Mood and Analyst Optimism and Accuracy*

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ABSTRACT

Does mood affect prediction performance? When analysts are in a positive (negative) mood, do they make more positively (negatively) biased and less (more) accurate forecasts? This study provides supportive evidence. Specifically, we find that analyst forecasts are more optimistic and have larger errors near holidays, but more pessimistic and have smaller errors when there is a disaster with significant fatalities. We further show that these results are neither driven by sentiment associated with contemporaneous economic or market conditions, nor by under-reaction or over-reaction to more bad news released on days immediately before weekends or holidays.

JEL codes: G24, G14, D03, G02

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1 Introduction

Conventionally, people are assumed to be fully rational. However, some studies suggest that the mood or psychological states of people affect their judgment (Frijda 1988; Schwarz and Clore 1983), information processing (Estrada et al. 1997), cognition (Isen 2001) and decision-making (Etzioni 1988), even though they are usually unaware of it. Based on a survey at the individual investor level, Kaplanski et al. (2015) provide direct evidence that happier investors, with respect to a variety of sentiment-related factors including general feeling, favorite sports team's results, perception of weather, influence of seasonal affective disorder, are more optimistic about expected performance of stock markets and have higher intentions to purchase stocks. This paper also studies mood, but focuses on analysts' optimism. In addition, prediction accuracy is our focus.

Wright and Bower (1992) show that people in a positive (negative) mood are more (less) optimistic and assign higher (lower) probabilities to positive events. Presumably, people are typically in a pleasant mood on holidays or when holidays are coming (Bollen et al. 2011; Sharpe 2014). So logically, a favorable mood has long been proposed as a plausible explanation for significantly higher pre-holiday returns in financial markets (Thaler 1987; Fabozzi et al. 1994; Frieder and Subrahmanyam 2004).[1] Hence, we hypothesize that analysts are happier on holidays and happiness increases as holidays are approaching closer, whereby making more bullish or more positively biased forecasts during these times.

In addition, the "mood-as-information" theory (Schwarz 1990) posits that people in a happy mood tend to react to irrelevant information whereas people in a negative mood generally process information more cautiously and respond strongly to actual relevant news. Therefore, we expect that analysts tend to make larger forecast errors prior to or on holidays when they are in a happy mood and the errors are larger when upcoming holidays are nearer.

Consistently, based on a sample of forecasts of the US firms over the 1983 to 2014 period, we find that the forecasts released in the week ending with a Thanksgiving Day, a Christmas Day or a New Year's Day[2] (hereafter "the holiday mood periods") are more optimistic and have larger errors, statistically significant at the 1% level, controlling for at least 18 explanatory variables, year, industry, firm and analyst fixed effects, and with robust standard errors based on two-way clustering at the firm and analyst levels. These additional optimism and additional errors are also economically significant: They amount to 16.8% and 18.5% of the unconditional mean forecast optimism and error, respectively. Moreover, the

[1] See also Autore et al. (2015) for a recent study on the pre-holiday effect on corporate announcements.

[2] According to Gallup, holidays, especially Thanksgiving Day and Christmas Day, are usually the happiest days in a year (Sharpe 2014).

incremental optimism and incremental inaccuracy are positively related with how close a forecast publication day is to a coming holiday. Furthermore, significant mood effects are robust for several additional analyses including use of other holidays or personal income tax shocks as an alternative mood proxy.

Lemmon and Portniaguina (2006) show that many macroeconomic variables are strongly contemporaneously correlated with consumer sentiment. Hence, people's mood is plausibly directly affected by macroeconomic conditions. We thus predict that the contraction stage of the business cycle will affect people's mood negatively, so forecast optimism and errors will be weaker in the contraction phases. In line with this prediction, we find that compared with the effects in non-contraction periods, in contraction periods the additional holiday mood effects are more negative on forecast optimism and errors, indicating the contraction stage diminishes the holiday mood effects.

Most economic statistics improve markedly around the holidays we study (Barsky and Miron 1989). It is conceivable that people generally have higher sentiment under the influence of the favorable economic conditions during these times. To address the concern that our holiday mood effects on forecast optimism and errors may be driven by the effect of the favorable economic conditions around these holidays, we add an explanatory variable that captures the effect of the time-varying economic condition on people's mood. We find that the holiday mood effects on forecast optimism and errors remain highly significant and have similar magnitude as before.

The literature suggests that companies strategically release more of their bad news just before weekends or holidays, taking advantage of people being inattentive and thus under-reacting to information on those days (e.g. DellaVigna and Pollet 2009). As a result, forecasts will have larger errors. Meanwhile, distraction can magnify general optimistic tendency of analysts for their forecasts, because of career concerns (Hong and Kubik 2003) and conflicts of interest (Mehran and Stulz 2007), whereby producing larger forecast errors on the positive side, i.e. more optimism. To examine whether our results are driven by the "under-reaction to more bad news", we thus additionally control for pre-holiday and Friday effects.[3] We find that our results remain.

Moreover, forthcoming holidays distract people from work so that analysts may respond less to news, which may explain our holiday mood effects on forecast error and optimism.[4] However, against the notion of limited attention, we find that analysts are as responsive to news during the holiday mood periods, whether it is the day immediately before a weekend/holiday, as during the other

[3] Since it is not unusual that it takes about 3-4 days to publish a forecast, we also control for lagged pre-holiday and Friday effects. We thank Peter Joos and Gilles Hilary for discussion regarding the process of forecast publications.

[4] See, for example, Hirshleifer and Teoh (2003), Peng and Xiong (2006), and Hong and Stein (2007) for studies on limited attention or distraction.

periods, in terms of the number of forecasts in relation to the number of news items and the percentages of these numbers.[5]

Finally, to further test our mood hypotheses from the opposite angle, we study disastrous events, proxies for negative mood. Studies suggest that disaster information induces negative mood or affects mood adversely (Johnson and Tversky 1983; Göritz and Moser 2006; Västfjäll et al 2008; Papousek et al 2014). We hypothesize that when there is a major disaster involving significant fatalities, analysts will be in a negative mood and thus make more pessimistic (Wright and Bower 1992) and more accurate (Schwarz 1990) forecasts.[6] We provide supportive evidence, controlling for the sentiment related with contemporaneous economic conditions and the effect of more bad news on the days immediately before weekends and holidays. We further document that the negative mood effects are stronger among those analysts located in areas where disasters occur.

Our work is related to two strands of research. First, we contribute to the analyst forecast literature. Many studies of analyst forecasts are sell-side research. Three exceptions, closely related to our study, are deHaan et al. (2015), Dong and Heo (2014) and Dolvin et al. (2009). deHaan et al. (2015) study weather-induced moods and find that analysts experiencing unpleasant weather have lower

[5] As discussed, it may take a few days to publish a forecast, so we also consider the numbers of lagged news items. Our results still hold.
[6] We exclude disasters with significant losses and those with terrorism. Hence, our results are unlikely explained by an economic- or risk-based reason.

forecasting activities and make more pessimistic forecasts than those experiencing pleasant weather. Dong and Heo (2014) show that higher flu intensity is associated with lower degree of disagreement among analysts, over-prediction (interpreted as more optimism) of target price for high-performing stocks, and under-prediction (interpreted as more pessimism) of target price for low-performing stocks. They suggest that their results are driven by analysts' limited attention and effort as a consequence of the distraction of experiencing flu symptoms by family members, relatives, colleagues and themselves. Dolvin et al. (2009) document that seasonal affective disorder is associated with pessimism, resulting in less analyst optimism. As Dolvin et al. (2009), we consider mood, which has barely received attention in the analyst forecast literature. However, we study both positive and negative mood while Dolvin et al. (2009) examine negative mood.

Second, research in behavioral finance has ample persuasive evidence that stock returns are associated with mood proxy variables, such as biorhythms, e.g. Seasonal Affective Disorder, daylight saving, lunar phases, (e.g. Kamstra et al. 2000; Kamstra et al. 2003; and Yuan et al. 2006) and weather, e.g. rain, temperature, wind, storms, (e.g. Saunders 1993; Hirshleifer and Shumway 2003; Goetzmann et al. 2015). These studies put forward that certain variables, including sports outcomes (Edmans et al. 2007; Kaplanski and Levy 2010b) and disastrous events (Kaplanski and Levy 2010a), affect the mood of investors, whereby affecting their decisions. As a result, asset prices and returns vary with their mood. Shu (2010) provides a theoretical model that shows how investor mood variations affect equilibrium asset prices and expected returns, and thus helps to explain the results in the empirical studies. While most of the studies in this literature focus on investment decisions, we look at prediction performance.[7]

The rest of this paper is organized as follows. Section 2 describes data and variables. Section 3 lays out methodology and states hypotheses. Section 4 reports summary statistics and results of univariate analysis. Section 5 presents and discusses results of our regression analysis. Section 6 concludes.

2 Data and Variables

We obtain realized earnings and analyst earnings forecasts from I/B/E/S Detail History files. The forecasts are over the 1982 to 2014 period. We only consider annual EPS (earnings per share) forecasts published after the end of the last fiscal year and before or at the end of the current fiscal year for which the annual EPS is forecasted.[8] We use I/B/E/S actual earnings, instead of Computat

[7] There are studies linking sentiment to future performance (e.g., Ali and Gurun 2009; Stambaugh et al 2012). One commonly used sentiment measure is Baker-Wurgler sentiment index, which is controlled for in this study. Moreover, this sentiment measure is largely market-based and thus is not the same as the mood exogenous to the market or economy condition, which is the subject of this study.

[8] Some previous studies do not use the forecasts published within the 30 days before the fiscal-year end (e.g. Clement 1999, Clement and Tse 2005). Two main reasons are given. First, these

ones, because I/B/E/S has a policy to report an actual earnings number that is consistent with forecasts: It excludes the same items from the actual EPS number that the majority of analysts exclude from their forecasts (Christensen 2007). The sources of accounting and financial data are Compustat and CRSP, respectively. The holiday dates come from http://www.timeanddate.com. Our definition of contraction periods is based on NBER (National Bureau of Economic Research) business cycle reference dates. We obtain the monthly consumer sentiment data from the University of Michigan surveys and the monthly consumer confidence index from the Conference Board surveys. The monthly Baker-Wurgler investor sentiment index (ended in December 2010) is downloaded from Wurgler's website. The daily news item number is obtained from Bloomberg. The dates of the disasters with at least 100 fatalities without a significant economic loss and without terrorism are retrieved from the website below or the webpages linked to this website:

forecasts tend to be made by analysts who follow other analysts rather than follow the companies. Second, these forecasts may be for the next fiscal year. However, there are at least three reasons why this is not a concern for us. First, we show in Section 4.2 that analysts who make forecast in the holiday mood period generally make their first forecast earlier than those who do not make forecast in the holiday mood period. Second, there is no reason why forecasts made by followers are more accurate. O'Brien (1988) finds that more recent forecasts are more accurate, and thus are unlikely made by followers. Finally, Guttman (2010) shows that analysts with higher learning ability tend to forecast later. Hence, recent forecasts tend to be made by capable forecasters rather than by followers. Furthermore, there are studies that use the most recent forecasts (Karamanou and Vafeas 2005; Hong and Kacperczyk 2010; Dhaliwal et al 2012; Fong et al 2013). Lastly, we have a data field to ensure that the forecasts are made for the current fiscal year.

https://en.wikipedia.org/wiki/List_of_disasters_in_the_United_States_by_death_toll. Our analysts' location data are based on the annual volumes of Nelson's Directory of Investment Research.[9] We obtain location information of the disasters from the websites of the Midwestern Regional Climate Center, Wikipedia, the Heat is Online and the National Oceanic and Atmospheric Administration (NOAA)'s National Centers for Environmental Information as well as two journal articles, Palecki et al. (2001) and Wolfe et al. (2001).

We have two key dummy variables of interest. First, MOOD takes a value of 1 if the forecast release day is in the week ending with a Thanksgiving Day, a Christmas Day or a New Year's Day, and 0 otherwise. Second, NEG_MOOD takes a value of 1 if the forecast release day is on a day or in any day of the 5 days immediately after a day when a disaster with at least 100 fatalities, without a significant economic damage, and without terrorism happens, and 0 otherwise. The list of these disasters is given in Appendix 1.

The other variables are defined in Appendix 2. In subsequent analysis, we only consider those observations without missing values for all variables used in the baseline regressions. The sample attrition is reported in Appendix 3. In all

[9] We acknowledge Kee-Hong Bae and Hongping Tan for providing us with the location data for the period 1995 – 2010. The procedure of identifying analysts' locations is the same as that in Bae, Stulz, and Tan (2008) and Bae, Tan, and Welker (2008). Using Nelson's Directories, we manually check cases with the same analyst, the same research firm and multiple locations. We exclude those observations that there is insufficient information to clearly identify the location of the analyst. The exclusion does not materially affect our results.

regressions, all variables, except count, time and dummy variables, are winsorized at 1% and 99% to minimize the influence of outliners and errors in data, such as recording errors. We include year, 3-digit SIC industry, firm and analyst fixed effects in all of our regressions. Our standard errors are based on two-way clustering at the firm and analyst levels.

3 Methodology and Hypotheses

3.1 The (Good) Mood Hypotheses

In this section, we describe the methods we use to empirically test the mood hypothesis. Our basic regression models are as follows:

$$OPTIMISM_{k,j,t} = a + b \cdot MOOD_t + c \cdot Controls + e_{k,j,t} \quad (1a)$$

$$ERROR_{k,j,t} = \alpha + \beta \cdot MOOD_t + \varphi \cdot OPTIMISM_{k,j,t} + \gamma \cdot Controls + \varepsilon_{k,j.t} \quad (1b)$$

where subscript k indexes analysts, j indexes firms and t indexes time. OPTIMISM is forecast optimism in percentage terms, calculated as the annual EPS forecast minus the actual EPS being forecasted, scaled by the market share price as of the end of the last fiscal year. ERROR is forecast error as a percentage, calculated as the absolute difference between the annual EPS forecast and the actual EPS being forecasted, scaled by the market share price as of the end of the last fiscal year. More optimistic forecasts have larger errors. Therefore, in the error regression, we include OPTIMISM as an explanatory variable, whereby we can show the effect of MOOD on ERROR beyond the effect of MOOD on OPTIMISM as we hold OPTIMISM constant. See Ke and Yu (2006) for an example of a regression specification in the same spirit.[10] The last terms in both equations are the error terms. The variable of interest is MOOD that takes a value of 1 if the forecast release day is in the week ending with a Thanksgiving Day, a Christmas Day or a New Year's Day and 0 otherwise. The prediction of the mood hypothesis is that there is more forecast optimism and error during the holiday mood periods than during the other times. In other words, the hypothesis predicts that both b and β are positive.

