.
Blaming the Industry	
Navigator, 2011:Q4	We view this as an acceptable outcome given the magnitude of the loss to the global insurance **industry**.
Sentence with Positive Description of the Economy	
Microsoft, 2010:Q1	We should start to see that improve going forward as we see the **economy** recover.
Sentences with Positive Descriptions of the Industries	
Honeywell, 2006:Q4	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, 2012:Q1	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 presents the summary statistics of variables. Panel A reports the summary statistics for the variables used in return reaction regressions. Panel B reports the summary statistics for the number of sentences with positive, negative, or neutral descriptions of the economy or industries in earnings conference calls. Panel C provides pairwise correlations for the explanatory variables used in return reaction regressions. CAR[-1,1] and CAR[2,60] are the cumulative abnormal returns (CARs), respectively, from trading day -1 to trading day 1 and from trading day 2 to trading day 60 relative to each earnings conference call day, based on the Fama-French three-factor model. The following variables are constructed based on the information available as of the time of each earnings conference call. BLAME is the percentage of the blame sentences in each earnings conference call. POSIE is the percentage of the sentences that contain positive descriptions of the economy or industries. FE is the latest earnings forecast error using the realized quarterly earnings and consensus (mean) of earnings forecasts for the corresponding quarter across analysts following. BM is the logarithm of book-to-market ratio from the end of the previous year. ME is the market equity (in $1,000) from the end of the previous year. MOMENTUM is the past 12-month cumulative return. ACCRUAL is the accrued earnings divided by total assets (=(IBCY-OANCFY)/ATQ) from the quarter associated with each conference call. NEG is the percentage of negative words in each earnings conference call. VOLATILITY is the annualized volatility of daily returns in the preceding month. INSTOWN is the percentage of institutional ownership in the preceding quarter. NUMEST is the number of analysts following from the latest forecast period. TURNOVER is the average daily share turnover in the preceding month. N(POSITIVE), N(NEGATIVE), and N(NEUTRAL) are, respectively, the numbers of sentences with positive, negative, and neutral descriptions of the economy or industries. N(SENTENCE) is the total number of sentences in each earnings conference call. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Panel A: Variables in Return Reaction Regressions

Variable	**Mean**	**Median**	**Std. Dev.**	**Q1**	**Q3**
CAR[-1,1]	0.347	0.249	10.115	-4.447	5.239
CAR[2,60]	0.316	0.011	20.528	-9.296	9.422
BLAME	0.201	0.000	0.329	0.000	0.293
POSIE	0.316	0.195	0.421	0.000	0.467
FE	-0.042	0.052	1.577	-0.103	0.243
BM	-0.790	-0.740	0.852	-1.264	-0.263
ME	4,996,017	863,327	19,108,962	312,097	2,666,794
MOMENTUM	6.392	6.531	40.782	-11.215	23.629
ACCRUAL	0.972	0.977	0.478	0.946	1.001
NEG	1.092	1.046	0.315	0.872	1.262
VOLATILITY	0.297	0.194	0.490	0.107	0.355
INSTOWN	0.721	0.771	0.206	0.606	0.879
NUMEST	8.524	7	6.515	4	12
TURNOVER	0.211	0.155	0.220	0.092	0.260

Panel B: Numbers of Sentences with Various Descriptions of the Economy or Industries

Variable	**Mean**	**Median**	**Std. Dev.**	**Q1**	**Q3**
N(POSITIVE)	1.505	1	2.004	0	2
N(NEGATIVE)	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

Panel C: Pairwise Correlations for Explanatory Variables in Return Reaction Regressions											
Variables	BLAME	POSIE	FE	BM	Log(ME)	MOMENTUM	ACCRUAL	NEG	VOLATILITY	INSTOWN	NUMEST
POSIE	0.324***										
FE	-0.070***	0.006*									
BM	0.122***	0.053***	-0.061***								
Log(ME)	-0.009**	0.027***	0.065***	-0.250***							
MOMENTUM	-0.099***	0.016***	0.137***	0.001	-0.041***						
ACCRUAL	-0.027***	-0.012***	0.132***	-0.062***	0.085***	0.024***					
NEG	0.286***	-0.005	-0.152***	0.149***	-0.034***	-0.142***	-0.070***				
VOLATILITY	0.030***	0.022***	-0.026***	0.077***	-0.278***	0.095***	-0.105***	0.049***			
INSTOWN	0.008**	0.020***	0.033***	0.011***	0.209***	0.003	0.026***	-0.016***	-0.072***		
NUMEST	-0.043***	0.014***	0.046***	-0.187***	0.684***	-0.018***	-0.018***	-0.082***	-0.121***	0.147***	
TURNOVER	-0.006	-0.021***	-0.024***	-0.101***	0.123***	0.038***	-0.028***	0.017***	0.096***	-0.030***	0.259***

