Heterogeneous Priors and Information Choices:

Evidence from Sell-Side Financial Analysts

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Abstract

We examine the effect of heterogeneous priors on economic agents' information choices and their belief formation. Drawing upon confirmation bias, we propose a Bayesian updating framework in which agents acquire information consistent with their heterogeneous priors affecting their posterior beliefs. Exploiting location- and time-specific variation in priors stemming from mood shifts after the Super Bowl, we find that positive shifts increase analysts' information acquisition, whereas negative shifts lead to negatively skewed information choices and less receptiveness of inconsistent information. In cross-sectional results, we show that the confidence in priors amplifies the bias in analysts' posterior beliefs. Overall, we provide empirical evidence on the causal chain of how heterogeneity in agents' priors affects information choices, explaining biases in posterior beliefs.

Keywords: information choices, prior beliefs, behavioral bias, disagreement, financial analyst

JEL Classification Code: G10, G29, G41

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I. INTRODUCTION

A fundamental question in modern economics revolves around how economic agents continuously process information to update their beliefs (Giacomini et al. 2020; Kempf & Tsoutsoura 2021; Malmendier & Veldkamp 2022). Theory predicts a rational benchmark according to which agents weight their prior beliefs and new information by the relative precisions. Yet, empirical evidence suggests that agents deviate from this rational benchmark, consistent with behavioral biases (Malmendier & Nagel 2016; DeHaan et al. 2017; Bourveau & Law 2021; Cuculiza et al. 2021; Dong et al. 2021; Wu 2023). It is, however, unclear how these biases manifest in posterior beliefs. In this paper, we provide empirical evidence along the causal chain of how heterogeneous priors affect information choices, explaining biases in posterior beliefs.

Drawing upon a Bayesian updating framework and evidence of confirmation bias in psychology, we predict that agents' heterogeneous prior beliefs will lead to (1) differences in information choices and consequently (2) biased posterior beliefs. Imagine two agents conducting the identical task of forecasting earnings for the same firm quarter. The first agent is negatively biased, leading to a pessimistic shift in prior beliefs. The second agent is unbiased, thus acting in line with the rational benchmark. We predict that the first agent's information choices will be biased towards more negative signals consistent with her negatively biased prior. As a result, negative information will feature more prominently in the individual belief formation of the biased analyst, leading to less optimistic forecasts (i.e., posterior) compared to the rational agent. We empirically test this prediction comparing treated and untreated financial sell-side analysts' (1) information choices in earnings conference calls, (2) earnings-per-share forecasts, and (3) incorporation of management guidance in response to a time-variant and local shock to analysts' priors.

Our treatment is the outcome of the final game of the NFL, namely the Super Bowl, affecting analysts' priors located in participating cities. The Super Bowl resembles a substantial and unambiguous event (i.e., one game and only win or loss) affecting a large proportion of the participating teams' cities. The rules and structure of the NFL ensure that participation in the Super Bowl is random (i.e., not correlated with time-variant characteristics of the local analysts such as their forecasting model or information signals), a non-lethal event (i.e., analysts continue to update their beliefs), and does not distort analysts' information production function (i.e., inattention). Yet, it does affect local analysts' priors in contrary directions (i.e., win or loss). Importantly, this setting allows us to uncover the entire causal chain linking exogenously caused differences in analysts' priors to their information choices and, ultimately, posterior beliefs.

In our empirical tests, we compare analysts whose local NFL team participates in the Super Bowl (treatment group) to those whose local NFL team does not (control group) (Bertrand & Mullainathan 2003). In the first step, we provide evidence of the direct effect of the Super Bowl outcome on local community priors to elaborate the causal chain of the treatment. We confirm that local priors are affected in the participating cities after the Super Bowl. Focusing on news that are topic-wise unrelated to the Super Bowl, we find that social media sentiment (X, formerly Twitter) and local newspaper sentiment (GDELT) are indeed positively (negatively) affected in cities winning (losing) the Super Bowl. These results are in line with our prediction of heterogeneity in treated analysts' priors, who are part of the local community.

Next, we explore how the shift in analysts' priors affects their information choices. We exploit earnings conference calls, which serve as the main information exchange platform between analysts and firms (Hollander et al. 2010). Our sample consists of about 90,000 quarterly firm-analyst interactions in earnings conference calls from 2002 to 2021 and contains about 2,900 unique analysts in 55 metropolitan areas. We find that heterogeneous priors matter for analysts' information choices. We include a granular set of fixed effects to account for time-invariant differences at the analyst, firm, brokerage house, and city level. We find that analysts located in cities whose NFL team lost the Super Bowl do not significantly change the number of interactions in conference calls. They do, however, use more negative language: their ratio of negative spoken words in comparison to the management increases by about 12%. Contrary, analysts located in cities whose NFL team has won the Super Bowl have 3% more interactions and about 3% longer interactions with the management during a conference call in comparison to interacting control analysts (who are located in cities that did not participate in the Super Bowl). These findings are consistent with insights from psychology, that disagreement is not caused by differences in information but biased interpretation (i.e., confirmation bias (Lord et al. 1979)).

Subsequently, we examine the impact of heterogeneous priors and information choices on analysts' posterior beliefs as revealed by their one-quarter-ahead earnings-per-share forecasts. Our outcome variable of interest is analysts' forecast optimism relative to the consensus (Bourveau & Law 2021). Importantly, by focusing on deviations from the consensus, we uncover variances in posteriors while holding (potentially confounding) firm-time-specific factors (i.e., news about the client firm) fixed. Using a sample of about 300,000 quarterly firm-analyst forecasts issued between 2000 and 2021, we show that the Super Bowl outcome affects local analysts' forecast optimism in the expected directions. Consistent with our prediction, we find that analysts located in cities whose NFL team has lost (won) the Super Bowl issue about 16% less optimistic (9% more optimistic) forecasts, relative to control analysts. The effect on treated analysts occurs after the Super Bowl, but not before, supporting the parallel trends assumption. Collectively, these findings suggest that analysts' heterogeneous priors and biased information acquisition ultimately manifest in their posterior beliefs.

To further corroborate our findings that confirmation bias is causing variance in posterior beliefs, we examine analysts' receptiveness to management guidance, which are issued as an alternative information signal directly after conference calls. We exploit the presence of opposing management guidance for the next firm quarter as we expect that treated analysts are not acquiring these information (i.e., inconsistent with their priors). We find that the negative (positive) shift in priors leads to a reduced receptiveness of opposing information from management. The results are consistent with our prediction that analysts' heterogeneous priors affect their information choices.

Lastly, we examine analysts' weighting mechanism of their prior by exploiting variation in analysts-specific characteristics and the precision of the information signal. We find that overconfidence amplifies the bias in analysts' posterior beliefs (i.e., forecasts). Further, we find the same effect for decreasing signal precision, which indicates that increased weights on priors are associated with more pronounced biases, confirming that heterogeneous priors (rather than heterogeneous information models) drive analysts' deviated belief formation (Patten & Timmermann 2010; Giacomini et al. 2020).

The contribution of our study is as follows. First, our study contributes to the literature on belief formation in financial markets. We provide large-scale empirical evidence that heterogeneous priors through information choices affects posterior beliefs (Veldkamp & Malmendier 2022). The direction in posterior beliefs is conditional on prior beliefs (i.e., confirmation bias) and likely not explained by inattention or heterogeneous information models (Patton & Timmermann 2010; Giacomini et al. 2020). Thus, we provide evidence that heterogeneous priors affect information acquisition, resulting in posterior belief variances.

Second, our study contributes to the literature on behavioral biases in analysts' forecast activities (DeHaan et al. 2017; Bourveau & Law 2021; Cuculiza et al. 2021; Dong et al. 2021; Wu 2023). Prior literature documents (negative) biases in analysts' posteriors. We uncover prior-dependent information choices as an important mechanism in the causal chain leading to positive and negative biases conditional on the direction of priors. These findings help to understand how biases in analysts' forecasts emerge.

More broadly, we contribute to the literature investigating asset pricing implications of behavioral biases documented after sports events (Edmans et al. 2007; Bernile & Lyandres 2011). Using time-variant variation in city-level affection towards sports, we show that the bias extends to a setting in which financial professionals are strongly incentivized to avoid biases and explicitly trained to assess risk (DeHaan et al. 2017; Bourveau & Law 2021; Dong et al. 2021).

II. BACKGROUND

Theoretical Framework

We propose a theoretical Bayesian framework of how analysts derive their posteriors (i.e., forecasts). In psychology, the tendency of people to hang on to their prior beliefs with unwarranted tenacity and confidence is called confirmation bias (Klayman 1995). People tend to accept "confirming" information at face value while they discount "inconsistent" information with their prior beliefs, resulting in biased support for their priors from acquiring information (Mahoney & DeMonbreun 1977, Koehler 1993, Gorman 1986, Gorman 1989). Thus, the result of exposing information to agents with heterogeneous priors may be not a narrowing of disagreement but rather an increase in polarization (i.e., increase in posterior variance) (Lord et al. 1979).

Following Baley & Veldkamp (2023), we draw upon a Baysian updating framework where the novel feature is a mood component that leads to heterogeneous priors (i.e., disagreement in prior beliefs) and allowing priors to influence the weighting of a signal. Our key assumptions are (1) that variation in mood affects the distribution of analysts' priors (Giacomini et al. 2020), (2) that analysts are Bayesian learners (Ortolova 2012), (3) that analysts update infrequently and at different times throughout the year, and (4) analysts have no mass (i.e., they cannot influence the average belief).