3.2 Contraction Periods and the Mood Effects

Next, we consider whether analysts' psychological state will be adversely affected in recessions. To this end, we augment the above models as follows:

[10] It is documented that analyst forecasts are generally positively biased. When we observe an error, it can be because there is actually an unbiased error. However, it can also result from a bias. To distinguish errors from bias, we thus control for OPTIMISM in the ERROR regression. We thank Sudipto Dasgupta for this specification suggestion. In our subsequent analysis, as a robustness check, we also exclude OPTIMISM and re-run the regression (1b). When we exclude the explanatory variable OPTIMISM from the error regressions, the estimated coefficients of MOOD increase from a range of 0.341 – 0.352 (with OPTIMISM as a control variable) to a range of 0.408 – 0.425, are still positive and significant at the 1% level. The estimated coefficients of the other explanatory variables are qualitatively the same. The results are reported in Table A9 in the supplementary file and available from the authors upon request.

$$OPTIMISM_{k,j,t} = A + B1 \cdot MOOD_t + B2 \cdot C \cdot MOOD_t$$
$$+D \cdot Controls + \epsilon_{k,j,t} \quad (2a)$$
$$ERROR_{k,j,t} = \delta + \theta1 \cdot MOOD_t + \theta2 \cdot C \cdot MOOD_t + \vartheta \cdot OPTIMISM_{k,j,t}$$
$$+ \pi \cdot Controls + \omega_{k,j.t} \quad (2b)$$

where C takes a value of 1 if the forecast is announced in a contraction period, and 0 otherwise. The last terms in both equations are the error terms. A dummy for contraction periods is also included as a control variable in (2a) and (2b). We expect that people are more frustrated, rather than happier, during holidays in contraction phases than in other phases. Therefore, we predict negative incremental MOOD effects in contraction periods. Thus, both B2 and θ2 are negative.

3.3 Sentiment and the Mood Effects

Around Thanksgiving Days, Christmas Days and New Year Days, economic statistics are generally remarkably better (Barsky and Miron 1989). Meanwhile, macroeconomic variables are typically strongly contemporaneously correlated with consumer sentiment (Lemmon and Portniaguina 2006). Therefore, it is plausible that people have generally higher sentiment during the holiday mood periods as they are affected by the prosperous economic conditions during these times. To investigate whether our MOOD effects documented above are driven by the sentiment associated with the economic conditions, we incorporate an additional sentiment measure into our regressions (2a) and (2b) and examine whether MOOD loses explanatory power. In particular, we consider the Michigan's consumer sentiment index (CSENT)[11], the Conference Board's consumer confidence index (CCON) and the Baker-Wurgler investor sentiment index (SENT) separately as the sentiment measure.

3.4 An Alternative Under-reaction/Limited Attention Hypothesis

If managers make use of people's limited attention prior to holidays and thus release more bad news during these times, they are most likely to do so on Friday, just before weekend, or the day immediately before holidays when people pay least attention, rather than any other days earlier. If analysts are less attentive or more distracted prior to holidays so that they underreact or react with a delay to bad company news disclosed more during these times, and the bad news announced is material to the corporate value being forecasted, then this may explain the forecast optimism in the week ending with a Thanksgiving Day, a Christmas Day or a New Year's Day. Optimism is due to the unadjusted and higher forecasts in relation to the new and lower level of actual earnings. To examine whether the MOOD effects are driven by under-reaction, we have the following expanded models:

[11] Walther and Willis (2013) consider CSENT as a measure of investor expectation.

$$OPTIMISM_{k,j,t} = A_1 + B1_1 \cdot MOOD_t + B2_1 \cdot C \cdot MOOD_t + B4_1 \cdot NON - B\_L1$$
$$+ B5_1 \cdot NON - B\_F3 + \ B6_1 \cdot NON - B\_F4$$
$$+ C_1 \cdot Controls + \epsilon_{k,j,t} \qquad (3a)$$

$$ERROR_{k,j,t} = \delta_1 + \ \theta1_1 \cdot MOOD_t + \theta2_1 \cdot C \cdot MOOD_t + \theta4_1 \cdot NON - B\_L1$$
$$+ \theta5_1 \cdot NON - B\_F3 + \ \theta6_1 \cdot NON - B\_F4$$
$$+ \vartheta_1 \cdot OPTIMISM_{k,j,t} + \pi_1 \cdot Controls \ + \omega_{k,j.t} \qquad (3b)$$

NON-B_L1 (**L**agged **One** Day of **Non-B**usiness Day) takes a value of 1 for the day immediately before a weekend or a holiday, based on the trading days of S&P 500, and 0 otherwise. It is important to realize that it may take about 3-4 days to publish a forecast although it probably will only take a couple of hours to release a new forecast when important and material news is released. Hence, we also include dummies for the third and fourth days after a weekend or a holiday, NON-B_F3 (the **3**rd Day **F**orward from a **Non-B**usiness Day) and NON-B_F4 (the **4**th Day **F**orward from a **Non-B**usiness Day). If under-reaction drives the MOOD effects, then both $B1_1$ and $\theta1_1$ will be insignificant while $B4_1$ and $\theta4_1$ (or $B5_1$ and $\theta5_1$, or $B6_1$ and $\theta6_1$) will be positive. On the other hand, the predictions of the mood hypotheses are that both $B1_1$ and $\theta1_1$ are positive.

If preparing for holidays or engaging in events around holidays diverts people's attention from work, analysts will have inadequate attention, respond less to news during the holiday mood periods. Hence, we test whether the number of forecasts during MOOD is significantly smaller in relation to the number of news items, as predicted by the limited attention hypothesis. We thus study the incremental sensitivity of the daily number of forecasts ($FNUM_t$) associated with MOOD with respect to the detrended daily number of news items ($NEWSNUM_t$).[12]

$$FNUM_t = \mu 0 + \mu 1 \times NEWSNUM_t + \mu 2 \times NEWSNUM_t \times MOOD_t + \mu 3 \times MOOD_t + e_t \qquad (4a)$$

Since it is expected that limited attention mainly occurs on the day just before a weekend or a holiday, we conduct the following robustness check. We partition MOOD into several dummy variables. PRE takes a value of 1 if MOOD = 1 and the day when the forecast is released is Friday or a day before a holiday, and 0 otherwise.[13] FREE takes a value of 1 if MOOD=1 and the day when the forecast is released is a weekend or a holiday. MOOD2 takes a value of 1 if MOOD=1, PRE≠1 and FREE≠1, and 0 otherwise. MOOD2 are the strictly defined days likely to be under the influence of a holiday mood, but unlikely to be

[12] As there is clearly a time trend for the number of news items, we de-trend the time series of the number of news items.
[13] In addition, we create a dummy variable (FRI) exclusively for all forecasts published on Friday to examine whether there is generally under-reaction to more bad news disclosed on Friday.

affected by under-reaction to bad news disclosed more on Fridays or the day immediately before holidays.

$$
\begin{aligned}
FNUM_t = {} & \mu0_1 + \mu1_1 \times NEWSNUM_t + \mu2_1 \times NEWSNUM_t \times MOOD2_t \\
& + \mu3_1 \times MOOD2_t + \mu4_1 \times NEWSNUM_t \times PRE_t + \mu5_1 \times PRE_t \\
& + \mu6_1 \times NEWSNUM_t \times FREE_t + \mu7_1 \times FREE_t \\
& + \mu8_1 \times NEWSNUM_t \times FRI_t + \mu9_1 \times FRI_t + \varepsilon_t \qquad (4b)
\end{aligned}
$$

As the dependent variable (the daily number of forecasts) in (4a) and (4b) is a count variable, we employ a Poisson model. We also estimate a Negative Binomial model as a robustness check. The limited attention hypothesis predicts that $\mu2 < 0$ and $\mu2_1 < 0$ as well as $\mu4_1 < 0$ and $\mu8_1 < 0$.

Besides the numbers (i.e. the level) themselves, we also consider the logarithmic transformation of the numbers ($LNFNUM_t$ and $LNNEWSNUM_t$), for which the slope coefficient of $LNNEWSNUM_t$ of the regression reflects the percentage change in the number of forecasts associated with an 1 percent increase in the number of news items. The predictions of the limited attention and under-reaction hypothesis are exactly the same as those for the level regressions discussed in the previous paragraph. Since it may take a few days to publish a forecast, we also consider daily numbers of lagged news items.

3.5 The Negative Mood Hypotheses

Finally, we revisit the mood hypotheses from the opposite perspective and consider occasions when people are likely in a negative mood. Specifically, we study disasters. We modify the models as follows:

$$OPTIMISM_{k,j,t} = A_0 + B_0 \cdot NEG_{MOOD_t} + C_0 \cdot Controls + \epsilon_{k,j,t} \qquad (5a)$$

$$ERROR_{k,j,t} = \delta_0 + \theta_0 \cdot NEG_{MOOD_t} + \vartheta_0 \cdot OPTIMISM_{k,j,t}$$
$$+ \pi_0 \cdot Controls + \omega_{k,j.t} \qquad (5b)$$

where NEG_MOOD takes a value of 1 if the day when the forecast is published is on a day or in any day of the 5 days immediately after a day when a disaster with at least 100 fatalities, without a significant economic damage, and without terrorism happens, and 0 otherwise. This six-day window takes into consideration that news may be released to the public on day *t*+1 and it may take about 3-4 days to publish a forecast. As Wright and Bower (1992) and Schwarz (1990), the mood hypotheses predict that there is more pessimism and more accuracy under the influence of a negative mood. Hence, we expect that the coefficients of NEG_MOOD are negative: $B_0 < 0$ and $\theta_0 < 0$.

We further postulate that local people (i.e. those live in states where disasters occur) are more affected by disasters because they receive more information about the events and these events are also more relevant to them

(Kaplanski and Levy 2010a).[14] To test this hypothesis, we create a new dummy variable LOC_NEG_MOOD which takes a value of 1 if the analyst is a local person, and 0 otherwise. We then add this dummy variable as an explanatory variable to equations (5a) and (5b). This variable captures the differential mood effect of local analysts that is incremental to that of non-local analysts. The prediction is that the coefficients of LOC_NEG_MOOD are negative.

4 Descriptive Statistics and Univariate Analysis

4.1 Descriptive Statistics

Our main periods of interest, "the holiday mood periods" ("MOOD") cover days in the week ending with a Thanksgiving Day, a Christmas Day and a New Year's Day from 1983 to 2014.[15] There are 56,736 analyst forecasts of annual EPS released during these periods. The numbers of annual EPS forecasts in November and December are 168,947 and 108,316, respectively. Hence, the forecasts in the holiday mood periods account for approximately 20.5% of those in November and December.[16] As for proxies for negative mood occasions, there are 17,169 analyst forecasts published on a day or in any day of the 5 days

[14] Recently, O'Brien and Tan (2015) study geographic proximity and analyst coverage decisions.
[15] Forecasts in earlier time cannot be used because we use lagged data to construct some control variables.
[16] The number of the forecasts in the holiday mood periods is about 3% of the total number of forecast in the sample.

immediately after a day when a disaster with at least 100 fatalities happens, amounting to 30.3% of those in the holiday mood periods.

Table 1 report the summary statistics, mean, standard deviation (S.D.), 25 percentile (25%), median, and 75 percentile (75%), of the variables used in this study. The variables are defined in Appendix 2. The mean (median) of forecast optimism and error are 0.72% and 1.84% (0.019% and 0.554%), respectively. These statistics are consistent with some summary statistics in the literature (e.g. Bushee et al. 2010 with a median error of 0.4% and Walther and Willis 2013 with a mean optimism of 0.76%). Table 2 shows the correlation matrix of the explanatory variables. Most of the correlation coefficients are small in magnitude. The two highest correlation coefficients are 0.725 between *LNSIZE* and *COVERAGE* and 0.723 between *NCO* and *NSIC2*. The next five strong correlation coefficients are 0.701 between *FIRM_MBIAS* and *FIRM_MERROR*, 0.644 between *ANALYS_MBIAS* and *ANALYS_MERROR*, 0.643 between *SP500* and *COVERAGE*, 0.633 between *SP500* and *LNSIZE* and -0.496 between *PROFIT* and *LOSS*. All of the (untabulated) variance inflation factors for the specifications used are smaller than 10. These values suggest that multicollinearity is not an issue.

4.2 Univariate Analysis

The mood hypothesis predicts that the forecasts made during the holiday mood periods are more optimistic and have larger errors. We first conduct univariate analysis to test the hypothesis. In particular, we test whether the forecast optimism and error are different between the holiday mood periods (MOOD) and the other periods (NON-MOOD).