Table 3: Determinants of the Blame Measure

This table investigates the determinants of BLAME and POSIE with negative and positive descriptions of the economy or industries, respectively. BLAME is the percentage of the blame sentences out of all sentences in each earnings conference call. POSIE is the percentage of the sentences that contain positive descriptions of the economy or industries (out of all sentences). BLAME or POSIE is used as the dependent variable in the panel regressions. The following explanatory variables are constructed based on the information available as of the time of each earnings conference call. FE is the latest earnings forecast error using the realized quarterly earnings and consensus (mean) of earnings forecasts for the corresponding quarter across analysts following. BM is the logarithm of book-to-market ratio from the end of the previous year. Log(ME) is the logarithm of the market equity (in $1,000) from the end of the previous year. MOMENTUM is the past 12-month cumulative return. ACCRUAL is the accrued earnings divided by total assets (=(IBCY-OANCFY)/ATQ) from the quarter associated with each conference call. NEG is the percentage of negative words in each earnings conference call. VOLATILITY is the annualized volatility of daily returns in the preceding month. INSTOWN is the percentage of institutional ownership in the preceding quarter. LNUMEST is the log of one plus the number of analysts following from the latest forecast period. TURNOVER is the average daily share turnover in the preceding month. Each panel regression is estimated with industry×quarter fixed effects based on the SIC-3 classifications. Each explanatory variable is standardized to have the mean of zero and the standard deviation of one. The standard errors are clustered by industry and reported in parenthesis. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1)	(2)	(3)	(4)
Variable	BLAME	BLAME	POSIE	POSIE
FE	-0.0420**	-0.0988***	0.0147	0.0292
	(0.0172)	(0.0183)	(0.0207)	(0.0218)
BM	0.0609***	0.132***	0.0731***	0.0549**
	(0.0190)	(0.0231)	(0.0255)	(0.0265)
Log(ME)	0.184***	0.249***	0.439***	0.422***
	(0.0192)	(0.0290)	(0.0270)	(0.0269)
MOMENTUM	-0.0619***	-0.122***	0.0145	0.0298
	(0.0195)	(0.0218)	(0.0228)	(0.0229)
ACCRUAL	0.0353**	0.0108	-0.0526**	-0.0463**
	(0.0155)	(0.0179)	(0.0222)	(0.0224)
NEG	0.650***		-0.166***	
	(0.0601)		(0.0242)	
VOLATILITY	-0.0169*	-0.0104	0.0205	0.0188
	(0.00867)	(0.00768)	(0.0151)	(0.0146)
INSTOWN	-0.0120	-0.0118	-0.0300*	-0.0300*
	(0.0133)	(0.0140)	(0.0161)	(0.0159)
LNUMEST	-0.145***	-0.216***	-0.163***	-0.145***
	(0.0257)	(0.0363)	(0.0272)	(0.0270)
TURNOVER	-0.0554***	-0.0423***	-0.0895***	-0.0928***
	(0.0154)	(0.0156)	(0.0190)	(0.0187)
Observations	66,811	66,811	66,811	66,811
R-squared	0.340	0.313	0.253	0.252