Consider analyst i, who chooses her forecast $\hat{a}_{\theta,t,j,i}$ to match an unknown target $a_{\theta,t,j}$ (i.e., actual earnings of firm j for the next quarter t depending on state θ). Deriving her forecast, the analyst can choose to acquire a common signal $z_{t,j} \sim \mathcal{N}(\theta|\tau_z^{-1})$.[1] Each analyst solves the following problem:

$$\mathcal{L} = \min_{\gamma_z(m_{t,i})} \mathbb{E}\left[(\hat{a}_{\theta,t,j,i} - a_{\theta,t,j})^2 | z_{t,j}\right] \quad [1]$$

The innovation of the model is to make analysts' priors dependent on a component of pessimism (optimism), which we call mood ($m_{t,i}$) leading to disagreement in initial beliefs affecting the weighting of a new signal. Using Bayesian updating, analyst's posterior belief is the weighted function of her mood-dependent prior ($p(m_{t,i})$) and her updating to the signal ($z_{j,t}$):

$$\hat{a}_{\theta,t,j,i} = \left(1 - \gamma_z(m_{t,i})\right) p(m_{t,i}) + \gamma_z(m_{t,i}) z_{t,j} \quad [2]$$

The mood component is driven by a location-specific exogenous shock, unrelated to prior beliefs (i.e., outside of the model). For simplicity, we assume it comes from a standard normal distribution $m_{t,i} \sim \mathcal{N}(0|1)$. The intuition behind the mood term is, that $m_{t,i}$ affects the prior and

[1] We exploit the Super Bowl outcome as a shock, which is (plausibly) uncorrelated with analysts' information choices and results in an optimistic (pessimistic) location-specific mood component. Therefore, any deviation from the average action is a result of analysts' differential weighting of the signal and her prior beliefs.[1]

the weights placed on the signals $\gamma_z(m_{t,i})$. Prior to being exposed to the signal, the analyst forms her prior. If $m_{t,i} = 0$, the weight of a new signal is solely conditional on the analyst's perceived precision of the signal (τ_z^{-1}). Given the mood component is non-zero, the signal can be consistent (C) or inconsistent (IC) with the analyst's biased prior. Her weighting function of the signal is:

$$\gamma_z(m_{t,i}) = \begin{cases} \left(\dfrac{\tau_z^{-1}}{\tau_{\hat{a}}^{-1} + \tau_z^{-1}}\right) if\ m_{t,i} = 0 \\ \left(\dfrac{\tau_z^{-1}}{\tau_{\hat{a}}^{-1} + \tau_z^{-1}} | m_{t,i}\right) if\ m_{t,i} \neq (0|C) \\ 0 \quad if\ m_{t,i} \neq (0|IC) \end{cases} \qquad [3]$$

Following Koehler (1993), given $m_{t,i} \neq 0$ it is shown that the probability of perceiving a precise signal is higher when the signal is consistent with prior beliefs. Put differently, negative (positive) signals receive higher weights if the analyst is pessimistic (optimistic), as negative signals confirm a pessimistic (optimistic) prior. Vice versa, the signal is not weighted in the posterior if it is inconsistent with prior beliefs. Therefore, we expect analysts to acquire information confirming prior beliefs.

Empirically, we test the presence of confirmation bias by comparing information choices of untreated analysts to treated analysts using a time-variant mood exposure from a quasi-experiment. The empirical strategy proceeds as follows. First, we begin by examining whether a Super Bowl loss (win) of the local NFL team affects mood positively (negatively) for local individuals (i.e., $m_{t,i} \neq 0$). Second, we test whether heterogeneous priors affect information choices by comparing treated and untreated analysts' interactions in conference calls. Third, we show that skewed priors and information choices lead to variance in posterior beliefs of treated analysts (i.e., $((\hat{a}_{\theta,t,j,i} | m_{t,i}) \neq \hat{a}_{\theta,t,j,i})$. Fourth, we test for confirmation bias, by examining incorporation of management guidance in analysts' posterior beliefs. Lastly, in cross-sectional analysis we exploit variation in the magnitude of the prior and the precision of signals. Psychology literature has shown that confidence affects the weight individuals place on priors. In particular, overconfidence leads to (1) overestimation of one's actual performance, (2) overplacement of one's performance relative to others, and (3) excessive precision in one's beliefs (Moore & Healy 2008; Hilary & Menzly 2006). Vice versa, underconfidence lead to notable instances of an underestimation, underplacement, and conservative precision, which is however less common (Moore & Healy 2008). Further, analysts' weighting mechanism is conditional on the precision of the signal (τ_z^{-1}) thus once the signal precision decreases analysts place more weight on their prior.

Heterogeneous Priors and Sell-Side Financial Analysts

We exploit the sell-side financial analyst setting, which offers granular data and observable information choices. Current literature focuses on events such as hurricanes, mass shootings, weather, or terror attacks (Bourveau & Law 2021; Cuculiza et al. 2021, DeHaan et al. 2017) that directly disrupt analysts' information production (i.e., threaten their personal health, their housing situation, or affect their resource allocation). Compared to these events, the Super Bowl does not affect analysts' resource allocation or information models. Further, decision-makers employ Bayes' rule in normal times but behave differently when facing "rare" events such as mass shootings, hurricanes, or terror attacks (Ortoleva 2012; Giacomini et al. 2020).[2]

Evidence in psychology suggests that sports events generate strong emotions that impact mood, individuals' opinions, and consequently decisions unrelated to sports (Schweitzer et al. 1992; Hirt et al. 1992; Schwartz et al. 2013). Spectators' level of testosterone is significantly

[2] In additional tests we confirm that there is no difference in effort between treated analysts and the control sample that could be affected by the event (number of forecasts, forecast accuracy, and conference call attendance).

influenced by the outcome of a sports game, even if they do not participate in the physical competition themselves (Mazur et al. 1992). Such emotions are amplified by social sharing. In particular, for events that strike collectively in a local area the reactivation process is intensified, as there are many sharing sources and every sharing reactivates the emotion (Rime 2007). Thus, we use the Super Bowl as a local shock on mood in a local community, affecting the priors of sell-side financial analysts (Wu 2023, Chhaochharia et al. 2020, Bauer et al. 2023).

The Super Bowl takes place on the first Sunday in February and the venue is determined by the NFL.[3] Teams' participation and the outcome of the Super Bowl, however, are unpredictable. The NFL ensures a competitive league structure by using salary cap regulation and a draft system.[4] Additionally, in most seasons, the 32 teams play just 17 games before the playoffs meaning they avoid almost half their potential opponents, introducing an element of luck. The Super Bowl title has not been won three years in a row by the same team and overall, the price has been shared by teams from 14 states. For endogeneity concerns the Super Bowl participation must correlate with analysts' time-variant characteristics and information choices, which is unlikely and would not explain our differential treatment effect for negatively and positively treated analysts.

[3] The 32 NFL teams are divided into two conferences and seven teams of each conference can qualify for the play-offs after the regular season. In each round, the play-off mechanism lets the highest-seeded (best) team of a conference play against the lowest-seeded (worst) team of the same conference, till there are two teams of each conference left that are playing for the conference championship and have the right to attend the Super Bowl. Venues that fulfill the requirements can apply with a presentation and the final venue is determined by the 32 team owners. The requirements can be seen in a 2013 leaked document: https://www.documentcloud.org/documents/1184220-20140605190910.html#document/p36 .

[4] For more information on the competitive structure of the NFL league and the draft system, please see: https://www.economist.com/culture/2023/02/24/how-socialism-boosts-american-sport & https://operations.nfl.com/journey-to-the-nfl/the-nfl-draft/the-rules-of-the-draft/ .

III. RESEARCH DESIGN AND DATA

Research Design

We use a quasi-experimental setting where a random mood shock, namely the outcome of the Super Bowl, affects the distribution of analysts' priors. Participation in the Super Bowl is random and dispersed over time and locations. We assign analysts based on the combined statistical area (CSA) to the treatment group if their local NFL team participates in the Super Bowl and expect the treatment effect to differ based on the outcome of the game. If the local team lost (won) the Super Bowl, we expect a downward (upward) shift in analysts' priors, information choices, and posteriors. Analysts in cities that do not participate in the Super Bowl serve as our control group. We exclude observations within the sample that are economically related to the Super Bowl (i.e., local companies, team sponsors, stadium sponsors, half-time advertisers, and sports equipment producers). Hence, our outcome variables should note be confounded by potential direct economic impacts of the Super Bowl.

Using a difference-in-difference setting and a shock to local mood, we compare treated to untreated analysts:

$$Y_{i,t} = \beta_1 Winner_{i,t} + \beta_2 Loser_{i,t} + \ Controls + \ FE + \varepsilon_{i,t} \qquad [4]$$

where $i \ and \ t$ denote analyst and time respectively. Our main variables of interest are *Super Bowl Loser* and *Super Bowl Winner*. Both are indicator variables taking the value of one if the local NFL team has lost (won) the Super Bowl for observations (i.e., news articles, tweets, forecasts, and conference calls) after the Super Bowl till the end of the first quarter. If the mood-induced Super Bowl treatment would not last until the end of the first quarter, this should attenuate our coefficient estimates. The coefficients of interest are the difference-in-difference estimates between treated and non-treated analysts which are captured in β_1 and β_2. For example, we compare differences in outcome variables (i.e., analysts' priors, information choices, and posteriors) before and after the Super Bowl of an analyst located in Denver – whose local team won the Super Bowl – and an analyst located in Tampa – whose local team lost the Super Bowl – to differences in outcomes of untreated analyst, all issuing forecasts for a firm located in Chicago, which has no connection to the Super Bowl.