Nevertheless, the major problem using raw forecast data for the tests is that the horizon, the number of days between the date when the forecast is released and the fiscal year-end date for which the earnings being forecasted, is systematically different between MOOD and NON-MOOD. Over 70% of the observations have the fiscal year-end in December, which is closer to the time when the forecasts released during the holiday mood periods than that during the other periods. Hence, forecasts for MOOD typically have a shorter horizon than those for NON-MOOD. Studies suggest that forecasts made in a longer horizon are generally more optimistic, for example, because analysts trade off some positive forecast bias (i.e. less accurate forecasts) to gain management access when information about companies' earnings prospects is less readily available (Lim 2001; Beyer 2008). The shorter the horizon, the more the information has been revealed over time. Therefore, the forecasts made closer to the fiscal year-end will be more accurate. As Byard et al. (2011), Jacob et al. (1999) and Clement and Tse (2003) suggest, to adjust the systematic difference in horizon between MOOD and NON-MOOD observations, we calculate the horizon-adjusted forecast optimism (error) as the residual from the regression of the raw/unadjusted forecast optimism (error) on LNHORIZON.[17]

Based on these horizon-adjusted forecast performance variables, Table 3 reports the test results. For the overall sample, consistent with the mood hypothesis, the forecasts for MOOD are, on average, more optimistic and have larger errors than those for NON-MOOD. The differences in horizon-adjusted optimism and error are 0.21% and 0.40%, significantly at the 1% level.[18]

Although horizon is taken into consideration, there is still a concern that the majority of NON-MOOD forecasts are made on days far away from the holiday mood periods, whereby these NON-MOOD forecasts do not provide a powerful comparison. Consequently, we consider three alternative, nearby and more comparable "control" groups, NOV Controls, JAN Controls and BNA ("Before aNd After") Controls1. NOV Controls consist of forecasts published in November, but not in the holiday mood periods. JAN Controls consist of forecasts published in January, but not in the holiday mood periods. BNA Controls1 consist of forecasts published between the week immediately before the week ending with a Thanksgiving Day and the week immediately after the week ending with a New Year's Day inclusively, but not in the holiday mood periods. The average

[17] The regression results are reported in Table A10 in the supplementary file and available from the authors upon request.
[18] Since the horizon-adjusted variables are regression residuals, their average value is zero.

horizon adjusted optimism and error for MOOD remain significantly more and larger than those for NON-MOOD. The magnitude of the differences is similar to that for the full sample.

There may be a day in a week, for example, Saturday, that there are forecasts for MOOD, but not for NON-MOOD, which may bias our results. Therefore, for the closest comparison group, BNA Controls1, we require that for each day of the week, there are forecasts for both the MOOD and NON-MOOD periods, which gives us the fourth control group, BNA Controls2. The differences in the horizon adjusted optimism and error between MOOD and NON-MOOD for BNA Controls2 are almost the same as those for BNA Controls1.

We expect that the unfavorable conditions associated with contractions moderate the holiday mood effects. In other words, we expect the additional forecast optimism and errors for MOOD over and above those for NON-MOOD are less pronounced in contractions than in non-contractions. As expected, the difference in optimism between MOOD and NON-MOOD is significantly positive for non-contractions while it is negative for contractions; the difference in error between MOOD and NON-MOOD is significantly positive for non-contractions while it is significantly negative for contractions.

People are likely to be in a more negative mood when there is a disaster, contrary to a positive mood over holiday periods. Hence, we anticipate that the forecasts released on a day or in any day of the 5 days immediately after a day when a disaster occurs (NEG_MOOD) are more pessimistic and more accurate. The results are shown in Panel B. In line with the prediction, the forecasts for MOOD are generally positive for both OPTIMISM and ERROR whereas those for NEG_MOOD are typically negative for both OPTIMISM and ERROR; the differences between MOOD and NEG_MOOD in OPTIMISM and ERROR are 0.478% and 0.837%, both significantly at the 1% level.

Furthermore, local people are plausibly in a more negative mood than non-local people when there is a disaster. Therefore, we expect that the forecasts made by local analysts are more pessimistic and more accurate than those by non-local analysts when a disaster happens. The results are reported in Panel C. Consistent with the expectation, the local analysts' forecasts are more negative for both OPTIMISM and ERROR; the differences are – 0.166% and – 0.302%, both significantly at the 1% level.

One possible reason why forecasts for MOOD are more positively biased and have larger errors than those for NON-MOOD may be due to difference in characteristics of analysts. For example, it is possible that senior analysts, with higher professional standards, avoid making forecasts during the holiday periods when they are more distracted and inattentive. On the other hand, junior analysts will be more active during these quiet times when it is easier to attract attention and thus have a better chance to increase their profile. Out of career concerns, the forecasts made by these junior analysts will tend to be more optimistic.

Meanwhile, there will be fewer senior analysts to generate useful information during these holiday periods so that the forecasts made during these times will have larger errors. As a result, we will observe more optimism and less accuracy for MOOD than for NON-MOOD. Therefore, we investigate whether characteristics are different between analysts for MOOD observations and those for NON-MOOD ones.

Panel A of Table 4 shows that the analysts releasing forecasts during the holiday mood periods generally make the first forecast earlier, are covering more firms and more industries, are slightly more likely to be a star analyst, have similar general and firm-specific forecasting experience.[19] Hence, there is no evidence that the analysts for MOOD are forecast followers, nor more junior than those for NON-MOOD. However, it is plausible that the MOOD analysts are busier as their coverage is larger (4.27 more firms and 1.25 more 2-digit SIC industries). Nonetheless, the analysts' characteristics and other explanatory variables are taken into consideration in the subsequent regression analyses.

Another question is whether firms with forecasts in the holiday mood period ("MOOD firms") are systematically different from those without forecasts in the same period ("NON-MOOD firms"). We find that MOOD and NON-MOOD firms generally have similar characteristics, except for size and

[19] We thank Ling Cen for providing us with data of star analysts, which cover the 2002 to 2012 period.

distributions of certain industries. As shown in Panel B of Table 4, MOOD firms are generally relatively smaller than NON-MOOD firms (median and mean of 2,070 and 8,548 million vs. 2,234 and 9,598 million, respectively). We control for firm size in all of our regressions. We also conduct a robustness check for results of the baseline regression based on firms only with a share price above $5. As shown in Panel C of Table 4, compared with NON-MOOD firms, MOOD firms are more in retail industry (14.57% vs. 10.01%), and less in finance and services industries (12.09% vs. 14.73% and 9.45% vs. 10.94%). Probably, holiday season sales are important for retail industry; there are more material updates during the holiday mood periods for this industry. We include 3-digit SIC fixed effects in all of our regressions.[20]

5 Empirical Results

5.1 The Baseline Results: (Good) Mood Effects

[20] Literature suggests that managers often provide guidance prior to holiday seasons. On average they tend to lower expectations of analysts to increase the probability of beating or meeting the earnings target. This is referred as "Walk Down Hypothesis", which should lead to more pessimistic and more accurate forecasts and thus bias against our mood hypothesis. Besides, there is no clear evidence that managerial guidance will generally affect analyst forecasts (e.g. Houston et al 2010).

Table 5 reports our baseline results. Consistent with the mood hypothesis, the estimated coefficients of MOOD are positive and statistically significant at the 1% level for both OPTIMISM and ERROR regressions. These show that the forecasts published during the holiday mood periods are generally more optimistic (positively biased) and have larger errors. These coefficients are also economically significant. As shown in Column (3), the incremental optimism during the holiday mood periods is, on average, 0.12%, representing 16.8% of the unconditional mean forecast optimism.[21] Dolvin et al. (2009) find a decrease of 0.0220% - 0.0302% in forecast optimism for the seasonal affective disorder periods. Hong and Kacperczyk (2010) report an estimate of an increase of 0.13% in mean forecast optimism for a decrease in coverage by one analyst. Our 95% confidence interval of the incremental optimism is (0.072%, 0.169%). As shown in Column (6), the additional error during the same periods is typically 0.34%, equivalent to 18.5% of the unconditional mean forecast error. Dolvin et al. (2009) find an increase of 0.0220% - 0.0302% in forecast accuracy for the seasonal affective disorder periods. Dhaliwal et al. (2012) report an improvement of 0.435% in forecast accuracy of firms with corporate social responsibility disclosure over those without such disclosure. The 95% confidence interval of the

[21] Kasser and Sheldon (2002) suggest that older people engage more and thus have happier holidays then younger people. Hence, we expect optimism associated with MOOD is more pronounced among more senior analysts. We find that it is actually the case, whereas seniority is measured by GENERAL_EXPERIENCE (the number of days for which the analyst has been a forecaster), in logarithmic form.

additional error is (0.293%, 0.388%). The magnitude of the coefficients remains similar whether we include firm fixed effects or further incorporate analyst fixed effects.[22] Regarding the explanatory power or goodness of fit of our baseline models, the adjusted R^2s of 0.282 and 0.648 are comparable to 0.356 and 0.500 in Walter and Willis (2013) and generally higher than those in other studies (e.g. 0.23 – 0.28 in Liang and Riedl 2014; 0.071 – 0.081in So 2013; 0.036 – 0.124 in Gu and Wu 2003)

As in the univariate analysis, the effects of the analyst characteristics on forecast optimism and accuracy in the multivariate setting are also explored as follows. Conceivably, there may be some analyst specific persistence in forecast optimism and accuracy (e.g. Butler and Lang 1991). We take this into account using the median optimism (ANALYS_MBIAS) and the median error (ANALYS_MERROR) of all the forecasts made by the analyst for the last fiscal year. If the analysts' forecast persistence in performance exists, then these variables should be positively related to OPTIMISM and ERROR. Our estimated coefficients of these variables are supportive of the persistence notion.

Generally, more senior analysts with more experience will follow a larger number of firms. The number of firms covered by an analyst (NCO) can be a

[22] We also consider brokerage fixed effects. We leave them out in the subsequent regressions because they only additionally explain 0.2 – 0.3% and the estimated coefficients are almost the same regardless of the incorporation of these effects. The results with the brokerage fixed effects are not tabulated, but available from the authors upon request.

proxy for the experience of the analyst. We expect and find that analysts with more experience generally make smaller forecast errors. On the other hand, the number of industries covered by an analyst (NSIC2) is associated with the forecasting complexity faced by the analyst. Consistent with Clement (1999), we anticipate and find that analysts following a larger number of industries typically make larger forecast errors.

While the length of time for which an analyst has followed a firm (LNEXPERIENCE_WITH_FIRM) can be a proxy for his experience with that firm, it is also likely to be positively associated with conflicts of interest. If the former is true, then this variable will be negatively related with ERROR. However, if the latter is correct, then this variable will be positively associated with OPTIMISM. We find that this time variable is unrelated with ERROR, but positively related with OPTIMISM, suggesting presence of a closer relationship and more conflicts of interest when the analyst has followed the firm for a longer time.

LNGENERAL_EXPERIENCE, the length of time for which an analyst has published forecasts, is negatively related to OPTIMISM and ERROR. These suggest that analysts with more experience generally have more conservative and more accurate forecasts.

5.1.1 The Baseline Results: Robustness Checks and Additional Analyses

We perform several robustness checks and additional analyses. First, we consider three alternative nearby periods and compare forecast optimism and accuracy during each of these periods with the holiday mood periods. Second, we examine whether the MOOD effect is stronger when the forecast published on a day closer to a holiday. Third, we re-run the baseline regressions only for firms with a share price above $5. Fourth, forecasts were often delivered to I/B/E/S in batches, not daily, before 1994 and thus the forecast publication date for pre-1994 forecasts in the database may be inaccurate (Hilary and Hsu 2013). Therefore, we re-run the baseline regressions only for forecasts published in and after 1994. Fifth, Regulation Fair Disclosure was promulgated in August 2000 and the Global Research Analyst Settlement was finalized on 28 April 2003, so we test whether the mood effects on optimism and accuracy remain for forecasts published after August 2000 or April 2003. Sixth, we study other holidays. Seventh, we consider personal income tax shocks as another mood proxy. Finally, we examine cross-sectional variation of the mood effects.

Table 6 reports the results for the nearby periods, NON-MOOD_NOV, NON-MOOD_JAN and NON-MOOD_BNA ("Before aNd After"). All of the coefficients for these nearby non-mood periods are statistically significantly smaller than the MOOD coefficients. Hence, these nearby non-mood forecasts are significantly less optimistic and more accurate than the forecasts in the holiday mood periods. The negative coefficients of NON-MOOD_NOV and the positive coefficients of NON-MOOD_JAN are consistent with the notion that there is more uncertainty earlier in a fiscal year and less uncertainty later in a fiscal year, whereby NON-MOOD_JAN forecasts are more optimistic and inaccurate whereas NON-MOOD_NOV forecasts are more pessimistic and accurate (Lim 2001; Beyer 2008). The negative coefficients of NON-MOOD_NOV may also reflect the winter blue. The positive coefficient of NON-MOOD_BNA of the error regression probably suggests that this nearby period is generally happier than the other times in a year (Ingraham 2014; Parry 2011).

We also have the following untabulated robustness results.[23] First, we find that a forecast published on a day closer to a holiday is more optimistic and inaccurate. The relationships between closeness and optimism and between closeness and error are statistically significant at the 1% level. Second, our results remain for firms with a share price above $5. Third, the MOOD results are also robust for the sub-period after 1993. Fourth, we find that there is generally a stronger mood effect on analyst optimism (0.17% vs. 0.12%) after August 2000 whereas the corresponding mood effect on analyst errors is smaller (0.257% vs.

[23] The closeness results are reported Table A1, the non-penny results in Table A5, the post-1993 results in Table A6 and the post-August 2000 results in Table A7 in the supplementary file and available from the authors upon request.

0.34%), but still highly significant. We obtain similar results for the post-April 2003 period.

As for the alternative holidays, we first consider Independence Days, Martin Luther King Days and Memorial Days. We obtain qualitatively the same results.[24] The estimated coefficient associated with the forecasts released in the week ending with these holidays is statistically indistinguishable from that of MOOD for the optimism regression, but is smaller (but still positively significant) for the error regression. We further check whether there are also mood effects for the commemoratory holidays and whether the new results are just driven by happy Independence Days. We thus only look at Martin Luther King Days and Memorial Days. We find that the results with and without Independence Days are highly comparable.[25]

Studies show there is generally a significant positive relationship between happiness and income (e.g. Sacks et al. 2012; Stevenson and Wolfers 2013). Hence, we postulate exogenous personal income tax shocks, unrelated to the current state of the economy, as a mood proxy: when there is an unanticipated decrease (increase) in the personal income tax, mood of analysts will improve (deteriorate), whereby the analysts will produce more optimistic (pessimistic) and

[24] The results are reported in Table A2 in the supplementary file and available from the authors upon request.
[25] The results are reported in Table A3 in the supplementary file and available from the authors upon request.

more inaccurate (accurate) forecasts. Using the tax shocks in Mertens and Ravn (2013), we have supportive evidence. Controlling for the contemporaneous corporate income tax shocks, the results remain. Moreover, the mood results do not appear in placebos, where occurrences of the personal income tax shocks are randomly assigned to calendar dates. [26]

Lastly, we find the following untabulated variation of the mood effects across analysts and firms. First, the mood effects on optimism and errors are less pronounced among analysts with more ANALS_MBIAS and ANALYS_MERROR, respectively. This may indicate that there is a limit about optimism and inaccuracy: The mood effects of those analysts who already tend to be more optimistic and inaccurate are weaker. Second, star analysts are generally perceived as more professional and expected to be less emotionally affected when making forecasts. However, we do not find that star analysts make less optimistic and more accurate forecasts than non-star analysts in the mood periods. Finally, our results are consistent with the notion that analysts are typically more conservative and cautious when accomplishing more difficult tasks. Specifically, we find that the mood effects are weaker when values of proxies for uncertainty of firms (SIGMA and FIRM_MERROR) are higher.[27]

[26] The results are reported in Tables A4A and A4B in the supplementary file and available from the authors upon request.