Table 4: Immediate Return Reaction

This table presents the test results that investigate how BLAME or POSIE measure relates to the short-term returns around each earnings conference call day. The dependent variable is the cumulative abnormal return, i.e., CAR[-1,1], from trading day -1 to trading day 1 relative to each earnings conference call day, based on the Fama-French three-factor model. The following explanatory variables are constructed based on the information available as of the time of each earnings conference call. BLAME is the percentage of the blame sentences in each earnings conference call. POSIE is the percentage of the sentences that contain positive descriptions of the economy or industries. FE is the latest earnings forecast error using the realized quarterly earnings and consensus (mean) of earnings forecasts for the corresponding quarter across analysts following. BM is the logarithm of book-to-market ratio from the end of the previous year. Log(ME) is the logarithm of the market equity (in $1,000) from the end of the previous year. MOMENTUM is the past 12-month cumulative return. ACCRUAL is the accrued earnings divided by total assets (=(IBCY-OANCFY)/ATQ) from the quarter associated with each conference call. NEG is the percentage of negative words in each earnings conference call. VOLATILITY is the annualized volatility of daily returns in the preceding month. INSTOWN is the percentage of institutional ownership in the preceding quarter. LNUMEST is the log of one plus the number of analysts following from the latest forecast period. TURNOVER is the average daily share turnover in the preceding month. All panel regressions include industry×quarter fixed effects based on the SIC-3 industry classifications. Each explanatory variable is standardized to have the mean of zero and the standard deviation of one. The slope coefficients are reported in percentage and their standard errors are clustered by quarter and reported in parenthesis. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Variable	(1) CAR[-1,1]	(2) CAR[-1,1]	(3) CAR[-1,1]	(4) CAR[-1,1]
BLAME	-0.384***	-0.134**		
	(0.0618)	(0.0561)		
POSIE			0.126***	0.00743
			(0.0367)	(0.0368)
FE		2.212***		2.214***
		(0.135)		(0.136)
BM		0.252***		0.249***
		(0.0568)		(0.0567)
Log(ME)		0.128		0.121
		(0.110)		(0.111)
MOMENTUM		-0.281***		-0.279***
		(0.0887)		(0.0887)
ACCRUAL		-0.345***		-0.346***
		(0.0603)		(0.0602)
NEG		-0.988***		-1.014***
		(0.0651)		(0.0660)
VOLATILITY		-0.00293		-0.00234
		(0.0505)		(0.0504)
INSTOWN		0.0444		0.0448
		(0.0534)		(0.0533)
LNUMEST		-0.111		-0.106
		(0.0786)		(0.0789)
TURNOVER		-0.197**		-0.195**
		(0.0901)		(0.0900)
Observations	66,561	66,561	66,561	66,561
R-squared	0.146	0.195	0.145	0.195

Table 5: Delayed Return Reaction

This table presents the test results that investigate how BLAME or POSIE measure relates to the subsequent returns after each earnings conference call. The dependent variable is the cumulative abnormal return, i.e., CAR[2,60], from trading day 2 to trading day 60 relative to each earnings conference call day, based on the Fama-French three-factor model. The following explanatory variables are constructed based on the information available as of the time of each earnings conference call. BLAME is the percentage of the blame sentences in each earnings conference call. POSIE is the percentage of the sentences that contain positive descriptions of the economy or industries. FE is the latest earnings forecast error using the realized quarterly earnings and consensus (mean) of earnings forecasts for the corresponding quarter across analysts following. BM is the logarithm of book-to-market ratio from the end of the previous year. Log(ME) is the logarithm of the market equity (in $1,000) from the end of the previous year. MOMENTUM is the past 12-month cumulative return. ACCRUAL is the accrued earnings divided by total assets (=(IBCY-OANCFY)/ATQ) from the quarter associated with each conference call. NEG is the percentage of negative words in each earnings conference call. VOLATILITY is the annualized volatility of daily returns in the preceding month. INSTOWN is the percentage of institutional ownership in the preceding quarter. LNUMEST is the log of one plus the number of analysts following from the latest forecast period. TURNOVER is the average daily share turnover in the preceding month. All panel regressions include industry×quarter fixed effects based on the SIC-3 industry classifications. Each explanatory variable is standardized to have the mean of zero and the standard deviation of one. The slope coefficients are reported in percentage and their standard errors are clustered by quarter and reported in parenthesis. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Variable	(1) CAR[2,60]	(2) CAR[2,60]	(3) CAR[2,60]	(4) CAR[2,60]
BLAME	-0.354***	-0.307**		
	(0.137)	(0.123)		
POSIE			-0.210*	-0.0353
			(0.108)	(0.0973)
FE		0.584**		0.588**
		(0.251)		(0.252)
BM		0.227		0.222
		(0.262)		(0.262)
Log(ME)		-0.836*		-0.846*
		(0.428)		(0.428)
MOMENTUM		-0.568		-0.563
		(0.516)		(0.516)
ACCRUAL		-1.021***		-1.025***
		(0.152)		(0.152)
NEG		-0.187		-0.251*
		(0.132)		(0.134)
VOLATILITY		0.366		0.368
		(0.308)		(0.308)
INSTOWN		-0.133		-0.132
		(0.124)		(0.124)
LNUMEST		-0.0808		-0.0662
		(0.282)		(0.282)
TURNOVER		-0.160		-0.155
		(0.226)		(0.226)
Observations	66,561	66,561	66,561	66,561
R-squared	0.218	0.224	0.218	0.224