To threaten our identification strategy, the participation in as well as the outcome of the Super Bowl must correlate with analysts' time-variant characteristics or information choices. This would imply that in each quarter, analysts in the winner (loser) city seek positive (negative) information about their portfolio firms. The correlation is unlikely and would not explain our differential treatment results. Therefore, reverse causality or unobservable characteristics do not explain the change in prior, information choices, and posterior beliefs after the Super Bowl.

Our empirical design resembles a reduced-form approach, as we cannot observe individual shifts in analysts' mood and do not expect that the shift in an analyst's priors after the Super Bowl is the sole channel of affecting their posteriors; (i.e., an instrumental variable approach would not be feasible). We proceed our analysis as follows: First, to elaborate the causal chain of the treatment, we examine the direct effect of the Super Bowl outcome on local community mood by examining local news articles and social media sentiment. Second, as the Super Bowl affects local analysts' priors, we examine in our main test whether agents acquire information consistent with their (positively or negatively biased) prior beliefs. We use analysts' earnings conference call interactions and incorporation of management guidance to shed light on analysts' information choices. Lastly, we examine whether skewed information choices and heterogeneous priors lead to variance in analysts' posterior beliefs. To proxy for analysts' posterior beliefs, we use relative forecast optimism of one quarter ahead earnings-per-share forecasts as defined by Bourveau & Law (2021).

***Data*[5]**

NFL information. We use a public dataset from Kaggle to obtain NFL game data, scores, and betting data. The dataset uses a variety of sources including ESPN, NFL.com, National Oceanic and Atmospheric Administration (NOAA), and Pro Football Reference.[6] We validate the dataset by hand matching Super Bowl dates and teams with data from the NFL website. We further match betting data (i.e., Odds and Spreads) to confirm the randomness of the Super Bowl result and exploit variance in expectations for the outcome.

Community information. Data on zip codes is provided by the U.S. Census Bureau and data on combined statistical area (CSA) by the National Bureau of Economic Research. We exploit the tone of local news and tweets to show that mood within communities is affected by the Super Bowl. We use the Global Database of Events, Language, and Tone (GDELT 2.0 Global Knowledge Graph)[7] that monitors online news articles and extracts each person's name, organization, company, and location from the article, resulting in an annotated metadata panel over the world's news each day. Tweets come from the Twitter APIv2.[8] We use tweets that provide a geotag and classify the sentiment with a (pre-trained on Twitter data) algorithm based on RoBERTa[9].

Analyst information. We use transcripts of quarterly earnings conference calls held by publicly listed firms from Refinitiv Eikon for the period of 2002 to 2021. We merge the transcripts

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[5] We obtain our data from multiple sources. Please refer to the Online Data Appendix for details on our different data sets and data cleaning procedures.
[6] See https://www.kaggle.com/datasets/tobycrabtree/nfl-scores-and-betting-data .
[7] See https://www.gdeltproject.org/ .
[8] See https://developer.twitter.com/en/docs/twitter-api .
[9] We deploy the algorithm by Loureiro et al. 2022, which can be downloaded here: https://huggingface.co/cardiffnlp/twitter-roberta-base-sentiment-latest .

with several data sets from IBES to obtain analysts' quarterly earnings-per-share forecasts (FPI = 6), forecasts' summary statistics, stock recommendations, and earnings-per-share actuals for the sample period 2000 to 2021. The use of one-quarter ahead forecasts ensures that our estimates are not affected by quarterly earnings announcement information (Barron et al. 2002; Zhang 2008; Lobo et al. 2017; Bourveau & Law 2021), thus we do not capture the additive effect of earnings release information (Bourveau & Law 2021). We scrape the full work history of each analyst including her broker affiliation and the office location from the BrokerCheck website by FINRA.[10] For latitude and longitude data of analyst location, we use Google's Geocoding API.

Firm information. We use CRSP for firms' stock data and Compustat for data on firm fundamentals. As Compustat backfills firms' corporate headquarters (Jennings et al. 2020), we use 10-Ks to obtain business addresses (Loughran & McDonald 2011) and the latitude/longitude of firm's headquarters. Management guidance is obtained from IBES Corporate.

Other information. We use hourly data from the Integrated Surface Database (ISD) by NOAA to proxy for analysts' sunshine exposure (DeHaan et al. 2017; Chen et al. 2022).

IV. RESULTS

Super Bowl and Heterogeneous Priors

We first provide evidence of the direct effect of the Super Bowl outcome on local community. We use local news outlets' tone as a proxy for community mood (Tetlock et al. 2007; Dougal et al. 2012; Garcia 2013). Local news outlets are produced frequently and the time between writing and publishing an article is arguably short. We use data from the Global Database of Events, Language,

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[10] See https://brokercheck.finra.org/.

and Tone (GDELT) that includes a tone measure of emotional valence in worldwide articles for the period from April 2015 to September 2021. The data is gathered from a large number of news outlets. We only include 145,468 articles from outlets that are manually matched to local cities via their names (i.e., Chicago Tribune) and that are not considered to report nationally (i.e., New York Times) to ensure that the author of the article likely resides in the treated metropolitan area. The tone measure lies in a range from -9.1 to 5.0 with a mean of -1.6 for our sample. The average score of articles by negatively (positively) treated news outlets lies at -1.9 (-0.9).

We further exploit Twitter (nowadays X) as an alternative information source to uncover the effect of the Super Bowl on local mood via social media. Tweets offer a highly frequent and due to the limited characters, comparable source of sentiment in social sharing. We exclude tweets containing NFL topics and classify the sentiment of 3,417,532 tweets in 13 metropolitan areas for the year 2016 by a RoBERTa-based model that is trained and fine-tuned on tweets from January 2018 to December 2021. [11] The model differentiates between a positive score measuring positive aspects of sentiment and a negative score, measuring the negative aspects of sentiment in each tweet. In this way, we can also take into account adverse language styles (e.g. sarcasm). The negative (positive) sentiment measure lies in a range from 0.1 to 96.7 (0.3 to 99.3) and both measures are not mechanically dependent. Agents' tweets in a negatively (positively) treated community represent an average negative score of 26.7 (24.46) and a positive score of 34.89 (37.59).

Comparing news and social media sentiment of treated to untreated cities, our coefficients of interest are the difference-in-difference estimates between treated and non-treated agents which are

[11] Due to X's shutdown of the academic API's, we are not able to extend the timeline of this test (see: https://devcommunity.x.com/t/all-of-our-academic-apis-were-finally-removed/197249).

captured in $Super\ Bowl\ Winner$ and $Super\ Bowl\ Loser$ (i.e., equation [4]). To account for time-variant differences between users and newspapers, we include *user (news outlet)-by-year fixed effects*. Further, we include a *date-fixed effect* to account for the sentiment of daily news, which could be shaped by macroeconomic events (i.e., wars, terror attacks). We cluster standard errors at the combined statistical area level.

The results are shown in Table 2. Panel A indicates that news outlets located in cities that won the Super Bowl, relative to untreated news outlets, use more positive words during the treatment period after the Super Bowl till the end of the first quarter. By contrast, outlets located in cities that have lost the game use more negative words. The relation is statistically significant in our main model (Column 4), suggesting that the Super Bowl affects the local community and the mood of agents residing in these communities. The high frequency of local news articles allows a time trend analysis around the treatment window, confirming the treatment effect local agents' priors. Figure 2 compares the non-parametric local linear regression of news sentiment for both treatment groups and the control group. The results show that the tone of non-related news by participating local news outlets before the game increases in comparison to the control group. After the game, the tone measure decreases sharply for the negatively treated local news outlets. The positively treated news outlets remain on the level above the control group during the treatment period, confirming the adverse effect of both treatment groups in comparison to the control group.

Table 2 Panel B indicates that the effect extends to social media. Private individuals located in cities that have lost (won) the Super Bowl tweet with a lower (higher) sentiment (i.e., use more negative or positive words in their tweets). Specifically, the positive score is positively affected by winning the Super Bowl and vice versa (Column 2). The negative score is only affected by individuals who reside in cities that lost the Super Bowl (Column 4). Collectively, the results corroborate our prediction that the Super Bowl affects local mood and shifts the priors of local agents residing in these communities.

Heterogeneous Priors and Analysts' Information Choices

Next, we examine whether heterogeneous priors through shifts in mood due to the Super Bowl affect information choices. To that end, we exploit the sell-side financial analyst setting, as it provides observable information choices in public earnings conference calls. Conference calls are the main information exchange platform between analysts and management (Hollander et al. 2010). We use interactions during the call as a proxy of analysts' information choice and one-quarter-ahead earnings-per-share forecasts as a proxy of analysts' posterior beliefs.

Calls are divided into a structured management presentation and an unstructured question and answer (Q&A) section. As analysts are resource-constrained, they need to decide "how much to invest" to acquire additional information (Veldkamp 2011; Hellwig & Veldkamp 2009). We explore both the extensive margin (i.e., the occurrence of analysts' interactions) and the intensive margin (i.e., the number/length/tone of analysts' interactions) of information choices. The extensive margin measures the decision to ask a question and to interact with the management. The intensive margin measures the preparation and willingness to get additional information in the form of follow-up questions or comments that trigger a reaction by the management. Our measure for tone of analysts uses the dictionary approach by Loughran & McDonald (2011)[12] and sets the ratio of negative words per analyst for all statements in a conference in relation to the ratio of negative words in the management presentation. Following this approach, we build an *abnormal negativity*

[12] See Loughran-McDonald Master Dictionary w/ Sentiment Word Lists // Software Repository for Accounting and Finance // University of Notre Dame

measure controlling for the current state of the firm (Hassen et al. 2019) and the time of the day (Chen et al. 2018).