[27] Kadous et al. (2006) find that analyst optimism is weaker when generating counter-explanations, acting as a heuristic cue, to explain why managers' plans could fail is relatively easy than when it

5.2 Contractions and the Mood Effects

We test the hypothesis that analysts' mood will be negatively affected in contractions, whereby the incremental effects on forecast optimism and errors of the holiday mood periods in contractions will be negative. Table 7 shows the results. Consistent with the expectation, the estimated coefficients of the interaction term between the contraction dummy (C) and MOOD are negative and statistically significant at the 1% level for both OPTIMISM and ERROR regressions. These coefficients are also economically significant. Their magnitude is 4.1 times and 0.8 times those for forecast optimism and errors in non-contractions, respectively. Regarding non-contraction times, the effects of the holiday mood are still significantly positive on both forecast optimism and errors. In fact, the estimated MOOD coefficient for optimism increases from 0.121% to 0.209% (1.7 times) whereas that for errors remains similar (changing from 0.341% to 0.398%).

5.3 Sentiment and the Mood Effects

Table 8 reports the results after controlling for sentiment. The MOOD coefficients are still positive and as statistically and economically significant as before, with comparable magnitude. They are in the range of 0.177% - 0.236%

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is relatively difficult. Plumlee (2003) suggests that analysts assimilate more complex information to a lesser extent than they assimilate less complex information.

(0.209% in Table 7) for OPTIMISM and in the range of 0.395% - 0.415% (0.398% in Table 7) for ERROR. Hence, the holiday mood effects are not driven by economic-associated sentiment. In line with the notion that analysts are more optimistic when they have higher sentiment associated with better economic/market conditions, the estimated coefficients of all of the three sentiment measures are positive and statistically significant at the 1% level for the OPTIMISM regressions. Columns (4) – (6) of Table 8 show that these sentiment measures generally also have a positive relationship with analyst forecast error although the relationship becomes insignificant when Baker-Wurgler Index is the sentiment measure.[28, 29] As a robustness check, based on financial columns of New York Times up to 2005 (García 2013), we also use the daily difference between the proportion of the number of positive and negative words as a sentiment measure. The MOOD coefficients are barely affected. This financial column-based sentiment measure has a positive and significant relationship with analyst forecast error, but no relationship with analyst forecast optimism.[30]

[28] Kaplanski and Levy (2010c) find that analyst recommendations and Baker – Wurgler Index are positively associated.

[29] Untabulated results show that the economic-associated sentiment magnifies the mood effects.

[30] The results are not tabulated, but available from the authors upon request.

5.4 The Alternative Under-reaction/Limited Attention Hypothesis

The under-reaction hypothesis predicts that the forecast optimism during the holiday mood periods is driven by analysts' under-reaction to more of bad company news released just before weekends or holidays. To examine whether our MOOD results are driven by the under-reaction, we additionally control for the pre-holiday and Friday effects using the dummy variable NON-B_L1 that takes a value of 1 if the forecast is published on the day just before Saturday or a holiday, and 0 otherwise. As it may take 3-4 days to publish forecasts, we also control for lagged pre-holiday and Friday effects by including two dummy variables NON-B_F3 for the third day after a weekend or a holiday and NON-B_F4 for the fourth day after a weekend or a holiday. We study whether the MOOD effects disappear with presence of these additional control variables. Table 9 reports the results. We find that the estimated coefficients of MOOD are still positive and significant at the 1% level. They are actually almost the same as before, in the range of 0.179% - 0.237% (0.177% - 0.236% in Table 8) for OPTIMISM and in the range of 0.397% - 0.416% (0.395% - 0.415% in Table 8) for ERROR. These suggest that our MOOD effects are not driven by under-reaction of analysts to bad news on the days just before weekends or holidays. The negative coefficients of NON-B_L1 and NON-B_F4 are probably driven by negative effects of more bad news that make the generally optimistic forecasts more accurate.

In addition, we test the limited attention hypothesis that analysts react less to news during the holiday mood periods, whereby leading to less accurate and more positively biased forecasts. Therefore, we study the incremental sensitivities of the number of forecasts with respect to the number of news items associated with MOOD, and separately with MOOD2. Columns (4) – (6) of Panel A in Table 10 report the results. We also consider the natural logarithmic transformation of the numbers. The corresponding results are shown in Columns (1) – (3) of Panel A in Table 10. The limited attention hypothesis predicts that the incremental sensitivities are negative (i.e. for a given increase in the number of news items, there will be a smaller increase in the number of forecasts). However, we find that the differential sensitivities associated with both MOOD and MOOD2 are insignificant, with magnitude close to zero. Hence, the number of forecasts, in relation to the number of news items, is not particularly smaller for MOOD and MOOD2. These suggest that there is no evidence of limited attention during the holiday mood periods and the "strict" holiday mood periods.[31,32,33,34]

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[31] We have further evidence against the limited attention hypothesis. First, we have qualitatively the same incremental findings for PRE as those for MOOD2. Second, there is significantly more news sensitivity on Friday. The magnitude is also large, as of 2.47–2.67 times that of the other days. Hence, there is more news reaction on Friday.

[32] The numbers of contemporaneous and lagged news items are highly correlated. Hence, we estimate their impacts in separate regressions. We consider the numbers of one-, two-, three-, four-

5.5 The Negative Mood Effects

We study US disasters with at least 100 fatalities, without a significant economic loss and without terrorism. The latter two conditions are imposed to minimize contamination of the economic- and risk-based effects. When these major unfortunate events happen, people are likely in a negative mood (Johnson and Tversky 1983; Papousek et al 2014; Sharpe 2014). When analysts are in a negative mood, they tend to make more pessimistic (Wright and Bower 1992) and more accurate (Schwarz 1990) forecasts. Hence, we test whether there is more forecast pessimism and accuracy on a day or in any day of the 5 days immediately after a day when a major disaster occurs. Columns (1) and (2) in Table 11 show the results. Consistent with the predictions of the negative mood hypotheses, NEG_MOOD is negatively related with OPTIMISM and ERROR. The relationship is statistically significant at the 1% level.[35]

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and five-day lags of news items. We find that the numbers of the three- and four-day lags of news items are most positively related with the number of forecasts (with largest and significant coefficients and highest R^2s), consistent with the notion that it typically takes 3-4 days to publish a forecast. The results for the four-day lags are presented in Panel B of Table 10. The results for the one-, two-, three- and five-day lags are not tabulated, but available from the authors upon request.

[33] We also find that the estimated coefficients of the interaction between FRI and NEWNUM and the interaction between FRI and LNNEWNUM are significantly positive, against the under-reaction hypothesis that predicts negative coefficients.

[34] The results of Negative Binomial models are essentially the same as those of Poisson models and are not tabulated, but available from the authors upon request.

[35] We separately consider major disasters with more than 150 fatalities while not imposing the “no significant economic loss” and “no terrorism” conditions. The results are qualitatively the same. The list of disasters and the results are shown in Appendix A1 and Table A8 in the supplementary file and available from the authors upon request.

While news of major disasters generally influence mood negatively, we expect that local people (i.e. those people who are located in areas where these disasters occur) are more affected because of greater media coverage, more information, and greater attention. Therefore, we predict that when major disasters happen, local analysts (in states where the disasters happen) normally make more pessimistic and more accurate forecasts than non-local counterparts, i.e. negative coefficients of LOC_NEG_MOOD. The results are consistent with our expectation, as shown in Columns (3) and (4) in Table 11. The estimated coefficients of LOC_NEG_MOOD are significantly negative for both OPTIMISM and ERROR regressions.

We perform several robustness checks and obtain similar results.[36] In particular, we use alternative market/economic-based sentiment controls, Michigan's consumer sentiment index and Baker-Wurgler investor sentiment index. Moreover, we include and exclude the 1994 disaster, with relatively fewer location data of the analysts. In addition, we include and exclude those states where the 1999 heat wave occurs, but mentioned in only one source. Finally, we only consider the set of firms that have forecasts of both local and non-local analysts when there are disasters.

[36] These results are not tabulated, but available from the authors upon request.

6 Conclusions

Using the US data over the 1982 to 2014 period, we find that analysts generally make more optimistic or positively biased forecasts and forecasts with larger errors in the week ending with a Thanksgiving Day, a Christmas Day or a New Year's Day, proxies for favourable mood. Further analyses show that the additional forecast optimism and inaccuracy are neither driven by higher sentiment under the influence of better economic conditions, nor by under-reaction of the analysts to more bad news released just before weekends or holidays. We also find that in relation to news stories, the forecasts are as many during the holiday mood periods as during the other periods. Finally, we find more analyst pessimism and accuracy, particularly among local analysts, when major disasters, proxies for negative mood, occur. As a whole, our results are consistent with the notion that analysts generally produce more optimistic (pessimistic) and less (more) accurate forecasts when they are in a favorable (unfavorable) mood.

References

Ali, A., Gurun, U. G., 2009, Investor sentiment, accruals anomaly, and accruals management, Journal of Accounting, Auditing & Finance, 24(3), 4154 – 431.

Autore, D. M., Bergsma, K., Jiang, D., 2015, The pre-holiday corporate announcement effect, SSRN Working Paper.

Bae, K-H., R. M. Stulz, and H. Tan, 2008, Do local analysts know more? A cross-country study of the performance of local analysts and foreign analysts, Journal of Financial Economics, 88, 581–606.

Bae, K-H., H. Tan, and M. Welker, 2008, International GAAP differences: The impact on foreign analysts, Accounting Review, 83, 593-628.

Barsky, R. B., Miron, J. A., 1989, The seasonal cycle and the business cycle, Journal of Political Economy, 97, 503-534.

Beyer, A., 2008, Financial analysts' forecast revisions and managers' reporting behaviour, Journal of Accounting and Economics, 46, 334 – 348.

Bollen, J., Pepe, A., Mao, H., 2011, Modeling public mood and emotion: Twitter sentiment and socio-economic phenomena, Proceedings of the Fifth International AAAI Conference on Weblogs and Social Media (ICWSM 2011), 17-21 July 2011, Barcelona, Spain.

Bushee, B. J., Core, J. E., Guay, W., Hamm, S. J. W., 2010, The role of the business press as an information intermediary, Journal of Accounting Research, 48, 1-19.

Butler, K. C., Lang, L. H. P., 1991, The forecast accuracy of individual analysts: Evidence of systematic optimism and pessimism, Journal of Accounting Research, 29:1, 150 – 156.

Byard, D., Li, Y., Yu, Y., 2011, The effect of mandatory IFRS adoption on financial analysts' information environment, Journal of Accounting Research, 49(1), 69 – 96.

Christensen, T. E., 2007, Discussion of "letting the `tail wag the dog': the debate over GAAP versus street earnings revisited", Contemporary Accounting Research, 24:3, 741-762.

Clement, M. B., 1999, Analyst forecast accuracy: do ability, resources, and portfolio complexity matter?, Journal of Accounting and Economics, 27, 285-303.

Clement, M. B., Tse, S. Y., 2003, Do investors respond to analysts' forecast revisions as if forecast accuracy is all that matters?, Accounting Review, 78(1), 227 – 249.

Clement, M. B., Tse, S. Y., 2005, Financial analyst characteristics and herding behaviour in forecasting, Journal of Finance, 60, 307 - 341 deHaan, E., Madsen, J., Piotroski, J. D., 2015, Weather, mood, and professional work output: Large sample evidence, Stanford University Graduate School of Business Research Paper No. 15 – 47.

DellaVigna, S., Pollet, J. M., 2009, Investor inattention and Fridays earnings announcements, Journal of Finance, 64, 709-749.

Dhaliwal, D. S., Radhakrishnan, S., Tsang, A., Yang, Y. G., 2012, Nonfinancial disclosure and analyst forecast accuracy: International evidence on corporate social responsibility disclosure, Accounting Review, 87:3, 723 – 759.

Dolvin, S. D., Pyles, M. K., Wu, Q., 2009, Analysts get SAD too: the effect of Seasonal Affective Disorder on stock analysts' earnings estimates, Journal of Behavioral Finance, 10, 214-225.

Dong, G. N., Heo, Y., 2014, Flu epidemic, limited attention and analyst forecast behavior, Working Paper, University of Columbia.

Drought – July 1999, August 1999. Retrieved August 8, 2016, from http://www.ncdc.noaa.gov/sotc/drought/199907

Edmans, A., García, D., Norli, Ø, 2007, Sports sentiment and stock returns, Journal of Finance, 64, 1967-1998

Estrada, C. A., Isen, A. M., Young, M. J., 1997, Positive affect facilitates integration of information and decreases anchoring in reasoning among physicians, Organizational Behavior and Human Decision Processes, 72, 117-135.

Etzioni, A, 1988, Normative-affective factors: towards a new decision-making model, Journal of Economic Psychology, 9, 125-150.

Fabozzi, F. J., Ma, C. K., Briley, J. E., 1994, Holiday trading in futures markets, Journal of Finance, 49, 307-324.

Fong, K., Hong, H., Kacperczyk, M., Kubik, J. D., 2013, Do security analysts discipline credit rating agencies?, American Finance Association Meeting 2013.

Frieder, L., Subrahmanyam, A., 2004, Nonsecular regularities in returns and volume, Financial Analysts Journal, 60(4), 29 – 34.

Frijda, N., 1988, The laws of emotion, Cognition and Emotion, 1, 235-258.

García, D., 2013, Sentiment during recessions, Journal of Finance, 68, 1267 – 1300.

Goetzmann, W. N., Kim, D., Kumar, A., Wang, Q., 2015, Weather-induced mood, institutional investors, and stock returns, Review of Financial Studies, 28, 73 - 111.