Table 6: Calendar Time Portfolios

This table investigates whether stocks with high blame measures underperform stocks with low blame measures by forming calendar time portfolios following Lyon et al. (1999). The holding period for each constituent stock of these portfolios is from trading day 2 to trading day 60 after the date of each earnings conference call. Panel A reports the performance of the BLAME-sorted hedging portfolios that take long positions in firms whose blame measures are equal to zero and that take short positions in firms whose blame measures are greater than the 80th percentile of the distribution of BLAME observations from the previous quarter. Panel B reports the performance of the BLAME-sorted hedging portfolios for the high and low FE groups separately. High and low FE groups include stocks whose FE values are, respectively, the top and bottom 30% of the distribution of realized FEs in the previous quarter. The monthly risk-adjusted returns, i.e., alphas, are reported in percentage and their standard errors are reported in parenthesis. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Panel A: Hedging Portfolio Sorted on BLAME				
ALPHA	MKTRF	SMB	HML	UMD
Excess Return				
0.518***				
(0.193)				
Fama-French Three-factor Model				
0.590***	-0.024***	0.010	-0.241***	
(0.181)	(0.007)	(0.015)	(0.016)	
Fama-French-Carhart Four-factor Model				
0.570***	0.003	-0.014	-0.153***	0.128***
(0.174)	(0.007)	(0.014)	(0.016)	(0.009)
Panel B: Hedging Portfolio Sorted on FE and BLAME				
ALPHA	MKTRF	SMB	HML	UMD
Low BLAME − High BLAME (among High FE Stocks)				
0.341*	-0.036***	-0.070***	-0.038***	0.107***
(0.185)	(0.008)	(0.015)	(0.018)	(0.010)
Low BLAME − High BLAME (among Low FE Stocks)				
0.616***	0.009	-0.044***	-0.117***	0.098***
(0.198)	(0.008)	(0.016)	(0.019)	(0.011)

Table 7: Industry-adjusted Calendar Time Portfolios

This table investigates whether stocks with high blame measures underperform stocks with low blame measures by forming calendar time portfolios following Lyon et al. (1999) after adjusting for industry-wide returns. First, the daily return of an individual stock is adjusted by subtracting the daily value-weighted return of the matched SIC-3 industry portfolio. Then, the same analysis as in Panel A of Table 6 is performed with the industry-adjusted return. The BLAME-sorted hedging portfolios take long positions in firms whose blame measures are equal to zero and take short positions in firms whose blame measures are greater than the 80th percentile of the distribution of BLAME observations from the previous quarter. The holding period for each constituent stock of these long and short portfolios is from trading day 2 to trading day 60 after the date of each earnings conference call. The monthly risk-adjusted returns, i.e., alphas, are reported in percentage and their standard errors are reported in parenthesis. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

ALPHA	MKTRF	SMB	HML	UMD
		Excess Return		
0.505***				
(0.154)				
		Fama-French Three-factor Model		
0.454***	-0.028***	0.078***	-0.003***	
(0.150)	(0.005)	(0.011)	(0.012)	
		Fama-French-Carhart Four-factor Model		
0.445***	0.036***	0.072***	0.022*	0.037***
(0.150)	(0.006)	(0.011)	(0.013)	(0.007)

Table 8: Security Analysts' Reactions: Earnings Surprises

This table investigates whether the blame measure can predict future earnings surprises proxied by the standardized unexpected earnings (SUE). The future SUE is defined similarly to FE in equation (3) but for the next quarter after each earnings conference call, scaled up by 10,000, and used as the dependent variable. The following explanatory variables are constructed based on the information available as of the time of each earnings conference call. BLAME is the percentage of the blame sentences in each earnings conference call. BM is the logarithm of book-to-market ratio from the end of the previous year. Log(ME) is the logarithm of the market equity (in $1,000) from the end of the previous year. MOMENTUM is the past 12-month cumulative return. ACCRUAL is the accrued earnings divided by total assets (=(IBCY-OANCFY)/ATQ) from the quarter associated with each conference call. NEG is the percentage of negative words in each earnings conference call. VOLATILITY is the annualized volatility of daily returns in the preceding month. INSTOWN is the percentage of institutional ownership in the preceding quarter. LNUMEST is the log of one plus the number of analysts following from the latest forecast period. TURNOVER is the average daily share turnover in the preceding month. All regressions include industry×quarter fixed effects with the SIC-3 industry classifications. Each explanatory variable is standardized to have the mean of zero and the standard deviation of one. Standard errors are clustered by quarter and reported in parenthesis. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1)	(2)
Variables	SUE	SUE
BLAME	-2.442***	-1.642**
	(0.785)	(0.783)
BM		-0.976
		(0.932)
Log(ME)		5.173***
		(1.052)
MOMENTUM		4.741***
		(0.920)
ACCRUAL		-1.339
		(0.920)
NEG		-1,129***
		(223.7)
VOLATILITY		-1.055
		(0.950)
INSTOWN		0.459
		(0.565)
LNUMEST		2.439
		(1.521)
TURNOVER		-1.225
		(0.966)
Observations	64,328	64,103
R-squared	0.186	0.192