Our identifying variation is time- and analyst-specific. We include a *firm fixed effect* limiting our analysis to within variation of the same firm, mitigating the concern that treated and non-treated analysts follow different firms. We further include an *analyst fixed effect* absorbing any time-invariant analyst characteristics (e.g., analyst's sports affection).[13] Therefore, we use the within variation for each analyst covering the same firm before and after the Super Bowl. We include a *broker (metropolitan) fixed effect* to account for time-invariant, unobservable broker (city) characteristics. Further, we control for macro shocks using *year fixed effects*.

Our coefficients of interest, as with the prior analysis, are *Super Bowl Loser* and *Super Bowl Winner* (i.e., equation [4]). Both are indicators capturing the treatment of the shift in priors of local analysts. We expect a negative (positive) sign for loser (winner) analysts. The set of control variables includes the number of firms that the analyst follows per quarter to control for analysts' workload (Clement 1999), specific analysts' company experience, the distance between the analyst's office location and the headquarters location of the target (Malloy 2005) to control for private information access, location-specific sunshine exposure to control for weather-induced mood (DeHaan et al. 2017) and, lastly, the distance between analysts' forecast announcement dates and the most recent consensus in our forecast optimism analysis to control for information advantages later in the forecast period (Lang & Lundholm 1996; Barron et al. 2002; Cowen et al 2006). We cluster standard errors by CSA.

[13] Given that our variation is an analyst- and time-specific indicator variable, controlling for time-variant unobservable characteristics through *analyst-by-time fixed effects* would remove identifying variation. Nonetheless, in our robustness tests we control for time-variant, unobservable analyst characteristics through *analyst-by-year fixed effects*, time-variant, unobservable metropolitan characteristics through *CSA-by-year fixed effects*, and limit the variation to within *firm-by-year*. We still find the same results.

We identify 88,812 analysts who participate in earnings conference calls spanning 2002-2021 and containing 2,901 unique analysts in 54 metropolitan areas with available posterior data in IBES to validate their location. Figure 1 reports the location distribution of analysts in our sample. Consistent with prior literature (Malloy 2005; Gerken et al. 2023), the majority of analysts are located around the agglomerations of New York, Los Angeles, Chicago, Dallas, and Minneapolis. Besides these concentrations, our sample displays substantial geographical variation in analysts' office locations across the USA with each metropolitan area hosting a different NFL team.

Table 3 shows the distribution of winner and loser treatments over our sample period indicating substantial variation in teams participating in the Super Bowl. The average analyst has 4.2 *Interactions* during a call participation with an average of 472 words per call as shown in Table 1. The mean abnormal negativity measure is about 0.294.

Table 4 presents our difference-in-differences results. The first outcome measure proxies the willingness to interact with the management by actively participating in the conference call and obtaining information. We show that the number of interactions (Column (1) to (2)) and length of interactions (Column (3) to (4)) is significantly higher for positively treated analysts, indicating that positively skewed priors are associated with a higher expected precision of additional information. The economic magnitude for the effect on interactions is about 3.39% more interactions for a one standard increase in Super Bowl Winner (=0.0941 ÷ 2.773) as well as about 2.77% longer interactions (= 19.7887 ÷ 714.375). Our results further indicate that negatively treated analysts significantly increase their usage of negative words (Column (5) to (6). The tone of conference calls deteriorates markedly over the day (Chen et al. 2018). We take such fluctuations into account by computing a measure of abnormal tone, which captures the incremental negative tone of analysts in comparison to the management in the same conference call. We also examine abnormal positivity but find no significant effect. The economic magnitude of the effect is about 12.41% (= 0.1276 ÷ 1.051)). This is in line with Tetlock (2007) and Loughran & McDonald (2016) who recommend limiting the sentiment measure to only negative words, as positive words can be used in non-positive circumstances that lead to noise (e.g. perfect storm). Overall, our results show that shifted priors affect analysts' information choices and information seems to be acquired consistent with analysts' prior beliefs.

Heterogeneous Priors, Information Choices, and Analysts' Posterior Beliefs

Lastly, we examine the impact of the treatment on analysts' posterior beliefs, reflected by their forecasts. We expect that heterogeneous priors and skewed information choices lead to variance in analysts' posterior beliefs. Empirically, we test the relation by examining whether analysts located in cities whose local NFL team lost (won) the Super Bowl issue less (more) optimistic forecasts. Forecast optimism is defined according to Bourveau & Law (2021):

$$Forecast\ Optimism_{i,j,t} = \frac{Forecast_{i,j,t} - Last\ Consensus\ Forecast_{j,t}}{Standard\ Deviation\ Consensus\ Forecast_{\ j,t}} \qquad [5]$$

Where i, j, t denotes analyst, firm, and time. A higher (lower) optimism means that forecasts are more (less) optimistic than the closest consensus forecast before the analyst's forecast (Bourveau & Law 2021). We use one-quarter ahead forecasts yielding the advantage of holding quarterly firm information constant across analysts.

We include a *firm, analyst, broker (metropolitan), and year fixed effect in our analysis.* The set of control variables includes the number of firms that the analyst follows per quarter, the analyst's company experience, the distance between the analyst's office and the firms headquarter, local sunshine, days to consensus, and lagged forecast optimism of the last analyst forecast for the same firm as a proxy for her prior beliefs. We cluster standard errors by CSA and the variables of interest are the difference-in-difference estimates of the treatments.

The sample contains 305,259 quarterly firm-analyst earnings forecasts spanning 2000-2021 and containing 4,036 unique analysts in 78 metropolitan areas. The mean of *Forecast Optimism* in our posterior beliefs sample is -0.521 as reported in Table 1. Further, the average analyst in both samples follows 15 firms, has 4 years of firm specific experience, and is based approximately about 400 miles from the target corporation away.

Table 5 presents the results with different fixed effects structures. The coefficients are significant and show that the negative (positive) outcome of the Super Bowl decreases (increases) the relative forecast optimism of treated analysts for firms. Column (5) displays the results of our main model. Relative to the standard deviation of Forecast Optimism, moving the Super Bowl loser (winner) from zero to one is associated with a 15.86% (= 0.3737÷ 2.345) (9.06% (=0.2121÷2.345)) decrease (increase) in Forecast Optimism. This finding is economically significant and consistent with the loss aversion theory as losses have a greater impact on individuals' preferences (Tversky & Kahneman 1991). Lastly, we control for analysts' prior information set by including lagged optimism of her prior forecast for the same firm. The inference remains unchanged.

The control variables *#Firms*, *company experience*, and *days to consensus* show constantly a negative coefficient, indicating that analysts with more firms covered, higher firm-specific experience, and later forecast relative to the published consensus issue less optimistic forecasts. The signs are consistent with the theory from prior literature (Clement & Tse, 2005). Lastly, the coefficient on *sunshine* indicates that higher sunshine leads to optimistic forecasts consistent with prior findings (DeHaan et al. 2017).

One could argue that treated analysts differ from the control group in their expectation formation prior to the Super Bowl and these differences are unrelated to the treatment. The parallel trend assumption seems to hold after including indicator variables for treated analysts for the time between the conference championship game (semifinal) and the Super Bowl (final) and the year before the Super Bowl in Columns (4) to (6), respectively. The results show that these indicators are insignificant and the parallel trend assumption holds. Collectively, the results suggest that heterogeneous priors and skewed information choices manifest in posterior beliefs leading to a wider distribution of analysts' forecasts.

Analysts Confirmation Bias

Our prior results indicates that analysts seem to acquire information consistent with their prior beliefs. Questions from analysts residing in losing cities are relatively more negative compared to non-treated analysts. This implies that analysts attempt to extract information from management that supports their negative perspective. To substantiate our findings, we exploit the differences in analysts' updating processes after an observable information signal, namely management guidance. During or after the conference call managers voluntarily issue earnings forecasts to align market participants' beliefs with managers' own beliefs (Ajinkya & Gift 1984). The extent to which management guidance successfully aligns sell-side financial analysts' and managers' beliefs hinges on the choice to incorporate the signal. Thus, we examine whether guidance forecasts above (below) the prior market consensus are considered by treated analysts. Exploiting managements guidance we can observe (1) an identical signal for all analysts and (2) the (in-)consistency with prior beliefs (i.e., distance of guidance signal to rational benchmark). If indeed biased priors affect analysts' information choices, we expect optimistic (pessimistic) analysts to ignore below (above) market expectation forecasts by managers.

We start by merging management forecasts of next quarter's earnings-per-share with our analysts' forecast data. We create an indicator variable that is equal to one whether the management forecast is above or below the prior analysts' consensus forecast. The results are reported in Table

5 Column (1) for above consensus guidance and in Column (2) for below consensus guidance. Consistent with our prediction, we find that negatively biased analysts are not issuing incremental optimistic forecasts despite positive news from the management (Column (1)). This suggests that negatively biased analysts seem to not to acquire (ignore) positive management guidance as these inconsistent with prior beliefs. Positive treated analysts, however, acquire these information into forecast as it is positive. Given that management guidance is less biased than analysts' priors and positive treated analyst rely on this information, the bias gets attenuated. Further, despite negative news from management (i.e., below last consensus), positively biased analysts incrementally issue more optimistic forecasts, contradicting the management's expectations (Column 2). Put differently, despite negative news from an insider of the firm, analysts issue more optimistic forecasts. The results are consistent with our preceding findings that analysts acquire information consistent with prior beliefs.