Göritz, A. S., Moser, K., 2006, Web-based mood induction, Cognition and Emotion, 20:6, 887 – 896.

Gu, Z., Wu, J. S., 2003, Earnings skewness and analyst forecast bias, Journal of Accounting and Economics, 35, 5-29.

Guttman, I., 2010, The timing of analysts' earnings forecasts, Accounting Review, 85:2, 513 – 545.

Hilary, G., Hsu, C., 2013, Analyst Forecast Consistency, Journal of Finance, 68, 271-297.

Hirshleifer, D., Shumway, T., 2003, Good day sunshine: Stock returns and the weather, Journal of Finance, 58, 1009-1062.

Hirshleifer, D., Teoh, S. H., 2003, Limited attention, information disclosure and financial reporting, Journal of Accounting and Economics, 36, 337-386.

Hong, H., Kacperczyk, M., 2010, Competition and bias, Quarterly Journal of Economics, 125, 1683-1725.

Hong, H., Kubik, J. E., 2003, Analyzing the analysts: Career concerns and biased earnings forecasts, Journal of Finance, 58, 313 – 351.

Hong, H., Stein, J. C., 2007, Disagreement and the stock market, Journal of Economic Perspectives, 21, 109-128.

Houston, J. F., Lev, B., Tucker, J. W., 2010, To guide or not to guide? Causes and consequences of stopping quarterly earnings guidance, Contemporary Accounting Research, 27(1), 143 – 185.

Ingraham, C., 2014, December 3, The Google misery index: The times of year we’re most depressed, anxious and stressed, Washington Post, Retrieved from https://www.washingtonpost.com/news/wonkblog/wp/2014/12/03/the-google-misery-index-the-times-of-year-were-most-depressed-anxious-and-stressed/

Isen, A. M., 2001, Some perspectives on positive effect on acceptable level of risk: The person with a large canoe has a large worry, Organizational Behavior and Human Decision Processes, 39, 145-154.

Jacob, J., Lys, T. Z., Neale, M. A., 1999, Expertise in forecasting performance of security analysts, Journal of Accounting and Economics, 28, 51 – 82.

Johnson, E. J., Tversky, A., 1983, Affect, generalization, and perception of risk, Journal of Personality and Social Psychology, 45:1, 20-31

Kadous, K., Krische, S. D., Sedor, L. M., 2006, Using counter-explanation to limit analysts’ forecast optimism, Accounting Review, 81:2, 377 – 397.

Kamstra, M. J., Kramer, L. A., Levi, M. D., 2000, Losing sleep at the market: The daylight-savings anomaly, The American Economic Review, 90, 1005-1011.

Kamstra, M. J., Kramer, L. A., Levi, M. D., 2003, Winter blues: A SAD stock market cycle, The American Economic Review, 93, 324-343.

Kaplanski, G., H. Levy, 2010a, Sentiment and stock prices: The case of aviation disasters, Journal of Financial Economics, 95, 174−201.

Kaplanski, G., H. Levy, 2010b, Exploitable predictable irrationality: The FIFA world cup effect on the U.S. stock market, Journal of Financial and Quantitative Analysis, 45, 535−553.

Kaplanski, G., H., Levy, 2010c, Sentiment effect on analysts' recommendations: Time-series and cross-section analyses, Working Paper of Bar-Ilan University and Hebrew University of Jerusalem.

Kaplanski, G., Levy, H., Veld, C., Veld-Merkoulova, Y., 2015, Do happy people make optimistic investors?, Journal of Financial and Quantitative Analysis, forthcoming.

Karamanou, I., Vafeas, N., 2005, The association between corporate boards, audit committees, and management earnings forecasts: An empirical analysis, Journal of Accounting Research, 43:3, 453 – 486.

Kasser, T., Sheldon, K. M., 2002, What makes for a merry Christmas? Journal of Happiness Studies, 3, 313 – 329.

Ke, B., Yu, Y., 2006, The effect of issuing biased earnings forecasts on analysts' access to management and survival, Journal of Accounting Research, 44:5, 965 – 999.

Lemmon, M., Portniaguina, E., 2006, Consumer confidence and asset prices: Some empirical evidence, Review of Financial Studies, 19, 1501-1529.

Liang, L., Riedl, E. J., 2014, The effect of fair value versus historical cost reporting model on analyst forecast accuracy, Accounting Review, 89(3), 1151 – 1177.

Lim, T., 2001, Rationality and analysts' forecast bias, Journal of Finance, 56, 369 – 385.

List of heat waves, n.d. Retrieved August 8, 2016, from https://en.wikipedia.org/wiki/List_of_heat_waves

Mehran, H., Stulz, R. M., 2007, The economics of conflicts of interest in financial institutions, Journal of Financial Economics, 85, 267 - 296.

Mertens, K., Ravn, M. O., 2013, The dynamic effects of personal and corporate income tax changes in the United States, American Economic Review, 103(4), 1212 - 1247.

O'Brien, P. C., 1988, Analysts' forecasts as earnings expectations, Journal of Accounting and Economics, 10, 53 – 83.

O'Brien, P. C., Tan, H., 2015, Geographic proximity and analyst coverage decisions: Evidence from IPOs, Journal of Accounting and Economics, 59, 41 – 59.

Papousek, I., Weiss, W. M., Schulter, G., Fink, A., Reiser, E. M., Lackner, H. K., 2014, Prefrontal EEG alpha asymmetry changes while observing disaster happening to other people: Cardiac correlates and prediction of emotional impact, Biological Psychology, 103, 184 – 194.

Parry, W. 2011, December 19, Twitter reveals when we're happier, Live Science, Retrieved from http://www.livescience.com/17552-happiness-measured-twitter.html.

Palecki, M. A., Changnon, S. A., 23 August 1999. MRCC Living with weather - Heatwaves. Retrieved August 8, 2016, from http://mrcc.isws.illinois.edu/living_wx/heatwaves/heatwave1999.html

Palecki, M. A., Changnon, S. A., Kunkel, K. E., 2001, The nature and impact of the July 1999 heat wave in the Midwestern United States: Learning from the lessons of 1995, Bulletin of the American Meteorological Society, 82(7), 1353-1367.

Peng, L., Xiong, W., 2006, Investor attention, overconfidence and category learning, Journal of Financial Economics, 80, 563-602.

Plumlee, M. A., 2003, The effect of information complexity on analysts' use of that information, Accounting Review, 78:1, 275 – 296.

Sacks, D. W., Stevenson, B. Wolfers, J., 2012, The new stylized facts about income and subjective well-being, Emotion, 12(6), 1181 – 1187.

Saunders Jr., E. M., 1993, Stock prices and Wall Street weather, The American Economic Review, 83, 1337-1345.

Schwarz, N., 1990. Feelings as information: informational and motivational functions of affective states. In: Higgins, E.T., Sorrentino, R.M. (Eds.), Handbook of Motivation and Cognition: Foundations of Social Behavior, Vol. 2. Guilford, New York, pp. 527–561.

Schwarz, N., Clore, G. L., 1983, Mood, misattribution, and judgments of well-being: informative and directive functions of affective states, Journal of Personality and Social Psychology, 45, 513-523.

Sharpe, L., 2014, January 28, Americans' moods still improve on holidays and weekends, Gallup, Retrieved from

http://www.gallup.com/poll/167060/americans-moods-improve-holidays-weekends.aspx.

Shu, H. C., 2010, Investor mood and financial markets, Journal of Economic Behavior and Organization, 76, 267-282.

So, E. C., 2013, A new approach to predicting analyst forecast errors: Do investors overweight analyst forecasts?, Journal of Financial Economics, 108(3), 615 – 640.

Stambaugh, R.F., Yu, J., Yuan, Y., 2012, The short of it: Investor sentiment and anomalies, Journal of Financial Economics, 104(2), 288 – 302.

Stevenson, B., Wolfers, J., 2013, Subjective well-being and income: Is there any evidence of satiation? NBER Working Paper 18992.

Thaler, R., 1987, Anomalies: seasonal movements in security prices II: weekend, holiday, turn of the month, and intraday effects, Journal of Economic Perspectives, 1, 169-177.

The heat is online, n.d. Retrieved August 8 2016 from http://www.heatisonline.org/contentserver/objecthandlers/index.cfm?id=3335

Västfjäll, D., Peters, E., Slovic, P., 2008, Affect, risk perception and future optimism after tsunami disaster, Judgement and Decision Making, 3:1, 64 – 72.

Walther, B. R., Willis, R. H., 2013, Do investor expectations affect sell-side analysts' forecast bias and forecast accuracy?, Review of Accounting Studies, 18, 207-223.

Wolfe, M. I., Kaiser, R., Naughton, M. P. , Mirabelli, M. C., Yoon, S. S., Hanzlick, R., Henderson, A. K., 2001, Heat-related mortality in selected United States cities, summer 1999, American Journal of Forensic Medicine and Pathology, 22(4), 352-357.

Wright, W.F., Bower, G.H., 1992, Mood effects on subjective probability assessment, Organizational Behavior and Human Decision Processes, 52, 276–291.

Yuan, K., Lu, Z., Zhu, Q., 2006, Are investors moonstruck? Lunar phases and stock returns, Journal of Empirical Finance, 13, 1-23.

Appendix 1 The Disaster List

This appendix lists disasters with at least 100 fatalities, without significant damage, and without terrorism during the sample period. * denotes single-source information

Date	Type	Description	Fatalities	Location [State(s)]
12-16 Jul 1995	Heat wave	Chicago Heat Wave of 1995	739	Chicago, Illinois [IL]
19-30 Jul 1999	Heat wave		271	Midwest and Northeast [CA*, CT*, DE*, GA*, IA*, IN, IL, KY, MD, MI, MN, NJ, NY, OH, OK*, PA, RI*, TN*, VA*, WA*, WI, WV]
12 Nov 2001	Accident - Aircraft	American Airlines Flight 587	265	Queens, New York [NY]
17 Jul 1996	Accident - Aircraft	TWA Flight 800	230	Long Island, New York [NY]
6 Aug 1997	Accident - Aircraft	Korean Air Flight 801	228	Nimitz Hill, Guam
31 Oct 1999	Accident - Aircraft	EgyptAir Flight 990	217	Atlantic Ocean near Nantucket, Massachusetts [MA]
16 Aug 1987	Accident - Aircraft	Northwest Airlines Flight 255	156	Detroit, Michigan [MI]
2 Aug 1985	Accident - Aircraft	Delta Air Lines Flight 191	137	Dallas, Texas [TX]
8 Sep 1994	Accident - Aircraft	USAir Flight 427	132	Pittsburgh, Pennsylvania [PA]
19 Jul 1989	Accident - Aircraft	United Airlines Flight 232	111	Sioux City, Iowa [IA]
11 May 1996	Accident - Aircraft	ValuJet Flight 592	110	Florida Everglades [FL]
20 Feb 2003	Fire (building)	The Station nightclub fire	100	West Warwick, Rhode Island [RI]

Appendix 2 Variables

This appendix lists the definition of all variables used in this paper.

A2.1 Dependent Variables

Forecast error (in percentage terms):

$$ERROR = \frac{|F - A|}{P} \times 100 \qquad (A2.1a)$$

where ERROR is forecast error, estimated as the absolute difference between F and A, scaled by P. F is an annual EPS (earnings per share) forecast. A is the actual value of the EPS being forecasted. P is the market share price as of the end of the last fiscal year.

Forecast optimism (in percentage terms):

$$OPTIMISM = \frac{F - A}{P} \times 100 \qquad (A2.1b)$$

where OPTIMISM is forecast optimism.

FNUM: the daily number of forecasts.

LNFNUM: the natural logarithm of 1 plus the daily number of forecasts.

A2.2 Test Variables

FREE takes a value of 1 if the forecast release day is a weekend or a holiday in the week ending with a Thanksgiving Day, a Christmas Day, or a New Year's Day, and 0 otherwise.

LOC_NEG_MOOD takes a value of 1 if the analyst is located in a state where there is a disaster with at least 100 fatalities, without significant economic damage, and without terrorism, and 0 otherwise.

LNNEWSNUM is the natural logarithm of 1 plus the daily number of news items (in thousands) for the US for the same day as the number of forecasts.

LNNEWSNUML4 is the natural logarithm of 1 plus the daily number of news items (in thousands) for the US for day *t*-4 where day *t* is the day for which the number of forecasts is calculated.

MOOD takes a value of 1 if the forecast release day is in the week ending with a Thanksgiving Day, a Christmas Day, or a New Year's Day, and 0 otherwise.

MOOD2 takes a value of 1 if the forecast release day with MOOD = 1, PRE ≠ 1 and FREE ≠ 1, and 0 otherwise.

NEG_MOOD takes a value of 1 for the forecast release days on a day or in any day of the 5 days immediately after a day when a disaster with at least 100 fatalities, without significant economic damage, and without terrorism happens, and 0 otherwise.

NEWSNUM is the daily number of news items (in thousands) for the US for the same day as the number of forecasts.

NEWSNUML4 is the daily number of news items (in thousands) for the US for day t-4 where day t is the day for which the number of forecast is calculated.

NON-MOOD_BNA takes a value of 1 for the forecast days, with MOOD $\neq$ 1, in the period between the week immediately before the week ending with a Thanksgiving Day and the week immediately after a New Year's Day, and 0 otherwise.

NON-MOOD_JAN takes a value of 1 for the forecast days in January, with MOOD $\neq$ 1, and 0 otherwise.

NON-MOOD_NOV takes a value of 1 for the forecast days in November, with MOOD $\neq$ 1, and 0 otherwise.

PRE takes a value of 1 if the forecast release day is a day just before a weekend or a holiday and in the week ending with a Thanksgiving Day, a Christmas Day, or a New Year's Day, and 0 otherwise.

A2.3 Control Variables

Following the literature (e.g. Hong and Kacperczyk 2010; Ke and Yu 2006; Gu and Wu 2003; Clement 1999), we have the following firm specific, analyst specific and time specific control variables for the baseline regressions.

Firm Specific Control Variables:

$COVERAGE_{j,t-1}$

A measure of analyst coverage, defined as the number of analysts covering firm j for fiscal year t-1 and constructed using I/B/E/S data.