Table 9: Security Analysts' Reactions: Recommendation Changes

This table investigates whether the blame measure can predict the future change of analysts' stock recommendation consensus. The change in analysts' recommendation consensus (mean), i.e., MEANRECCHG, is defined as the difference between the consensus over the 60-trading-day period, starting from two days after each earnings conference call, and the consensus over the two-trading-day period, including the conference call day and the next day. MEANRECCHG is used as the dependent variable. The following explanatory variables are constructed based on the information available as of the time of each earnings conference call. BLAME is the percentage of the blame sentences in each earnings conference call. FE is the latest earnings forecast error using the realized quarterly earnings and consensus (mean) of earnings forecasts for the corresponding quarter across analysts following. BM is the logarithm of book-to-market ratio from the end of the previous year. Log(ME) is the logarithm of the market equity (in $1,000) from the end of the previous year. MOMENTUM is the past 12-month cumulative return. ACCRUAL is the accrued earnings divided by total assets (=(IBCY-OANCFY)/ATQ) from the quarter associated with each conference call. NEG is the percentage of negative words in each earnings conference call. VOLATILITY is the annualized volatility of daily returns in the preceding month. INSTOWN is the percentage of institutional ownership in the preceding quarter. LNUMEST is the log of one plus the number of analysts following from the latest forecast period. TURNOVER is the average daily share turnover in the preceding month. All regressions include industry×quarter fixed effects with the SIC-3 industry classifications. Each explanatory variable is standardized to have the mean of zero and the standard deviation of one. Standard errors are clustered by quarter and reported in parenthesis. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Variables	(1) MEANRECCHG	(2) MEANRECCHG
BLAME	-0.0190**	-0.0181**
	(0.00794)	(0.00892)
FE		0.0195*
		(0.0115)
BM		0.0151
		(0.00943)
Log(ME)		0.0618***
		(0.0101)
MOMENTUM		0.0327*
		(0.0172)
ACCRUAL		0.0182
		(0.0828)
NEG		-0.0120
		(0.00872)
VOLATILITY		0.00287
		(0.00845)
INSTOWN		-0.00855
		(0.00592)
LNUMEST		-0.00593
		(0.0115)
TURNOVER		-0.00299
		(0.00784)
Observations	40,401	40,274
R-squared	0.233	0.241

Table 10: Blame Effect and Decomposition of Past Returns

This table investigates whether the blame effect is more salient when firms experience poor past performance by conducting similar regression tests to Tables 5, 8, and 9, where the dependent variables are CAR[2,60], SUE, and MEANRECCHG, respectively. Based on equation (5), FRETDUM is an indicator variable that equals one if the firm-specific return over the past 90-day period is negative. SRETDUM is an indicator variable that equals one if the systematic return over the same 90-day period is negative. For each of the three regression estimations in this table, additional control variables corresponding to those in each of Tables 5, 8, and 9 are included but their coefficients are not reported for brevity. All regressions include industry×quarter fixed effects based on the SIC-3 industry classifications. Each explanatory variable (except indicators and interaction terms) is standardized to have the mean of zero and the standard deviation of one. The slope coefficients and their standard errors in Column (1) are reported in percentage. Standard errors are clustered by quarter and reported in parenthesis. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Variables	(1) CAR[2,60]	(2) SUE	(3) MEANRECCHG
BLAME	-0.296**	1.358	-0.0445***
	(0.145)	(0.826)	(0.0141)
FRETDUM	-0.147	-7.675***	-0.0114
	(0.182)	(0.780)	(0.0209)
FRETDUM×BLAME	-0.187	-2.973***	-0.0405**
	(0.208)	(1.007)	(0.0147)
SRETDUM	0.649**	-0.908	0.0114
	(0.288)	(1.190)	(0.0209)
SRETDUM×BLAME	0.0117	-1.445	0.0999
	(0.219)	(1.067)	(0.0156)
Additional Control Variables	Yes	Yes	Yes
Observations	65,591	64,103	40,274
R-squared	0.219	0.191	0.241