Analyst Prior Weighting and Confidence

In cross-sectional tests, we aim to shed light on the underlying weighting mechanism in analysts' expectation updating by examining differences in the weighting of heterogeneous priors. Psychology literature has shown that confidence affects the weighting function, in particular, overconfidence leads to (1) overestimation of one's actual performance, (2) overplacement of one's performance relative to others, and (3) excessive precision in one's beliefs (Moore & Healy 2008).

In our analyses, we have established that analysts located in winning (losing) cities overestimate (underestimate) the performance of firms, confirming their biased priors and skewed information choices. To examine whether heterogeneous priors also adjust the analysts' weighting functions, we interact the *Super Bowl Loser* and *Super Bowl Winner* indicators with time-variant proxies for individual confidence. The results are reported in Table 7.

In Column (1) we use an indicator variable for firms whose headquarters are also located in the winning (losing) city of the Super Bowl (i.e., overplacement). The positive and significant coefficient of the interaction shows that winning analysts overplace the performance of firms located in the same city. Interestingly, those optimistic forecasts do not result in an increased forecast accuracy ruling out the possibility of superior information (untabulated results) and supporting the overconfidence channel. Contrary, we find a negative coefficient on the interaction for losing cities and *Super Bowl Loser*, which is however not significant. In Column (2), we condition the sample on updated forecasts of analysts for the same firm and examine the precision of beliefs in the preceding quarter. We proxy for preceding belief precision by using analysts' forecast accuracy of her preceding forecast for the same firm. The interaction shows that the optimism (pessimism) bias incrementally increases (decreases) with more accurate preceding forecasts showing that precise analysts place more weight on their biased priors.

Further, evidence suggests that professionals tend to be more overconfident relative to inexperienced individuals (Griffin & Tversky 1992) and that overconfidence is more pronounced for males than for females (Huang & Kisgen 2013). First, we use experience from FINRA's BrokerCheck website to proxy for analysts' sell-side experience and find that the overconfidence effect is amplified for more experienced analysts (Column (3)). Second, we split the pre- and last-names of all analysts in our sample and use a gender prediction algorithm to determine the gender of each analyst.[14] The algorithm differentiates between female, male, mostly female, and mostly male. We hand-checked names that were not clearly determined and excluded any analyst names,

[14] We use the gender guesser algorithm by David Arcos that is trained on a dictionary of 40,000 first names and the number of genders occurrences. The dictionary is primarily built for European countries but also holds for the US, China, India, and Japan: https://pypi.org/project/gender-guesser/ . Furthermore, we differentiate only between female and male as a lack of data and no proper method to identify other genders.

which could not be divided into one of the subgroups. We test the relative affection of women in comparison to men in our sample in Column (4). The significant and negative interaction indicates that the optimism effect of overconfidence is muted for female analysts.

Next, we shift the focus to the perceived precision of the information signal (i.e., management guidance) and create an indicator variable that is equal to one if the management forecast is a range estimate (i.e., earnings-per-share is between 0.3 and 0.4). The variable is zero when the forecast is a point estimate. We expected that the information signal would be less precise once it includes a range and thus increase analysts' weight on priors. We find that negatively biased analysts seem to ignore management guidance, as the interaction term between *SB Loser* and *Range Estimate* is insignificant (Column 5). For positively biased analysts, however, we find a statistically positive coefficient for the interaction between *SB Winner* and *Range Estimate* suggesting that once the precision of the information signal decreases her reliance on her prior increases – which amplifies the behavioral bias (extensive margin). Further, we provide evidence that our results hold at the intensive margin. Rather than using an indicator to differentiate between range and point forecasts, we use the continuous value of the range (i.e., the difference between the upper and lower bound provided by the management). We find consistent results where the behavioral bias increases once the precision of the signal decreases and the priors weight increases (Column 6). Overall, our cross-sectional results support our prior findings that analysts acquire information consistent with prior beliefs.

V. ROBUSTNESS

Inattention and Differences in Effort as Alternative Explanations

We conduct several robustness tests. We predict that the Super Bowl affects analyst forecasts via shifts in heterogeneous priors and information choices. Yet, one could also argue that the Super Bowl affects analysts' resource allocation or attention, distorting their information production. For instance, analysts might be distracted if their team participates in the Super Bowl, and hence invest fewer resources or efforts into their forecasts, resulting in inattention (Giacomini et al. 2020).

To address the concern about inattention, we examine if there are systematic differences in observable effort between treated and control analysts. We use the total number of earnings forecasts at the analyst-quarter level as our first proxy for analysts' effort provision (Bourveau & Law 2021). Table 8 states the results, and we find no evidence that effort provision significantly changes due to the treatment. Additionally, we use analysts' forecast accuracy as our second proxy for effort allocation (Lang & Lundholm 1996). The results in Column (2) show no statistically significant decline in accuracy controlling for known determinants of forecast accuracy.

Lastly, we examine whether treated analysts are less likely to attend conference calls following the Super Bowl. Similarly, to the previous tests, we could not find a significant effect as shown in Column (3). Conclusively, the evidence indicates that analysts' response to the Super Bowl does not result from changes to their information production function, but rather from exposure to changes in mood. Further, a change in the information production function would not explain the differential results for winners and losers and especially the increased information acquisition for "winner analysts".

Sensitivity Analyses

The sensitivity analyses are reported in Table 9. First, we exclude forecasts of negatively treated analysts for the *Winner* coefficient and vice versa in Columns (1) and (2) to address the concern that the significant impact is mainly driven by the difference between the two treatment groups. In Column (3) we tighten the fixed structure by including *analyst-by-year, metropolitan–by–year*, and *firm-by-year fixed effects* to control for time-variant analyst, metropolitan, and firm characteristics. The coefficients remain significant and the inferences are unchanged.[15] Further, the fixed effect accounts for time-variate characteristics of analysts' previous forecasting history (Hong et al. 2000). Instead of quarterly earnings forecasts, we use full-year earnings-per-share forecasts (FPI = 1). The results are reported in the Online Appendix and confirm our prior findings.

In untabulated results, we control for the impact of COVID-19 on analysts' expectation formation by including the average deaths per 100k inhabitants as a control variable. The data is provided by the New York Times. Our results do not change. Further, we examine analysts residing in the venue city of the Super Bowl. Our results show no significant association between the Super Bowl and community mood, information choices, and forecast optimism for analysts residing in the venue city. In additional tests, we exploit betting data to account for cross-sectional differences in the Super Bowl outcome (i.e., accounted by our fixed effects structure). We do not find a significant relation between outcome expectation and analysts' forecast optimism. Alternatively, using the number of years since the last Super Bowl title of the local team instead of betting quotes, does not change our results.

[15] To overcome the small number of treated forecasts we replicated the analysis for yearly EPS forecasts and find similar results, see Appendix B.

Falsification Test

In Figure 3, we show results from a falsification test (Bourveau & Law 2021). We randomly assign 20 placebo Super Bowl events during the first quarter of the year in the metropolitan area. We then draw randomly 4,295 forecasts and construct a *random treatment* dummy that equals one. We re-estimate 10,000 times the baseline model from equation (4) with the *random treatment* indicator variable. The red lines indicate our coefficients from the baseline model (i.e., Table 4 Column (5)). Overall, the distribution indicates that there is no consistent trend of a shift in analysts' forecast optimism following a placebo Super Bowl.

VI. CONCLUSION

We provide empirical evidence that heterogeneous prior affect information choices (Veldkamp & Malmendier 2022). Variance in priors can color the focus on signals (e.g., good news vs. bad news), which results in biased posteriors. We shed light on how behavioral biases get incorporated into forecasts through heterogeneous priors and biased information choices. These findings help to understand the disagreement among economic agents and how biases in analysts' forecasts emerge. Further, we provide novel insights into the direction of mood. Recent literature exclusively focuses on pessimism. We show that positive life experiences can impact analysts' mood differentially, namely increase analysts' information acquisition and forecast optimism, which to the best of our knowledge has not been shown before. More broadly, we contribute to literature investigating asset pricing implications of behavioral biases documented after sports events providing evidence that mood affect economic decision making of agents residing in affected cities (Edmans et al. 2007; Bernile & Lyandres 2011).

VARIABLE DESCRIPTION

Variables	Description	Source
Dependent Variables		
# Interactions	The number of occurrences of the analyst in the transcript (e.g., follow-up questions or comments on answers).	REFINITIV
Length of Interactions	The cumulative number of words of all interactions in one transcript.	REFINITIV
Abnormal Negativity	The ratio of negative words in all statements of analyst i minus the ratio of negative words in the management presentation of the same conference call	REFINITV
Forecast Optimism	$\frac{AF_{i,t,j} - Mean\ Consenus_{t,j}}{SD\ Consenus_{t,j}}$ winsorized at the 1st and 99th percentiles (Bourveau & Law 202)	IBES
# Forecasts	Number of earnings forecasts issued by an analyst in a given quarter	IBES
Forecast Accuracy	$\frac{-\lvert EPS_{j,t} - AF_{i,t,j}\rvert}{P_{t,j}}$ winsorized at the 1st percentile (Lang & Lundholm 1996)	IBES & CRSP
CC Attendance	An indicator variable that takes the value of one if the analyst is listed in the participation list of quarterly earnings conference calls and publishes an IBES forecast in the respective quarter for the same firm. If the analyst publishes a forecast without attending the call the variable is equal to zero. (i.e., listed in the participation list)	REFINITIV& IBES
Local News Tone	The tone of a news article given by the GDELT database, that is based on the ratio of positive and negative emotional words in an article. The emotional words are classified by a state-of-the-art pre-trained AI model by GDELT	GDELT
Twitter Sentiment	The sentiment of tweets that contain a geotag and can be allocated to a specific city in the U.S.. The sentiment measure is derived from a natural language model on the basis of RoBERTa and is pre-trained to classify sentiment in social media data (e.g. to identify sarcasm) The positive (negative) score identifies positive (negative) aspects of an individual tweet and weighs them.	TWITTER
Independent Variables		
Super Bowl Loser (Winner)	An indicator variable that takes the value of one if the analyst's office is located in a combined statistical area that has lost (won) the Super Bowl within the first quarter of the year (after the Super Bowl)	KAGGLE & NFL & FINRA