$FIRM\_MBIAS_{j,t-1}$ and $FIRM\_MERROR_{j,t-1}$

The median bias (i.e. optimism) and error of all forecasts for firm j for fiscal year t-1, using I/B/E/S data.[37]

$LNBM_{j,t-1}$

The natural logarithm of firm j's book value of equity divided by its market capitalization at the end of fiscal year t-1.

LNBM = ln(ceq/(csho x prcc_f)) [from Compustat]

$LNSIZE_{j,t-1}$

[37] FIRM_MBIAS and FIRM_MERROR are included as control variables because they capture different degrees of optimism and forecasting difficulty associated with different firms.

The natural logarithm of firm j's market capitalization at the end of fiscal year t-1.

LNSIZE = ln(csho x prcc_f) [from Compustat]

$MNMD_{j,t}$

A skewness measure, defined as the difference between mean and median of EPS, scaled by the market share price for the end of fiscal year t-1, for firm j for the period between fiscal year t-4 and fiscal year t+4, excluding fiscal year t, using I/B/E/S data.

$PROFIT_{j,t-1}$

The operating income of firm j for fiscal year t-1 over the book value of asset of the firm as of the end of fiscal year t-2.

PROFIT = ib/lagged ceq [from Compustat]

$RET_{j,t-1}$

The average monthly stock returns for firm j for the past 12 months in relation to the data date of the last actual annual earnings, using I/B/E/S and CRSP data.

$SIGMA_{j,t}$

The variance of the raw monthly stock returns for firm j for the past 12 months, in relation to the month in which the forecast is released, using I/B/E/S and CRSP data.

$SP500_{j,t}$

An indicator equals one if firm j is in the S&P 500 index when the forecast is released, and 0 otherwise.

$VOLROE_{j,t-1}$

The variance of the residuals from an AR(1) model for firm j's annual ROE using the past ten-fiscal-year series. ROE is calculated as the ratio of the earnings to the beginning book value of equity.

ROE = ib/lagged ceq [from Compustat]

Analyst Specific Control Variables:

$ANALYS\_MBIAS_{k,t-1}$ and $ANALYS\_MERROR_{k,t-1}$

The median bias (i.e. optimism) and error of all forecasts made by analyst k for fiscal year t-1, using I/B/E/S data.

$LNGENERAL\_EXP_{k,t}$

The natural logarithm of 1 plus the number of days since analyst k published the first annual EPS forecast, using I/B/E/S data.

$LNEXP\_WITH\_FIRM_{k,j,t}$

The natural logarithm of 1 plus the number of days since analyst k published the first annual EPS forecast for firm j, using I/B/E/S data.

$LOSS_{k,j,t}$

An indicator equals one if the forecast made by analyst k is negative, and 0 otherwise.

$NCO_{k,t}$

The number of firms analyst k made annual EPS forecasts for in fiscal year t, using I/B/E/S data.

$NSIC2_{k,t}$

The number of 2-digit SIC industries analyst k made annual EPS forecasts for in fiscal year t, using I/B/E/S data.

Time Specific Control Variables:

C

A dummy takes a value of 1 if the month is in a NBER contraction period, Dec 1973 – March 1975, February 1980 – July 1980, August 1981 – November 1982, August 1990 – March 1991, April 2001 – November 2001, or January 2008 – June 2009, inclusive, and 0 otherwise.

$CCON_t$ (based on the Conference Board surveys)

The consumer confidence index for the month in which the forecast is announced.

$CSENT_t$ (based on the University of Michigan surveys)

The consumer sentiment index for the month in which the forecast is announced.

FRI

A dummy variable that takes a value of 1 if the forecast publication day is on Friday, and 0 otherwise.

$LNHORIZON_{k,j,t}$

The natural logarithm of 1 plus the number of days between the release date of analyst k's earnings forecast for firm j and the data date of the earnings being forecasted, using I/B/E/S data.

NON-B_L1

A dummy variable that takes a value of 1 for the days just before the non-business days, based on the non-trading days of S&P 500, and 0 otherwise.

NON-B_F3

A dummy variable that takes a value of 1 for the third days after the non-business days, based on the non-trading days of S&P 500, and 0 otherwise.

NON-B_F4

A dummy variable that takes a value of 1 for the fourth days after the non-business days, based on the non-trading days of S&P 500, and 0 otherwise.

$\mathbf{RETTODATE}_{k,j,t}$

The cumulative stock returns (using monthly data) for firm j between the data date of the last annual earnings and the date on which the earning forecast by analyst k is released, using I/B/E/S and CRSP data.

$\mathbf{SENT}_{t}$

The Baker-Wurgler investor sentiment index for the month in which the forecast is announced.

Appendix 3 Sample Attrition

	Non-missing observations	Observations left	Attrition
Step 1. OPTIMISM	3,236,914	3,236,914	
Step 2. ERROR	3,236,914	3,236,914	0
Step 3. COVERAGE	3,534,052	3,085,141	151,773
Step 4. LNSIZE	3,393,093	3,083,363	1,778
Step 5. LNBM	3,324,938	3,023,699	59,664
Step 6. RET	3,089,228	2,720,480	303,219
Step 7. SIGMA	3,127,157	2,720,053	427
Step 8. VOLROE	2,785,911	2,298,295	421,758
Step 9. PROFIT	3,191,491	2,287,207	11,088
Step 10. MNMD	3,379,846	2,287,185	22
Step 11. FIRM_MBIAS	3,514,291	2,285,613	1,572
Step 12. ANALYS_MBIAS	3,514,291	2,285,613	0
Step 13. FIRM_MERROR	3,204,332	2,064,761	220,852
Step 14. ANALYS_MERROR	3,204,332	2,064,761	0
Step 15. HORIZON	3,805,300	2,064,761	0
Step 16. RETTODATE	3,805,300	2,064,761	0
Step 17. NCO	3,805,300	2,064,761	0
Step 18. NSIC2	3,805,300	2,064,761	0
Step 19. FIRM_ANALYS_TIME	3,805,300	2,064,761	0
Step 20. ANALYS_TIME	3,805,300	2,064,761	0

Table 1. Summary Statistics

This table reports summary statistics. OPTIMISM (ERROR) in percentage terms is forecast EPS, for a given firm j in month m in the fiscal year t by analyst k, minus actual EPS (the absolute difference between forecast EPS and actual EPS) over the market share price at the end of fiscal year t-1. COVERAGE is the number of analysts covering firm j for fiscal year t-1. LNSIZE is the natural logarithm of firm j's market capitalization at the end of fiscal year t-1.LNBM is the nature logarithm of firm j's book value divided by its market capitalization at the end of fiscal year t-1. RET is the average monthly stock returns for firm j for the past 12 months in relation to the data date of the last actual annual earnings. SIGMA is the standard deviation of the raw monthly stock returns for firm j for the past 12 months, in relation to month m. VOLROE is the variance of the residuals from an AR(1) model for firm j's annual ROE using the past ten-year series. ROE is calculated as the ratio of the earnings to the beginning book value of equity. PROFIT is operating income of firm j for fiscal year t-1 over the book value of asset of the firm as of the end of fiscal year t-2. SP500 equals one if firm j is in the S&P 500 index on the day when the forecast is released, and 0 otherwise. MNMD is the difference between mean and median of EPS, scaled by the market share price for the end of fiscal year t-1, for firm j for the period between fiscal year t-4 and fiscal year t+4, excluding fiscal year t. LOSS equals one if the forecast made by analyst k is negative, and 0 otherwise. FIRM_MBIAS/MERROR is the median bias (i.e. optimism)/error of all forecasts for firm j for fiscal year t-1. ANALYS_MBIAS/MERROR is the median bias/error of all firms for analyst k for fiscal year t-1. HORIZON is the number of days between the release of analyst k's earnings forecast for firm j and the data date of the earnings being forecasted. RETTODATE is the cumulative stock returns (using monthly data) for firm j between the last annual earnings and the release of the earning forecast by analyst k. NCO is the number of firms analyst k has made annual EPS forecasts in fiscal year t. NSIC2 is the number of 2-digit SIC industries analyst k has made annual EPS forecasts in fiscal year t. EXPERIENCE_WITH_FIRM is the number of years since analyst k published the first annual EPS forecast for firm j. GENERAL_EXPERIENCE is the number of years since analyst k published the first annual EPS forecast.

	Mean	S.D.	25%	Median	75%
OPTIMISM	0.722	3.902	-0.380	0.019	0.820
ERROR	1.843	4.034	0.176	0.554	1.626
COVERAGE	20	12	11	18	27
LNSIZE	7.738	1.735	6.554	7.710	8.917
LNBM	-0.820	0.688	-1.230	-0.760	-0.350
RET	0.014	0.034	-0.005	0.013	0.030
SIGMA	0.105	0.057	0.066	0.091	0.129
VOLROE	0.072	0.359	0.002	0.006	0.022
PROFIT	0.131	0.218	0.067	0.142	0.214
SP500	0.451	0.498	0.000	0.000	1.000
MNMD	-0.001	0.021	-0.004	0.000	0.005
LOSS	0.073	0.260	0.000	0.000	0.000
FIRM_MBIAS	0.096	0.608	-0.060	0.000	0.110
ANALYS_MBIAS	0.044	0.224	-0.030	0.001	0.060
FIRM_MERROR	0.296	0.732	0.040	0.100	0.256
ANALYS_MERROR	0.177	0.245	0.060	0.110	0.198
HORIZON (days)	184	97	90	176	260
RETTODATE	0.030	0.265	-0.080	0.033	0.167
NCO	29	100	13	17	24
NSIC2	8	16	3	5	9
EXPERIENCE_WITH_FIRM (years)	3.5	3.5	1.1	2.4	4.9
GENERAL_EXPERIENCE (years)	7.2	5.5	2.9	5.8	10.1

Table 2. Correlation Matrix of Explanatory Variables

This table reports the correlation coefficient between the explanatory variables. Refer to Table 1 for the definition of the variables.

	MOOD	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
OPTIMISM (2)	-0.009																				
COVERAGE (3)	0.000	-0.049																			
LNSIZE (4)	-0.011	-0.152	0.725																		
LNBM (5)	0.004	0.160	-0.168	-0.357																	
RET (6)	0.003	-0.121	-0.055	0.066	-0.344																
SIGMA (7)	-0.004	0.080	-0.178	-0.310	-0.019	-0.018															
VOLROE (8)	-0.005	0.011	-0.067	-0.072	-0.162	0.027	0.157														
PROFIT (9)	0.006	-0.089	0.147	0.272	-0.140	0.169	-0.335	-0.134													
LOSS (10)	0.003	0.105	-0.111	-0.222	0.045	-0.147	0.384	0.171	-0.496												
MNMD (11)	0.000	-0.145	0.070	0.134	-0.119	0.074	-0.111	-0.023	0.147	-0.135											
SP500 (12)	0.008	-0.049	0.643	0.633	-0.135	-0.046	-0.203	-0.071	0.152	-0.124	0.051										
FIRM_MBIAS (13)	0.001	0.222	-0.033	-0.148	0.159	-0.267	0.168	0.007	-0.299	0.231	-0.228	-0.030									
ANALYS_MBIAS (14)	0.002	0.154	-0.019	-0.111	0.175	-0.228	0.122	-0.009	-0.149	0.141	-0.089	0.001	0.378								
FIRM_MERROR (15)	-0.002	0.207	-0.033	-0.107	0.144	-0.131	0.183	0.033	-0.254	0.236	-0.216	-0.024	0.701	0.250							
ANALYS_MERROR (16)	-0.001	0.131	0.019	-0.013	0.201	-0.111	0.123	0.014	-0.119	0.143	-0.100	0.031	0.278	0.644	0.346						
LNHORIZON (17)	-0.284	0.062	0.015	0.025	-0.018	-0.009	0.012	0.004	0.000	-0.042	0.003	-0.004	-0.005	-0.011	-0.004	-0.009					
RETTODATE (18)	-0.013	-0.115	0.017	-0.028	0.094	-0.041	-0.085	-0.022	0.022	-0.148	0.043	0.024	-0.063	-0.042	-0.060	-0.041	-0.013				
NCO (19)	0.007	0.007	-0.001	-0.030	0.027	0.009	-0.022	-0.010	0.005	-0.014	-0.006	0.003	0.005	-0.014	0.003	-0.025	-0.010	0.009			
NSIC2 (20)	0.013	0.020	-0.037	-0.067	0.026	0.01	-0.026	-0.022	0.024	-0.032	0.002	0.006	0.013	0.012	-0.001	-0.034	-0.017	0.013	0.723		
LNEXP_WITH_FIRM (21)	0.002	-0.022	0.119	0.149	0.006	-0.052	-0.066	-0.031	0.024	-0.014	0.02	0.126	-0.004	-0.024	0.004	0.003	-0.046	0.002	-0.003	-0.004	
LNGENERAL_EXP (22)	0.008	-0.06	-0.021	0.147	-0.045	-0.024	-0.017	0.006	0.016	-0.004	0.023	0.041	-0.042	-0.044	-0.024	0.002	-0.06	0.013	0.08	0.078	0.424

Table 3. Univariate Tests of Analyst Forecast Optimism and Error

This table reports results of t-tests that OPTIMISM (ERROR) is different between NON-MOOD and MOOD observations, and between NEG_MOOD and MOOD observations. Horizon-adjusted OPTIMISM (ERROR) is the residual from the regression of unadjusted/raw OPTIMISM (ERROR) on LNHORIZON, where unadjusted/raw OPTIMISM (ERROR) in percentage is forecast EPS minus actual EPS (the absolute difference between forecast EPS and actual EPS) over the market share price at the end of the last fiscal year and LNHORIZON is the natural logarithm of 1 plus the number of days between the release of analyst k's earnings forecast for firm j and the data date of the earnings being forecasted. MOOD takes a value of 1 for the forecast release days in the week ending with a Thanksgiving Day, a Christmas Day or a New Year's Day, and 0 otherwise. NEG_MOOD takes a value of 1 for the forecast release days on a day or in any day of the 5 days immediately after a day when a disaster with at least 100 fatalities, without significant damage, and with terrorism happens, and 0 otherwise. NOV Controls consist of non-MOOD forecasts published in November. JAN Controls consist of non-MOOD forecasts published in January. BNA ("Before aNd After") Controls1 consist of non-MOOD forecasts published between the week immediately before the week ending with a Thanksgiving Day and the week immediately after the week ending with a New Year's Day. BNA Controls2 is the same as BNA Controls1, except that for each day of the week, we require that there are forecasts in both MOOD and NON-MOOD periods. Contractions cover the months between NBER peaks and the first subsequent NBER troughs and include the trough months. Non-Contractions cover the remaining months. *** indicates the 1% level of significance. Local analysts are those analysts located in a state where the disasters happen. The remaining analysts are non-local analysts.