Table 11: Blame Effect and CEO Turnover

Using yearly probit regressions, this table investigates how the blame measure affects the relation of CEO's performance and turnover as in Jenter and Kanaan (2006). The dependent variable is an indicator variable for the forced CEO turnover in year $y+1$, which equals one if the CEO is fired under 65 and zero otherwise. The explanatory variables are defined in year y as follows. BLAMEDUM is an indicator variable for BLAME, which equal to one if BLAME is positive for any quarter in year y and zero otherwise. LAGRET is the cumulative return in year y. Based on equation (5), SRET and FRET are the systematic and firm-specific components of LAGRET, respectively. ROA is the return on assets constructed using the latest annual report. CEO Age is the age of the CEO reported in ExecComp. RETIRE is a CEO's retirement-related indicator variable, which equals one if the CEO age is equal to or greater than 60, and zero otherwise. Each explanatory variable (except indicators and interaction terms) is standardized to have the mean of zero and the standard deviation of one. Yearly dummies are added into the probit regressions as additional controls but their coefficients are not reported for brevity. Standard errors are clustered by industry and reported in parenthesis. Based on Ai and Norton (2003), each column labelled as "Margins" presents the marginal effects of the corresponding coefficient estimates in the previous column. The bottom panel presents the average interaction effects of the interaction terms. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Variables	CEO TURNOVER	Margins	CEO TURNOVER	Margins
BLAMEDUM	0.00501	0.00100	0.00531	0.00107
	(0.0515)	(0.0515)	(0.0519)	(0.0104)
LAGRET	-0.259***	-0.0520***		
	(0.0457)	(0.0457)		
BLAMEDUM×LAGRET	0.124**	0.0249**		
	(0.0612)	(0.0123)		
SRET			-0.186***	-0.0373***
			(0.0344)	(0.00691)
FRET			-0.207***	-0.0415***
			(0.0372)	(0.00742)
BLAMEDUM×SRET			0.0729	0.0146
			(0.0650)	(0.0130)
BLAMEDUM×FRET			0.105**	0.0211**
			(0.0534)	(0.0107)
ROA	-0.0425***	-0.00851***	-0.0433***	-0.00868***
	(0.0123)	(0.00246)	(0.0128)	(0.00255)
CEO Age	0.117***	0.0235***	0.117***	0.0235***
	(0.0414)	(0.00830)	(0.0415)	(0.00831)
RETIRE	0.264***	0.0530***	0.264***	0.0530***
	(0.0955)	(0.0190)	(0.0955)	(0.0190)
Pseudo R-squared	0.1088		0.1088	
Observations	7,076	7,076	7,076	7,076
	Average Interaction Effect			
BLAMEDUM×LAGRET	0.0245***			
	(0.00774)			
BLAMEDUM×SRET			0.0149	
			(0.00910)	
BLAMEDUM×FRET			0.0194**	
			(.00847)	

Figure 1: Time-series Plots of the Aggregate Blame Measures and GDP Growth

We present in this figure the time-series plots of the cross-stock average of the blame measure (BLAME), the percentage of firms with at least one blame sentence, and the GDP growth from the first quarter in 2003 to the fourth quarter in 2012. The quantities for the cross-stock average of BLAME (in blue solid line) and the percentage of firms with at least one blame sentence (in orange dashed line) are exhibited on the left vertical axis. The quantity for the GDP growth (in grey dash-dotted line) is exhibited on the right vertical axis. The GDP growth data are based on Table 1.1.1 from the BEA website (https://apps.bea.gov).

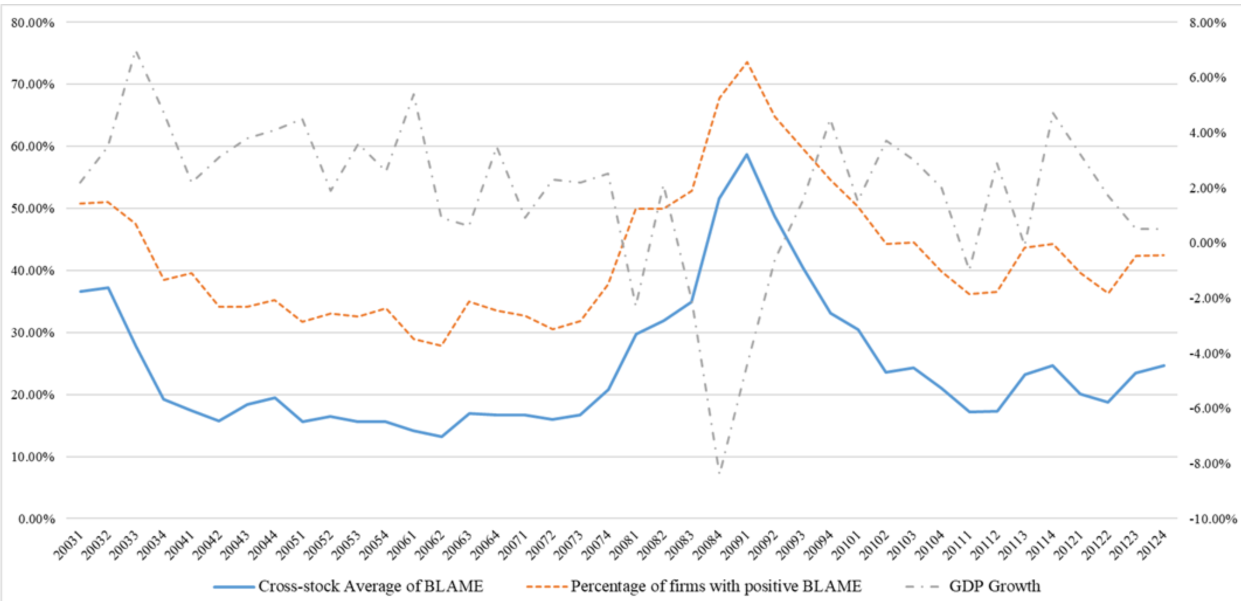

Figure 2: CARs for the BLAME-sorted Portfolios around the Earnings Conference Call Day