Before Super Bowl	An indicator variable that takes the value of one if the analyst's office is located in a CSA that has attended the Super Bowl within the time between the conference final (NFL semifinal) and the Super Bowl. (Kaggle & NFL)	KAGGLE & NFL & FINRA
Cross-Sectional Variables		
Loser (Winner) City	An indicator that is equal to one if the coverage firm's headquarters is located in the same city as the winning (losing) analysts.	KAGGLE & NFL & FINRA
Lagged Accuracy	Analysts' forecast accuracy of the latest forecast for the same firm before the current forecast.	IBES & CRSP
Experience	Analysts experience as a sell-side financial analyst	FINRA
Female (Male)	An indicator variable that takes the value of one if an analyst's first name is classified by a gender guesser algorithm (David Arcos) as female/make	FINRA & IBES
Guidance	An indicator variable that takes the value of one if the management provides EPS guidance	IBES
Control Variables		
Lagged Forecast Optimism	Lagged (last) forecast optimism of analysts i forecast for the same firm j.	IBES
Year Before	An indicator variable that takes the value of one if an analyst's office location is in a CSA during the year before a Super Bowl is won (lost) in the city	KAGGLE & NFL
# Firms	Number of firm's analyst i provides forecasts measured quarterly	IBES
Company Experience	No. of years analysts i issued forecasts in the IBES database for the respective firm j	IBES
Forecast Horizon	Natural logarithm of one plus the difference between the forecast date and the forecast period end date	IBES
Days to Consensus	Number of days from the current IBES consensus	IBES
Distance	Natural logarithm of one plus the distance between analyst's location and the headquarters of the covering firm defined on the zip code level.	(10K & FINRA)
Sunshine	Daily sky cover index averaged by the hourly sky cover between 6 a.m. and 6 p.m. taken from the Integrated Surface Database (ISD) The index is calculated as the average daily sunshine index over a 7-day window preceding the earnings forecast window for weather stations in a 50-mile radius around the analyst location. For ease of interpretation, the sunshine index is multiplied by -1 such that higher values of the sunshine index reflect greater sunshine exposure.	NOAA

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APPENDIX A: FIGURES & TABLES

Figure 1: Location of Analysts in Sample

Note: The figure below shows the distribution of analysts' locations over the sample period 2001 to 2021. We use analysts' working histories from FINRA's BrokerCheck website to obtain analysts' locations. We classify the analyst's location as equal to the city at which the brokerage site the analyst is/was employed. The figure shows the distribution of analysts over the sample period.

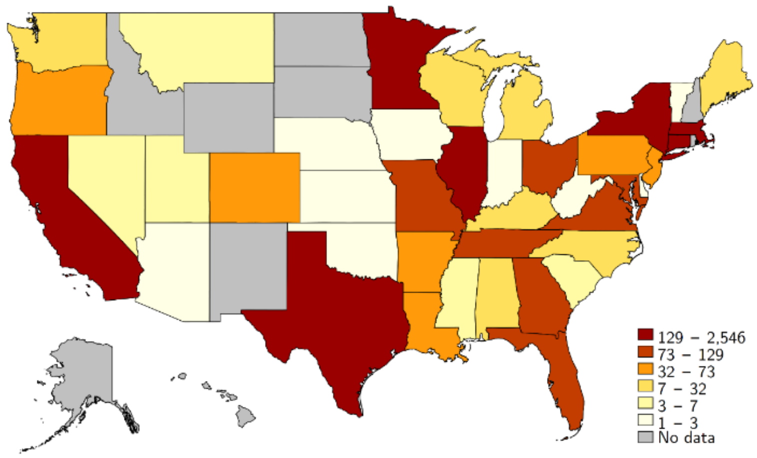

Figure 2: Local News Paper Sentiment

Note: The figure compares the non-parametric local linear regression of news sentiment for both treatment groups and the control groups. The line graphs represent the tone of a news article given by the GDELT database that is based on the ratio of positive and negative emotional words in an article. The emotional words are classified by a state-of-the-art pre-trained AI model by GDELT. The bars represent the number of positively and negatively treated news articles per week for the local linear regression.

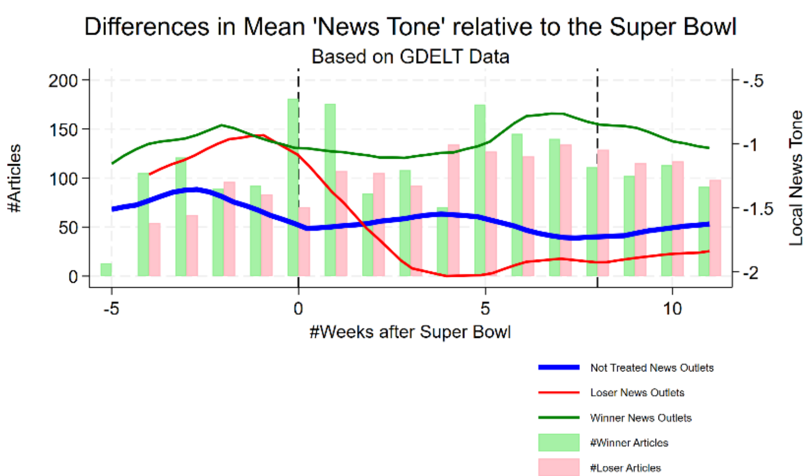

Figure 3: Placebo Test

Note: The figure plots the distribution of the random treatment estimate. During the process, we randomly assign 20 Super Bowl events to the metropolitan area in the first quarter of the year. Random treatment is one for 4,295 randomly drawn forecasts of the Super Bowl events. We re-estimate the baseline specification from equation (4) with the Random Treatment 10,000 times. The distribution is shown below, the red lines show the Super Bowl Loser (Winner) coefficients from our main tests.

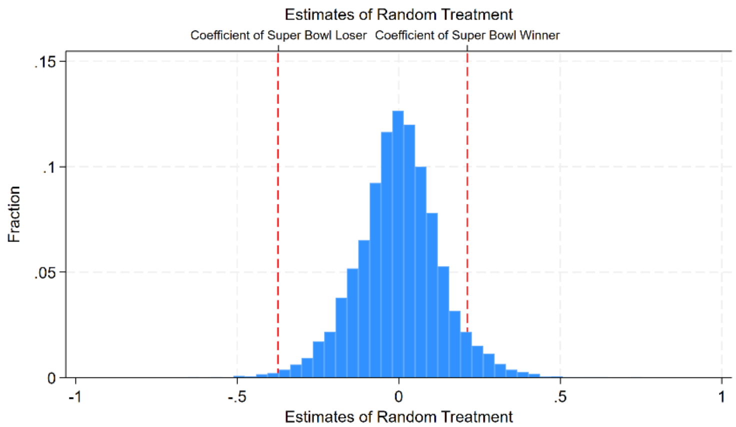

Table 1: Summary Statistics

Note: This table provides summary statistics of the main variables used in the subsequent regression analyses. The number of observations for each variable corresponds to the number of observations in the main regression (after dropping singletons). Please refer to the Appendix for definitions of all other variables.

	N	Mean	SD	p25	Median	p75
Table 2 Heterogeneous Priors						
Local News Tone	145,468	-1.615	2.986	-3.54	-1.409	.437
Local Social Media Sentiment Positive	3,417,532	34.516	35.405	3.315	18.822	66.685
Local Social Media Sentiment Negative	3,417,532	27.821	34.532	1.223	5.488	63.631
Table 4 Analyst Information Choices						
# Interactions	88,812	4.191	2.773	2	4	5
Length of Interactions	88,812	471.871	714.375	126	272	548
Abnormal Negativity of Analysts	88,812	.294	1.051	-.439	.184	.849
Super Bowl Loser	88,812	.004	.066	0	0	0
Super Bowl Winner	88,812	.017	.128	0	0	0
Sunshine	88,812	-1.875	.699	-2.366	-1.886	-1.381
# Firms	88,812	15.204	6.613	11	15	19
Company Experience	88,812	4.813	3.591	2	4	6
Distance Analyst & Firm	88,812	6.06	1.718	5.409	6.596	7.256
Table 5 Analyst Posterior Beliefs						
Forecast Optimism	305,259	-.521	2.345	-1.02	-.2	.5
Super Bowl Loser	305,259	.007	0.086	0	0	0
Super Bowl Winner	305,259	.014	0.118	0	0	0
Before Super Bowl	305,259	.001	0.027	0	0	0
Year before	305,259	.001	0.023	0	0	0
Lagged Optimism	305,259	.096	0.295	0	0	0
Sunshine	305,259	-1.9	0.691	-2.388	-1.916	-1.424
# Firms	305,259	14.864	7.297	10	14	19
Company Experience	305,259	4.08	3.435	2	3	5
Days to Consensus	305,259	2.342	0.873	1.792	2.565	3.091
Distance Analyst & Firm	305,259	6.093	1.719	5.465	6.607	7.261
Table 6 Analyst Inconsistent Prior						
Above Expectations	51,827	.391	0.488	0	0	1
Below Expectations	51,827	.565	0.496	0	1	1
Table 7 Analyst Prior Weighting						
Winner City	260,657	.034	0.182	0	0	0
Forecast Accuracy (lagged)	233,390	-.014	0.045	-.007	-.002	-.001
Experience	305,259	19.086	7.057	14	19	23
Female	293,534	.096	0.294	0	0	0
Range (Indicator)	51,827	.864	0.343	1	1	1
Range	51,736	.048	0.268	0	.02	.049
Table 8 Analyst Inattention						
# Forecasts	84,869	1.308	0.594	.693	1.099	1.609
Forecast Accuracy	254,632	-1.431	4.523	-.715	-.211	-.069
CC Attendance	305,259	.345	0.475	0	0	1