	(1)	(2)	(1) – (2)	(3)	(4)	(3) – (4)
Panel A: NON-MOOD Vs. MOOD						
	MOOD	NON-MOOD	DIFF	MOOD	NON-MOOD	DIFF
	Horizon-Adjusted Optimism			Horizon-Adjusted Error		
Full Sample	0.207	-0.006	0.212***	0.392	-0.011	0.403***
NOV Controls	0.207	-0.005	0.212***	0.392	0.020	0.372***
JAN Controls	0.207	-0.056	0.263***	0.392	-0.093	0.485***
BNA Controls1	0.207	0.094	0.113***	0.392	0.190	0.202***
BNA Controls2	0.207	0.088	0.119***	0.392	0.182	0.210***
Non Contractions	0.163	-0.088	0.252***	0.367	-0.105	0.471***
Contractions	0.600	0.665	-0.065	0.620	0.745	-0.125***
Panel B: NEG_MOOD Vs. MOOD						
	MOOD	NEG_MOOD	DIFF	MOOD	NEG_MOOD	DIFF
	Horizon-Adjusted Optimism			Horizon-Adjusted Error		
Full Sample	0.207	-0.271	0.478***	0.392	-0.445	0.837***
Panel C: Local Analysts Vs. Non-local Analysts						
	Local Analysts	Non-local Analysts	DIFF	Local Analysts	Non-local Analysts	DIFF
	Horizon-Adjusted Optimism			Horizon-Adjusted Error		
1995 - 2010	-0.676	-0.509	-0.166***	-1.105	-0.802	-0.302***

Table 4. Analysts' Characteristics, Firm Characteristics and Industry Distribution

This table reports summary statistics of analysts' characteristics, firm characteristics and industry distribution of MOOD and NON-MOOD observations. FIRST FORECAST DAY is the number of days that an analyst's first forecast for a particular firm for a particular fiscal year is published from the beginning of the fiscal year. STARS is the proportion of forecasts that are made by star analysts. STARS data only cover the 2002 to 2012 period. SIZE (in million dollars) is firm j's market capitalization at the end of fiscal year t-1.BM is firm j's book value divided by its market capitalization at the end of fiscal year t-1. Refer to Table 1 for the definition of the other variables.

	MOOD Mean	MOOD Median	NON-MOOD Mean	NON-MOOD Median
Panel A: Analysts' Characteristics				
FIRST FORECAST DAY	102.0	65	122.5	89
GENERAL_EXPERIENCE	7.2	5.9	7.1	5.8
EXPERIENCE_WITH_FIRM	3.6	2.6	3.5	2.4
NCO	33.5	18	29.3	17
NSIC2	9.2	6	8.0	5
STARS (proportion)	10.5%		9.5%	
Panel B: Firm Characteristics				
COVERAGE	19.80	19	19.79	18
SIZE	8,548	2,070	9,598	2,234
BM	0.545	0.474	0.545	0.468
RET	0.014	0.013	0.014	0.013
SIGMA	0.104	0.091	0.105	0.091
VOLROE	0.063	0.005	0.072	0.006
PROFIT	0.139	0.146	0.130	0.142
MNMD	-0.001	0.000	-0.001	0.000
FIRM_MBIAS	0.099	0.000	0.096	0.000
FIRM_MERROR	0.285	0.100	0.296	0.100

	MOOD Proportion (%)	NON-MOOD Proportion (%)
Panel C: Industry Distribution		
Agriculture, Forestry and Fishing (SIC = 0xxx)	0.13	0.13
Mining (SIC = 10xx – 14xx)	7.49	7.92
Construction (SIC = 15xx – 17xx)	0.87	0.99
Manufacturing (SIC = 20xx – 39xx)	41.94	41.99
Transportation, Communications and Utilities (SIC = 4xxx)	10.84	10.99
Wholesale Trade (SIC = 50xx or 51xx)	2.33	2.12
Retail Trade (SIC = 52xx – 59xx)	14.57	10.01
Finance, Insurance and Real Estate (SIC = 6xxx)	12.09	14.73
Services (SIC = 70xx – 89xx)	9.45	10.94
Nonclassifiable Firms (SIC = 99xx)	0.28	0.17

Table 5. Holiday Mood Periods and Analyst Forecast Optimism and Error

This table reports the results of baseline regressions, regarding the incremental effects of holiday mood periods on analyst forecast optimism and error. The dependent variable is either OPTIMISIM or ERROR. OPTIMISM (ERROR) in percentage terms is forecast EPS, for a given firm j in month m in the fiscal year t by analyst k, minus actual EPS (the absolute difference between forecast EPS and actual EPS) over the market share price at the end of fiscal year t-1. MOOD takes a value of 1 for the forecast release days in the week ending with a Thanksgiving Day, a Christmas Day or a New Year's Day, and 0 otherwise. Refer to Table 1 for the definition of the other variables. NCO and NSIC2 are in hundreds. The table reports the estimated coefficients and the robust standard errors in parentheses. ***, **, * and # indicate the 1%, 5%, 10% and one-sided 10% level of significance, respectively.

(to be continued)

Table 5 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)
	OPTIMISM	OPTIMISM	OPTIMISM	ERROR	ERROR	ERROR
MOOD	0.124***	0.125***	0.121***	0.352***	0.348***	0.341***
	(0.027)	(0.024)	(0.025)	(0.028)	(0.023)	(0.024)
OPTIMISM				0.599***	0.562***	0.561***
				(0.012)	(0.012)	(0.013)
COVERAGE	0.000	0.000	0.002	0.006***	0.012***	0.011***
	(0.003)	(0.004)	(0.004)	(0.002)	(0.003)	(0.003)
LNSIZE	-0.164***	0.110**	0.096*	-0.260***	-0.954***	-0.979***
	(0.021)	(0.052)	(0.052)	(0.022)	(0.043)	(0.042)
LNBM	0.478***	0.671***	0.664***	0.550***	0.214***	0.194***
	(0.044)	(0.067)	(0.068)	(0.038)	(0.042)	(0.041)
RET	-6.763***	-7.376***	-7.418***	-2.074***	-1.927***	-2.089***
	(0.712)	(0.740)	(0.743)	(0.510)	(0.485)	(0.472)
SIGMA	3.125***	1.842***	1.636***	7.047***	5.396***	5.473***
	(0.483)	(0.530)	(0.522)	(0.410)	(0.414)	(0.405)
VOLROE	0.172***	-0.141#	-0.147*	0.112**	-0.043	-0.057
	(0.056)	(0.090)	(0.088)	(0.047)	(0.079)	(0.071)
PROFIT	0.500***	0.447***	0.468***	-0.180*	-0.750***	-0.790***
	(0.122)	(0.151)	(0.151)	(0.099)	(0.109)	(0.108)
SP500	0.122**	0.003	0.008	0.311***	0.356***	0.359***
	(0.053)	(0.090)	(0.084)	(0.047)	(0.070)	(0.065)
MNMD	-13.593***	3.109#	4.503*	-6.776***	-2.997*	-2.809*
	(1.784)	(2.424)	(2.382)	(1.422)	(1.589)	(1.519)
LOSS	0.403***	-0.197#	-0.291**	1.535***	1.199***	1.169***
	(0.110)	(0.124)	(0.120)	(0.090)	(0.092)	(0.090)
FIRM_MBIAS	0.812***	0.366***	0.337***			
	(0.080)	(0.081)	(0.080)			
ANALYS_MBIAS	0.746***	0.751***	0.437***			
	(0.102)	(0.099)	(0.118)			
FIRM_MERROR				0.584***	0.335***	0.307***
				(0.070)	(0.050)	(0.049)
ANALYS_MERROR				0.437***	0.309***	0.157**
				(0.072)	(0.053)	(0.063)
LNHORIZON	0.367***	0.366***	0.358***	0.520***	0.527***	0.524***
	(0.016)	(0.015)	(0.016)	(0.015)	(0.015)	(0.016)
RETTODATE	-1.444***	-1.167***	-1.096***	0.579***	0.143***	0.112***
	(0.072)	(0.071)	(0.071)	(0.045)	(0.043)	(0.041)
NCO	-0.060***	-0.053***	-0.031#	0.014	-0.031***	-0.029**
	(0.033)	(0.016)	(0.023)	(0.016)	(0.011)	(0.012)
NSIC2	0.354***	0.301***	0.236	0.020	0.297***	0.446**
	(0.210)	(0.104)	(0.316)	(0.105)	(0.071)	(0.199)
LNEXP_WITH_FIRM	0.009**	0.014***	0.019***	0.008***	0.002	0.003
	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
LNGENERAL_EXP	-0.002	-0.010#	-0.088***	-0.002	-0.012**	-0.039**
	(0.007)	(0.006)	(0.027)	(0.006)	(0.005)	(0.018)
Observations	2,064,761	2,064,761	2,064,761	2,064,761	2,064,761	2,064,761
R-squared	0.130	0.265	0.289	0.564	0.641	0.652
Adjusted R-squared	0.130	0.262	0.282	0.564	0.640	0.648
Year Fixed Effects	Y	Y	Y	Y	Y	Y
3-digit SIC Fixed Effects	Y	Y	Y	Y	Y	Y
Firm Fixed Effects		Y	Y		Y	Y
Analyst Fixed Effects			Y			Y
S.E. Clustering	firm	firm	firm analyst	firm	firm	firm analyst

Table 6. Holiday Mood Periods, Nearby Periods and Analyst Forecast Optimism and Error

This table contrasts results of the incremental effects of holiday mood periods on analyst forecast optimism and error with those of the nearby periods (i.e. more comparable non-mood forecasts). The dependent variable is either OPTIMISIM or ERROR. OPTIMISM (ERROR) in percentage terms is forecast EPS, for a given firm j in month m in the fiscal year t by analyst k, minus actual EPS (the absolute difference between forecast EPS and actual EPS) over the market share price at the end of fiscal year t-1. MOOD takes a value of 1 for the forecast release days in the week ending with a Thanksgiving Day, a Christmas Day or a New Year's Day, and 0 otherwise. NON-MOOD_NOV takes a value of 1 for the forecast days in November, but not in the week ending with a Thanksgiving Day, and 0 otherwise. NON-MOOD_JAN takes a value of 1 for the forecast days in January, but not in the week ending with a New Year's Day, and 0 otherwise. NON-MOOD_BNA ("Before aNd After") takes a value of 1 for the forecast days, with MOOD ≠ 1, in the period between the week immediately before the week ending with a Thanksgiving Day and the week immediately after the week ending with a New Year's Day, and 0 otherwise. The results for the control variables are not reported for brevity. The regressions include year, 3-digit SIC, firm and analyst fixed effects. The table reports the estimated coefficients and the robust standard errors, based on the two-way clustering at the firm and analyst levels, in parentheses. ***, **, * and # indicate the 1%, 5%, 10% and one-sided 10% level of significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	OPTIMISM	ERROR	OPTIMISM	ERROR	OPTIMISM	ERROR
MOOD	0.101***	0.323***	0.121***	0.344***	0.127***	0.388***
	(0.025)	(0.025)	(0.025)	(0.024)	(0.027)	(0.028)
NON-MOOD_NOV	-0.096***	-0.089***				
	(0.020)	(0.017)				
NON-MOOD_JAN			0.046*	0.163***		
			(0.025)	(0.021)		
NON-MOOD_BNA					0.025	0.195***
					(0.021)	(0.021)
Observations	2,064,761	2,064,761	2,064,761	2,064,761	2,064,761	2,064,761
R-squared	0.289	0.652	0.289	0.652	0.289	0.652
Adjusted R-squared	0.282	0.648	0.282	0.648	0.282	0.648
Statistics of F tests:						
MOOD = NON-MOOD_NOV	54.49***	291.83***				
MOOD = NON-MOOD_JAN			5.32**	36.87***		
MOOD = NON-MOOD_BNA					17.79***	95.65***

Table 7. Contractions, Holiday Mood Periods and Analyst Forecast Optimism and Error

This table reports the regression results of incremental effects of holiday mood periods on forecast optimism and error in recessions. The dependent variable is either OPTIMISM or ERROR. OPTIMISM (ERROR) in percentage terms is forecast EPS, for a given firm j in month m in the fiscal year t by analyst k, minus actual EPS (the absolute difference between forecast EPS and actual EPS) over the market share price at the end of fiscal year t-1. MOOD takes a value of 1 for the forecast release days in the week ending with a Thanksgiving Day, a Christmas Day or a New Year's Day, and 0 otherwise. C takes a value of 1 if the forecast is released in any month in a NBER contraction period, Dec 1973 – March 1975, February 1980 – July 1980, August 1981 – November 1982, August 1990 – March 1991, April 2001 – November 2001, or January 2008 – June 2009, inclusive, and 0 otherwise. The results for the control variables are not reported for brevity. The regressions include year, 3-digit SIC, firm and analyst fixed effects. The table reports the estimated coefficients and the robust standard errors, based on the two-way clustering at the firm and analyst levels, in parentheses. ***, ** and * indicate the 1%, 5% and 10% level of significance, respectively.