We present in this figure the cumulative abnormal returns (CARs) over the [-120,120] trading days relative to the earnings conference call day for firms with high BLAME measures (in red dashed line), firms with no blame statements (in blue solid line), and their difference (in cyan dash-dotted line). We calculate the abnormal returns based on the Fama-French 3-factor model.

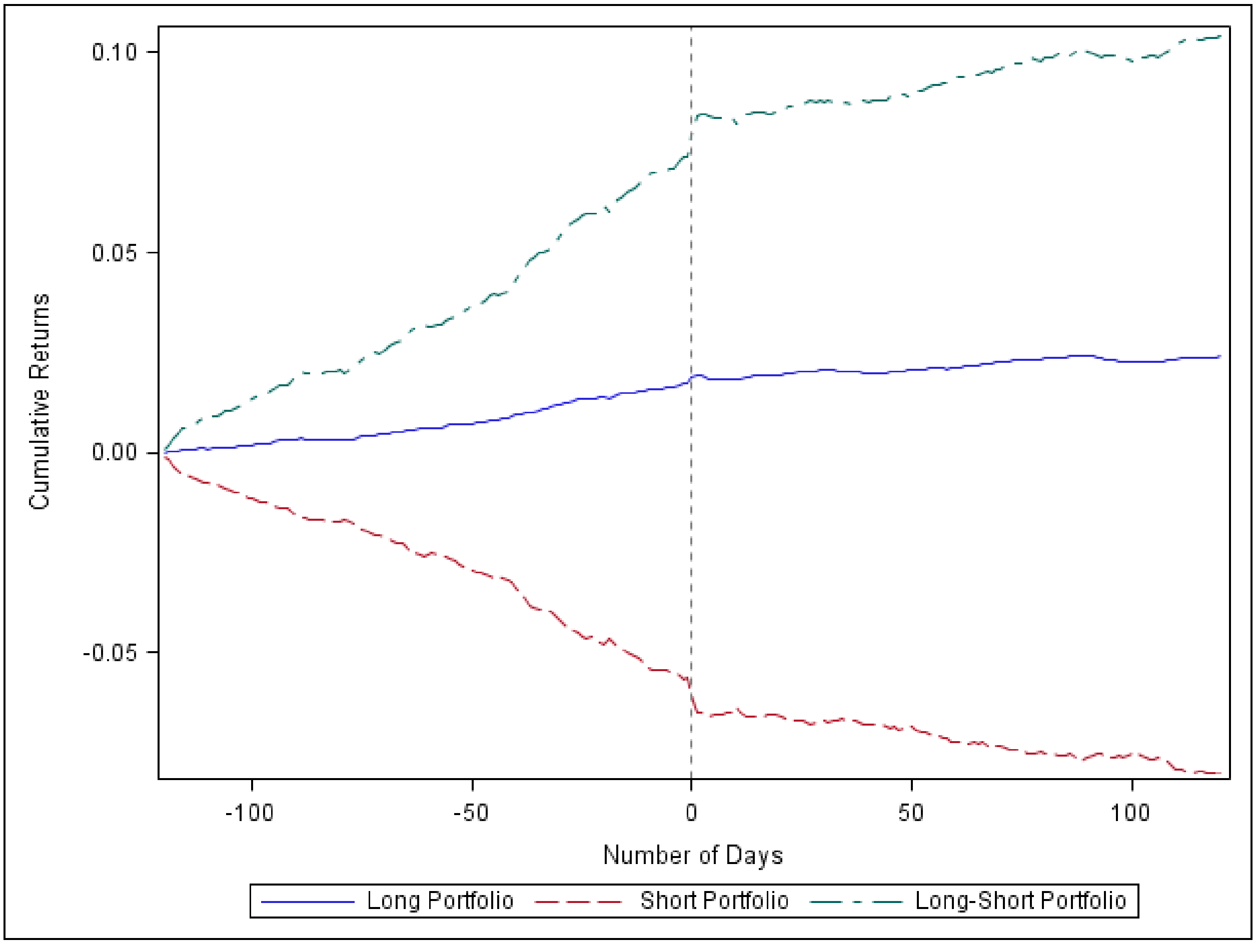

Table A1: Delayed Return Reaction: Alternative PEAD Proxy

This table repeats the tests in Table 5 by replacing FE with EADCAR[-1,1] as an alternative proxy for the PEAD following Frazzini (2006) and presents their results. EADCAR[-1,1] is the cumulative abnormal return over the three-trading-day period from one-day before and one-day after each earnings announcement day, which is obtained by controlling for the contributions of the three factors under Fama and French (1993). The most recent EADCAR[-1,1] before each earnings conference call is employed as an explanatory variable in the regressions. The dependent variable is CAR[2,60] after each earnings conference call day. The following explanatory variables are constructed based on the information available as of the time of each earnings conference call. BLAME is the percentage of the blame sentences in each earnings conference call. BM is the logarithm of book-to-market ratio from the end of the previous year. Log(ME) is the logarithm of the market equity (in $1,000) from the end of the previous year. MOMENTUM is the past 12-month cumulative return. ACCRUAL is the accrued earnings divided by total assets (=(IBCY-OANCFY)/ATQ) from the quarter associated with each earnings conference call. NEG is the percentage of negative words in each earnings conference call. VOLATILITY is the annualized volatility of daily returns in the preceding month. INSTOWN is the percentage of institutional ownership in the preceding quarter. LNUMEST is the log of one plus the number of analysts following from the latest forecast period. TURNOVER is the average daily share turnover in the preceding month. All panel regressions include industry×quarter fixed effects based on the SIC-3 industry classifications. Each explanatory variable is standardized to have the mean of zero and the standard deviation of one. The slope coefficients are reported in percentage and their standard errors are clustered by quarter and reported in parenthesis. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Variables	CAR[2,60]	CAR[2,60]
BLAME	-0.398***	-0.370***
	(0.119)	(0.113)
EADCAR[-1,1]	0.257	0.234
	(0.212)	(0.209)