Table 2: Super Bowl and Heterogeneous Priors

Note: This table reports the regression estimates using OLS. In Panel A the dependent variable is Local News Tone derived from the GDELT database, calculated by the ratio of positive and negative emotional words in a news article. In Panel B the dependent variable is Local Social Media Sentiment derived from 3,417,532 Tweets. The sample of tweets represents all tweets published in 2016 from 13 metropolitan areas in the US. Further, these tweets: are from non-certified Twitter accounts to make sure they are not pre-written and do not cover the topic NFL. The sentiment measure is derived from a natural language model based on RoBERTa and is pre-trained to classify sentiment in social media data (e.g. to identify sarcasm). It derives two scores for positive and negative sentiment. Super Bowl Loser (Winner) is an indicator variable equal to one for a local news article/tweet during the quarter following the Super Bowl that was published by a local news publisher/user within the city (CSA) that has lost (won) the game. Definitions of variables are shown in the Appendix. Standard errors are clustered by the publishers residing in cities and reported in parentheses. The intercepts are included but not reported. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level respectively.

Panel A: Local News Tone (GDELT)

	Local News Tone (GDELT)			
	(1)	(2)	(3)	(4)
Super Bowl Winner	0.6894***	0.6511***	0.0303	0.0791
	(0.1654)	(0.1898)	(0.0825)	(0.0676)
Super Bowl Loser	-0.2700**	-0.1640**	-0.3433*	-0.3358**
	(0.1211)	(0.0821)	(0.1981)	(0.1570)
News Outlet fixed effect?	N	N	Y	N
News Outlet-by-year fixed effect?	N	N	N	Y
Date FE	N	Y	Y	Y
N	145,468	145,468	145,468	145,468
Adj. R-squared	0.000407	0.0341	0.113	0.128
Cluster (Number)	CSA (78)	CSA (78)	CSA (78)	CSA (78)

Panel B: Local Social Media Sentiment (Twitter)

	Positive Score		*Negative Score*	
	(1)	(2)	(3)	(4)
Super Bowl Winner	0.2332*	0.2229*	-0.1667	-0.1368
	(0.1117)	(0.1042)	(0.0983)	(0.0966)
Super Bowl Loser	-0.2831***	-0.2617***	0.4037***	0.3955***
	(0.0487)	(0.0528)	(0.0635)	(0.0654)
User fixed effect?	Y	N	Y	N
User-by-CSA fixed effect?	N	Y	N	Y
Date fixed effect?	Y	Y	Y	Y
N	3,417,532	3,417,532	3,417,532	3,417,532
Adj. R-squared	0.1441	0.1441	0.1660	0.1660
Cluster (Number)	CSA (13)	CSA (13)	CSA (13)	CSA (13)

Table 3: Super Bowl Participants and Treated Analysts

Note: This table reports the attending cities (teams) at the Super Bowl and how many analysts participating (obs.) and forecasts are treated per year.

			Information Choices Sample						**Posterior Beliefs Sample**					
season	*winner city*	*loser city*	*#analyst obs.*	*#analysts*	*#winner obs.*	*#winner analysts*	*#loser obs.*	*#loser analysts*	*#forecasts*	*#analysts*	*#winner forecasts*	*#winner analysts*	*#loser forecasts*	*#loser analysts*
2000	STLOUIS	NASHVILLE							7,192	772	94	32	2	1
2001	BALTIMORE	NEWYORK							9,218	906	43	22	898	280
2002	BOSTON	STLOUIS	428	255			2	2	8,536	939	15	7	149	41
2003	TAMPA	OAKLAND	1,688	584	1	1	19	19	9,466	1,008	4	2	74	38
2004	BOSTON	CHARLOTTE	2,39	661	11	7	6	6	10,337	1,123	33	14	17	9
2005	BOSTON	PHILADELPHIA	2,84	753	6	5	3	2	11,19	1,221	30	17	9	4
2006	PITTSBURGH	SEATTLE	3,334	827					11,929	1,303			2	2
2007	INDIANAPOLIS	CHICAGO	3,424	864			24	17	11,631	1,361			57	30
2008	NEWYORK	BOSTON	4,696	907	484	236	12	8	15,482	1,358	1,442	442	52	21
2009	PITTSBURGH	GLENDALE	4,728	961					13,647	1,379				
2010	NEWORLEANS	INDIANAPOLIS	4,814	1,069	11	4			13,334	1,532	25	8		
2011	GREENBAY	PITTSBURGH	5,63	1,164					15,99	1,687				
2012	NEWYORK	BOSTON	6,416	1,280	812	397	26	16	18,723	1,759	2,075	641	76	31
2013	BALTIMORE	SANFRANCISCO	5,717	1,194	36	20	65	45	17,121	1,737	132	44	175	77
2014	SEATTLE	DENVER	5,88	1,235	1	1	24	9	17,946	1,769	3	3	89	11
2015	BOSTON	SEATTLE	5,842	1,190	29	17			17,465	1,741	84	32		
2016	DENVER	CHARLOTTE	5,143	1,095	28	11			15,74	1,643	100	13	5	1
2017	BOSTON	ATLANTA	4,823	1,045	27	18	31	12	15,705	1,544	88	38	80	22
2018	PHILADELPHIA	BOSTON	4,944	1,039	4	3	17	14	15,513	1,491	22	8	69	27
2019	BOSTON	LOSANGELES	4,893	1,002	17	10	23	11	14,881	1,460	72	31	55	16
2020	KANSAS	SANFRANCISCO	6,976	1,027	5	1	133	46	21,487	1,434	29	2	440	73
2021	TAMPA	KANSAS	4,206	874	1	1			12,726	1,313	5	2	6	1
			88,812		1,473		385		305,259		4,296		2,255	

Table 4: Analyst Information Choices and Heterogeneous Priors

Note: This table reports the regression estimates using OLS. The dependent variables are the number and length of an analyst's interactions, and abnormal negativity in a conference call. The number of interactions is defined as the total number of statements in a conference call (initial questions, follow-up questions, or comments), and length is the cumulative length of all interactions in one call. Abnormal Negativity is defined as the analyst's ratio of negative words in all statements in a conference call minus the ratio of negative words in the management presentation in the same conference call. Super Bowl Loser is an indicator variable equal to one for analysts' conference call participation during the quarter following the Super Bowl and that resides within the city (CSA) that has lost the game. Definitions of variables are shown in the Appendix. Standard errors are clustered by analysts' residing cities and reported in the parentheses. The intercepts are included but not reported. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level respectively.

	# Interactions		*Length of Interactions*		*Abnormal Negativity*	
	(1)	(2)	(3)	(4)	(5)	(6)
Super Bowl Loser	0.1855	0.1790	7.5530	6.3426	0.1270***	0.1276***
	(0.1661)	(0.1676)	(36.5392)	(36.6212)	(0.0423)	(0.0425)
Super Bowl Winner	0.1046***	0.0941***	21.9733***	19.7887***	0.0087	0.0087
	(0.0221)	(0.0240)	(5.9229)	(5.7845)	(0.0082)	(0.0083)
# Firms		-0.0030**		-0.5337		-0.0016**
		(0.0012)		(0.3764)		(0.0006)
Company Experience		0.0381***		8.2853***		-0.0043***
		(0.0031)		(0.7716)		(0.0012)
Distance Analyst & Firm		-0.0089		-2.7130		-0.0022
		(0.0106)		(2.1946)		(0.0033)
Sunshine		-0.0085		-1.2154		-0.0003
		(0.0114)		(2.9606)		(0.0033)
Analyst fixed effect?	Y	Y	Y	Y	Y	Y
Broker fixed effect?	Y	Y	Y	Y	Y	Y
Year fixed effect?	Y	Y	Y	Y	Y	Y
Firm fixed effect?	Y	Y	Y	Y	Y	Y
CSA fixed effect?	Y	Y	Y	Y	Y	Y
N	88,812	88,812	88,812	88,812	88,812	88,812
Adj. R-squared	0.487	0.488	0.367	0.368	0.121	0.121
Cluster (Number)	CSA (55)	CSA (55)	CSA (55)	CSA (55)	CSA (55)	CSA (55)

Table 5: Analyst Posterior Beliefs, Heterogeneous Priors and Information Choices

Note: This table reports the regression estimates using OLS. The dependent variable is Relative Forecast Optimism (Bourveau & Law 2021) defined as the analyst's forecast of firm's quarterly earnings minus the closest consensus forecast before the forecast, divided by the standard deviation of the consensus forecast. Super Bowl Loser (Winner) is an indicator variable equal to one for analysts' forecasts during the quarter following the Super Bowl and that reside within the city (CSA) that has lost (won) the game. Before the Super Bowl is an indicator variable that takes the value of one for days after the Conference Champion Game and prior to the Super Bowl for analysts in both (winner/loser) cities (CSA). Column 6 includes the lagged optimism from analysts prior forecast before the Super Bowl. Definitions of variables are shown in the Appendix. Standard errors are clustered by analysts' residing cities (CSA) and reported in the parentheses. The intercepts are included but not reported. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level respectively.