	(1)	(2)
	OPTIMISM	ERROR
MOOD	0.209***	0.398***
	(0.026)	(0.025)
C*MOOD	-0.860***	-0.335***
	(0.090)	(0.058)
C	-0.121*	0.360***
	(0.066)	(0.045)
Observations	2,064,761	2,064,761
R-squared	0.290	0.652
Adjusted R-squared	0.283	0.648
Test of overall mood effect for contractions: MOOD + C*MOOD = 0		
Coefficient	-0.651***	0.063
t statistics	-7.67	1.11

Table 8. Sentiment, Holiday Mood Periods and Analyst Forecast Optimism and Error

This table reports the regression results of incremental effects of holiday mood periods on forecast optimism and error, controlling for sentiment measure. The dependent variable is either OPTIMISM or ERROR. OPTIMISM (ERROR) in percentage is forecast EPS, for a given firm j in month m in the fiscal year t by analyst k, minus actual EPS (the absolute difference between forecast EPS and actual EPS) over the market share price at the end of fiscal year t-1. MOOD takes a value of 1 for the forecast release days in the week ending with a Thanksgiving Day, a Christmas Day or a New Year's Day, and 0 otherwise. C takes a value of 1 if the forecast is released in any month in a NBER contraction period, Dec 1973 – March 1975, February 1980 – July 1980, August 1981 – November 1982, August 1990 – March 1991, April 2001 – November 2001, or January 2008 – June 2009, inclusive, and 0 otherwise. CSENT is the Michigan's consumer sentiment index in month m. CCON is the Conference Board's consumer confidence index in month m. SENT is the Baker-Wurgler investor sentiment index in month m. The results for the other control variables are not reported for brevity. The regressions include year, 3-digit SIC, firm and analyst fixed effects. The table reports the estimated coefficients and the robust standard errors, based on the two-way clustering at the firm and analyst levels, in parentheses. ***, **, * and # indicate the 1%, 5%, 10% and one-sided 10% level of significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	OPTIMISM	OPTIMISM	OPTIMISM	ERROR	ERROR	ERROR
MOOD	0.202***	0.177***	0.236***	0.395***	0.395***	0.415***
	(0.026)	(0.026)	(0.028)	(0.025)	(0.025)	(0.026)
C*MOOD	-0.796***	-0.644***	-0.710***	-0.308***	-0.312***	-0.346***
	(0.088)	(0.085)	(0.089)	(0.058)	(0.057)	(0.060)
C	-0.042	0.032	-0.157**	0.394***	0.377***	0.355***
	(0.065)	(0.066)	(0.066)	(0.046)	(0.046)	(0.045)
CSENT	1.031***			0.447***		
	(0.166)			(0.104)		
CCON		1.210***			0.130**	
		(0.118)			(0.066)	
SENT			0.574***			-0.046#
			(0.044)			(0.032)
Observations	2,064,761	2,064,761	1,730,762	2,064,761	2,064,761	1,730,762
R-squared	0.290	0.291	0.309	0.652	0.652	0.672
Adjusted R-squared	0.283	0.283	0.301	0.648	0.648	0.668

Table 9. Pre-Non-Business Days, Holiday Mood Periods and Analyst Forecast Optimism and Error

This table reports the regression results of incremental effect of holiday mood periods on forecast optimism and error, controlling for sentiment measure and the days just before non-business days. The dependent variable is either OPTIMISM or ERROR. OPTIMISM (ERROR) in percentage terms is forecast EPS, for a given firm j in month m in the fiscal year t by analyst k, minus actual EPS (the absolute difference between forecast EPS and actual EPS) over the market share price at the end of fiscal year t-1. MOOD takes a value of 1 for the days in the week ending with a Thanksgiving Day, a Christmas Day or a New Year's Day, and 0 otherwise. NON-B_L1 takes a value of 1 for the days just before the non-business days, based on the non-trading days of S&P 500, and 0 otherwise. NON-B_F3 takes a value of 1 for the third days after the non-business days, and 0 otherwise. NON-B_F4 takes a value of 1 for the fourth days after the non-business days. C takes a value of 1 if the forecast is released in any month in a NBER contraction period, Dec 1973 – March 1975, February 1980 – July 1980, August 1981 – November 1982, August 1990 – March 1991, April 2001 – November 2001, or January 2008 – June 2009, inclusive, and 0 otherwise. CSENT is the Michigan's consumer sentiment index in month m. CCON is the Conference Board's consumer confidence index in month m. SENT is the Baker-Wurgler investor sentiment index in month m. The results for the other control variables are not reported for brevity. The regressions include year, 3-digit SIC, firm and analyst fixed effects. The table reports the estimated coefficients and the robust standard errors, based on the two-way clustering at the firm and analyst levels, in parentheses. ***, **, * and # indicate the 1%, 5%, 10% and one-sided 10% level of significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	OPTIMISM	OPTIMISM	OPTIMISM	ERROR	ERROR	ERROR
MOOD	0.203***	0.179***	0.237***	0.397***	0.397***	0.416***
	(0.026)	(0.026)	(0.028)	(0.025)	(0.025)	(0.026)
C*MOOD	-0.795***	-0.644***	-0.709***	-0.307***	-0.312***	-0.346***
	(0.088)	(0.085)	(0.089)	(0.058)	(0.057)	(0.060)
C	-0.043	0.032	-0.157**	0.395***	0.377***	0.355***
	(0.065)	(0.066)	(0.066)	(0.046)	(0.046)	(0.045)
CSENT	1.028***			0.450***		
	(0.166)			(0.103)		
CCON		1.209***			0.131**	
		(0.118)			(0.066)	
SENT			0.574***			-0.046#
			(0.044)			(0.032)
NON-B_L1	-0.009	-0.009	-0.014	-0.017**	-0.017**	-0.011
	(0.010)	(0.010)	(0.012)	(0.008)	(0.008)	(0.009)
NON-B_F3	0.012#	0.012#	0.015#	-0.002	-0.001	-0.003
	(0.008)	(0.008)	(0.009)	(0.006)	(0.006)	(0.006)
NON-B_F4	0.005	0.005	0.005	-0.019***	-0.018***	-0.011*
	(0.008)	(0.008)	(0.009)	(0.006)	(0.006)	(0.006)
Observations	2,064,761	2,064,761	1,730,762	2,064,761	2,064,761	1,730,762
R-squared	0.290	0.291	0.309	0.652	0.652	0.672
Adjusted R-squared	0.283	0.283	0.301	0.648	0.648	0.668

Table 10. Number of Forecasts Regressions on Number of News Items

This table reports the regression results of incremental sensitivity of detrended daily number of news items on daily number of forecasts during non-strict and strict holiday mood periods. The dependent variable is either FNUM or LNFNUM. FNUM is the daily number of forecasts. LNFNUM is the natural logarithm of 1 plus the daily number of forecasts. NEWSNUM is the detrended daily number of contemporaneous news items (in thousands). LNNEWSNUM is the natural logarithm of 1 plus the detrended daily number of contemporaneous news items (in thousands). NEWSNUML4 is the detrended daily number of news items (in thousands) as of day *t*-4. LNNEWSNUML4 is the natural logarithm of 1 plus the detrended daily number of news items (in thousands) as of day *t*-4. MOOD takes a value of 1 for the days in the week ending with a Thanksgiving Day, a Christmas Day or a New Year's Day, and 0 otherwise. PRE takes a value of 1 for Fridays and the days just before holidays with MOOD=1, and 0 otherwise. FREE takes a value of 1 for weekends and holidays with MOOD=1, and 0 otherwise. MOOD2 takes a value of 1 if MOOD=1, PRE≠1 and FREE≠1, and 0 otherwise. FRI takes a value of 1 if the day is Friday, and 0 otherwise. The table reports the estimated coefficients and the robust standard errors in parentheses. ***, ** and * indicate the 1%, 5% and 10% level of significance, respectively.

(to be continued)

Table 10 (continued)

Panel A: Number of Contemporaneous News Items						
	OLS Regressions			**Poisson Regressions**		
	(1)	(2)	(3)	(4)	(5)	(6)
	LNFNUM	LNFNUM	LNFNUM	FNUM	FNUM	FNUM
LNNEWSNUM	0.913***	0.910***	0.718***			
	(0.021)	(0.022)	(0.023)			
NEWSNUM				0.103***	0.102***	0.084***
				(0.003)	(0.003)	(0.003)
MOOD*LNNEWSNUM		-0.024				
		(0.108)				
MOOD*NEWSNUM					-0.013	
					(0.015)	
MOOD2*LNNEWSNUM			-0.051			
			(0.126)			
MOOD2*NEWSNUM						-0.013
						(0.017)
PRE*LNNEWSNUM			-0.095			
			(0.176)			
PRE*NEWSNUM						-0.041
						(0.028)
FREE*LNNEWSNUM			1.118			
			(1.460)			
FREE*NEWSNUM						0.124
						(0.352)
FRI*LNNEWSNUM			1.058***			
			(0.053)			
FRI*NEWSNUM						0.140***
						(0.008)
MOOD		-0.447***			-0.462***	
		(0.153)			(0.073)	
MOOD2			-0.400**			-0.464***
			(0.182)			(0.084)
PRE			-0.395*			-0.379***
			(0.237)			(0.128)
FREE			-1.728			-1.595**
			(1.281)			(0.686)
FRI			-1.552***			-0.643***
			(0.075)			(0.037)
CONSTANT	4.049***	4.075***	4.379***	5.227***	5.249***	5.341***
	(0.033)	(0.034)	(0.036)	(0.015)	(0.015)	(0.016)
Observations	7,862	7,862	7,862	7,862	7,862	7,862
R^2	0.224	0.228	0.294			
Pseudo R^2				0.159	0.169	0.206
Adjusted R^2	0.224	0.228	0.293			

(to be continued)

Table 10 (continued)

Panel B: Number of News Items as of Day *t*-4						
	OLS Regressions			**Poisson Regressions**		
	(1)	(2)	(3)	(4)	(5)	(6)
	LNFNUM	LNFNUM	LNFNUM	FNUM	FNUM	FNUM
LNNEWSNUML4	1.251***	1.252***	1.074***			
	(0.029)	(0.030)	(0.036)			
NEWSNUML4				0.127***	0.126***	0.102***
				(0.004)	(0.004)	(0.004)
MOOD*LNNEWSNUML4		-0.065				
		(0.137)				
MOOD*NEWSNUML4					-0.017	
					(0.013)	
MOOD2*LNNEWSNUML4			-0.097			
			(0.167)			
MOOD2*NEWSNUML4						-0.011
						(0.014)
PRE*LNNEWSNUML4			-0.042			
			(0.220)			
PRE*NEWSNUML4						-0.039
						(0.024)
FREE*LNNEWSNUML4			0.797			
			(1.240)			
FREE*NEWSNUML4						0.059
						(0.251)
FRI*LNNEWSNUML4			0.569***			
			(0.061)			
FRI*NEWSNUML4						0.092***
						(0.009)
MOOD		-0.349*			-0.401***	
		(0.202)			(0.071)	
MOOD2			-0.114			-0.284***
			(0.255)			(0.080)
PRE			-0.637**			-0.540***
			(0.304)			(0.131)
FREE			-1.738			-1.505**
			(1.347)			(0.689)
FRI			-0.760***			-0.255***
			(0.089)			(0.041)
CONSTANT	3.442***	3.461***	3.705***	4.952***	4.971***	5.034***
	(0.044)	(0.045)	(0.056)	(0.017)	(0.017)	(0.019)
Observations	4,350	4,350	4,350	4,350	4,350	4,350
R^2	0.333	0.336	0.357			
Pseudo R^2				0.222	0.231	0.260
Adjusted R^2	0.333	0.336	0.356			

Table 11. Disasters and Analyst Forecast Optimism and Error

This table reports the regression results of incremental negative mood effects on analyst forecast optimism and error. The dependent variable is either OPTIMISM or ERROR. OPTIMISM (ERROR) in percentage terms is forecast EPS, for a given firm j in month m in the fiscal year t by analyst k, minus actual EPS (the absolute difference between forecast EPS and actual EPS) over the market share price at the end of fiscal year t-1. NEG_MOOD takes a value of 1 for the forecast release days on a day or in any day of the 5 days immediately after a day when a disaster with at least 100 fatalities, without significant damage, and without terrorism happens, and 0 otherwise. LOC_NEG_MOOD takes a value of 1 if the analyst is located in a state where the disasters occur, and 0 otherwise. The disasters are listed in Appendix 1. MOOD takes a value of 1 for the forecast release days in the week ending with a Thanksgiving Day, a Christmas Day or a New Year's Day, and 0 otherwise. C takes a value of 1 if the forecast is released in any month in a NBER contraction period, Dec 1973 – March 1975, February 1980 – July 1980, August 1981 – November 1982, August 1990 – March 1991, April 2001 – November 2001, or January 2008 – June 2009, inclusive, and 0 otherwise. NON-B_L1 takes a value of 1 for the days just before the non-business days, based on the non-trading days of S&P 500, and 0 otherwise. NON-B_F3 takes a value of 1 for the third days after the non-business days, and 0 otherwise. NON-B_F4 takes a value of 1 for the fourth days after the non-business days. CCON is the Conference Board's consumer confidence index in month m. The results for the other control variables are not reported for brevity. The regressions include year, 3-digit SIC, firm and analyst fixed effects. The table reports the estimated coefficients and the robust standard errors, based on the two-way clustering at the firm and analyst levels, in parentheses. ***, **, * and # indicate the 1%, 5%, 10% and one-sided 10% level of significance, respectively.

	(1)	(2)	(3)	(4)
	OPTIMISM	ERROR	OPTIMISM	ERROR
NEG_MOOD	-0.115***	-0.189***	-0.026	-0.152***
	(0.033)	(0.027)	(0.046)	(0.036)
LOC_NEG_MOOD			-0.129**	-0.114**
			(0.062)	(0.051)
MOOD	0.178***	0.396***	0.204***	0.436***
	(0.026)	(0.025)	(0.032)	(0.032)
C*MOOD	-0.634***	-0.296***	-0.842***	-0.366***
	(0.086)	(0.057)	(0.103)	(0.077)
C	0.032	0.378***	-0.049	0.422***
	(0.066)	(0.046)	(0.077)	(0.061)
NON-B_L1	-0.009	-0.017**	-0.022*	-0.025***
	(0.010)	(0.008)	(0.013)	(0.009)
NON-B_F3	0.012#	-0.001	0.018#	0.001
	(0.008)	(0.006)	(0.012)	(0.008)
NON-B_F4	0.005	-0.018***	-0.015#	-0.012#
	(0.008)	(0.006)	(0.010)	(0.008)
CCON	1.208***	0.131**	1.082***	-0.018
	(0.118)	(0.066)	(0.146)	(0.079)
Observations	2,064,761	2,064,761	1,056,424	1,056,424
R-squared	0.291	0.652	0.290	0.616
Adjusted R-squared	0.283	0.648	0.281	0.611