BM		0.314
		(0.284)
Log(ME)		-0.677
		(0.415)
MOMENTUM		-0.422
		(0.580)
ACCRUAL		-1.058***
		(0.194)
NEG		-0.202
		(0.165)
VOLATILITY		0.419
		(0.332)
INSTOWN		-0.162
		(0.115)
LNUMEST		-0.0442
		(0.299)
TURNOVER		-0.0826
		(0.228)
Observations	66,561	66,561
R-squared	0.177	0.182

Table A2: Longer-term Return Reaction

This table investigates how our blame measure (BLAME) relates to longer-term returns after quarterly earnings conference calls. In the panel regressions, the dependent variable is the cumulative abnormal return, i.e., CAR[61,252], from trading day 61 to trading day 252 after each earnings conference call day, based on the Fama-French three-factor model. The following explanatory variables are constructed based on the information available as of the time of each earnings conference call. BLAME is the percentage of the blame sentences in each earnings conference call. FE is the latest earnings forecast error using the realized quarterly earnings and consensus (mean) of earnings forecasts for the corresponding quarter across analysts following. BM is the logarithm of book-to-market ratio from the end of the previous year. Log(ME) is the logarithm of the market equity (in $1,000) from the end of the previous year. MOMENTUM is the past 12-month cumulative return. ACCRUAL is the accrued earnings divided by total assets (=(IBCY-OANCFY)/ATQ) from the quarter associated with each earnings conference call. NEG is the percentage of negative words in each earnings conference call. VOLATILITY is the annualized volatility of daily returns in the preceding month. INSTOWN is the percentage of institutional ownership in the preceding quarter. LNUMEST is the log of one plus the number of analysts following from the latest forecast period. TURNOVER is the average daily share turnover in the preceding month. All panel regressions include industry×quarter fixed effects based on the SIC-3 industry classifications. Each explanatory variable is standardized to have the mean of zero and the standard deviation of one. The slope coefficients are reported in percentage and their standard errors are clustered by quarter and reported in parenthesis. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Variables	CAR[61,252]	CAR[61,252]
BLAME	-0.104	-0.338
	(0.319)	(0.267)
FE		-0.487
		(0.346)
BM		0.263
		(0.311)
Log(ME)		-0.943
		(0.637)
MOMENTUM		-0.959
		(0.705)
ACCRUAL		-0.548*
		(0.291)
NEG		0.530
		(0.412)
VOLATILITY		-0.459
		(0.306)
INSTOWN		0.165
		(0.200)
LNUMEST		0.139
		(0.418)
TURNOVER		-0.931**
		(0.353)
Observations	66,561	66,561
R-squared	0.018	0.021