	Forecast Optimism					
	(1)	(2)	(3)	(4)	(5)	(6)
Super Bowl Loser	-0.4054**	-0.3793**	-0.3680**		-0.3737**	-0.4185**
	(0.1721)	(0.1631)	(0.1573)		(0.1575)	(0.1886)
Super Bowl Winner	0.2188***	0.2223***	0.2153***		0.2121***	0.2499***
	(0.0514)	(0.0565)	(0.0573)		(0.0587)	(0.0469)
Super Bowl Before (W)				0.0542	0.0759	0.0086
				(0.1051)	(0.0921)	(0.0382)
Super Bowl Before (L)				-0.1219	-0.1595	-0.1777
				(0.0864)	(0.1097)	(0.2060)
Year Before				-0.0311	-0.0321	-0.0087
				(0.0193)	(0.0198)	(0.0298)
Lagged Optimism						-0.0000
						(0.0000)
Sunshine			0.0654***	0.0661***	0.0655***	0.0689***
			(0.0110)	(0.0110)	(0.0109)	(0.0120)
# Firms			-0.0047***	-0.0047***	-0.0047***	-0.0024
			(0.0014)	(0.0014)	(0.0014)	(0.0019)
Company Experience			-0.0139***	-0.0138***	-0.0139***	-0.0036*
			(0.0015)	(0.0015)	(0.0015)	(0.0018)
Days to Consensus			-0.1081***	-0.1085***	-0.1081***	-0.1283***
			(0.0054)	(0.0053)	(0.0053)	(0.0068)
Distance Analyst-Firm			-0.0063	-0.0062	-0.0063	-0.0133***
			(0.0038)	(0.0038)	(0.0038)	(0.0046)
Analyst fixed effect?	Y	Y	Y	Y	Y	Y
Broker fixed effect?	Y	Y	Y	Y	Y	Y
Year fixed effect?	Y	Y	Y	Y	Y	Y
Firm fixed effect?	N	Y	Y	Y	Y	Y
CSA fixed effect?	N	N	Y	Y	Y	Y
N	305,259	305,259	305,259	305,259	305,259	233,476
Adj. R-squared	0.0580	0.116	0.118	0.118	0.118	0.127
Cluster (Number)	CSA (77)	CSA (77)	CSA (77)	CSA (77)	CSA (77)	CSA (67)

Table 6: Analyst Information Choices and Consistent Priors

Note: This table reports the regression estimates using OLS. The dependent variable is relative forecast optimism defined according to Bourveau & Law 2021. Super Bowl Loser is an indicator variable equal to one for analysts' conference call participation during the quarter following the Super Bowl and that resides within the city (CSA) that has lost the game. Columns 1 and 2 show the interaction with an indicator that is equal to one if the management guidance is above (below) the last consensus forecast. Definitions of variables are shown in the Appendix. Standard errors are clustered by analysts' residing cities and reported in the parentheses. The intercepts are included but not reported. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level respectively.

	Forecast Optimism	
	(1)	(2)
Super Bowl Loser	-0.4921*	-0.8663**
	(0.2840)	(0.3606)
Super Bowl Winner	0.4321***	0.2003**
	(0.1132)	(0.0768)
Above Expectations	1.4115***	
	(0.0366)	
Below Expectations		-1.4486***
		(0.0378)
SB Loser×Above Expect.	-0.7434***	
	(0.1529)	
SB Winner×Above Expect	-0.2526**	
	(0.1007)	
SB Loser×Below Expect		0.1314
		(0.4671)
SB Winner×Below Expect.		0.2145**
		(0.0965)
Controls	Y	Y
Analyst fixed effect?	Y	Y
Broker fixed effect?	Y	Y
Year fixed effect?	Y	Y
Firm fixed effect?	Y	Y
CSA fixed effect?	Y	Y
N	51,827	51,827
Adj. R-squared	0.268	0.267
Cluster (Number)	CSA (54)	CSA (54)

Table 7: Analyst Prior Weighting and Confidence

Note: This table reports the regression estimates using OLS. The dependent variable is Relative Forecast Optimism (Bourveau & Law 2021) defined as the analyst's forecast of firm's quarterly earnings minus the closest consensus forecast before the forecast, divided by the standard deviation of the consensus forecast. Super Bowl Loser (Winner) is an indicator variable equal to one for analysts' forecasts during the quarter following the Super Bowl and that reside within the city (CSA) that has lost (won) the game. Column 1 shows the interaction with an indicator that is equal to one if the coverage firm's headquarters is located in the same city as the winning (losing) analysts. Column 2 reports the interaction of the winner (loser) indicator and analysts' forecast accuracy of the latest forecast for the same firm before the current forecast. Column 3 reports the results of an interaction with analysts' experience based on FINRA's BrokerCheck website. Column 4 reports the results of an interaction with an indicator variable based on analysts' gender using a name prediction model by David Arcos. Column 5 reports the interaction with an indicator that is equal to one if the management guidance is a range forecast. Column 6 reports the interaction with the range of the management guidance. We use the same fixed effects structure as in our main tests. Definitions of variables are shown in the Appendix. Standard errors are clustered by analysts' residing cities (CSA) and reported in the parentheses. The intercepts are included but not reported. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level respectively.

	Forecast Optimism					
	(1)	(2)	(3)	(4)	(5)	(6)
	Winner City	Lagged Accuracy	Experience	Female/Male	Indicator	Range
Super Bowl Loser	-0.3146**	-0.4508**	-0.6273*	-0.3932**	-0.7052**	-0.7346***
	(0.1497)	(0.2059)	(0.3489)	(0.1688)	(0.3370)	(0.1966)
Super Bowl Winner	0.1650***	0.2644***	0.0030	0.2411***	-0.1003	0.3099***
	(0.0588)	(0.0521)	(0.1048)	(0.0649)	(0.1258)	(0.1134)
SB Loser×Winner City	0.1807					
	(0.5520)					
SB Loser×Loser City	-0.1480					
	(0.1286)					
SB Winner×Loser City	0.1035					
	(0.0662)					
SB Winner×Winner City	0.1542***					
	(0.0331)					
SB Loser×Accuracy		-2.4304**				
		(0.9685)				
SB Winner×Accuracy		0.8331**				
		(0.3299)				
SB Loser×Experience			0.0127			
			(0.0097)			
SB Winner×Experience			0.0107***			
			(0.0032)			
SB Loser×Female				-0.0432		
				(0.3243)		
SB Winner×Female				-0.2583***		
				(0.0582)		
SB Loser×Range					-0.1182	-2.5605
					(0.3039)	(2.2727)
SB Winner×Range					0.4861**	0.5801***
					(0.2355)	(0.1973)
Analyst, broker, year, firm, CSA fixed effect?	Y	Y	Y	Y	Y	Y
Controls included?	Y	Y	Y	Y	Y	Y
N	260,613	233,448	305,259	293,534	51,827	51,735
Adj. R-squared	0.120	0.127	0.118	0.116	0.235	0.235

Table 8: Analyst Inattention

Note: This table reports the regression estimates using OLS. The dependent variable in Column 1 is the number of forecasts defined as the number of quarterly earnings forecasts issued by an analyst within a quarter. All observations are at the analyst-quarter level and control variables refer to the means at the analyst-quarter level. The dependent variable in Column 2 is Forecast Accuracy (Lang & Lundholm 1996) defined as the negative of the absolute value of analysts' quarterly forecast error, deflated by the stock price. The dependent variable in Column 3 is Conference Call Attendance which is an indicator variable that is equal to one if the analysts is listed in the participation list of the quarterly earnings conference call of the respective corporation. The variable is equal to zero for analysts publishing a quarterly EPS forecast in I/B/E/S and not attending the conference call. Super Bowl Loser (Winner) is an indicator variable equal to one for analysts' forecasts during the quarter following the Super Bowl and resides within the city (CSA) that has lost (won) the game. Before Super Bowl is an indicator variable that takes the value of one for days after the Conference Champion Game and prior to the Super Bowl for analysts in both (winner/loser) cities (CSA). Definitions of variables are shown in the Appendix. Standard errors are clustered by analysts' residing cities (CSA) and reported in the parentheses expected Column 1. The intercepts are included but not reported. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level respectively.

	# Forecasts	*Forecast Accuracy*	*CC Attendance*
	(1)	(2)	(4)
Super Bowl Loser	0.0417	0.0217	-0.0112
	(0.0341)	(0.0232)	(0.0099)
Super Bowl Winner	-0.0226	-0.0328	0.0015
	(0.0232)	(0.0284)	(0.0047)
Analyst fixed effect?	Y	Y	Y
Firm fixed effect?	N	N	Y
Firm-by-quarter fixed effect?	N	Y	N
Year fixed effect?	Y	Y	Y
Broker fixed effect?	Y	Y	Y
CSA fixed effect?	Y	Y	Y
Controls included?	Y	Y	Y
N	84,869	254,632	305,259
Adj. R-squared	0.4476	0.9616	0.3433
Cluster (Number)	CSA (72)	CSA (73)	CSA (77)

Table 9: Robustness

Note: This table reports the regression estimates using OLS. The dependent variable is Relative Forecast Optimism (Bourveau & Law 2021) defined as the analyst's forecast of firm's quarterly earnings minus the closest consensus forecast before the forecast, divided by the standard deviation of the consensus forecast. Super Bowl Loser (Winner) is an indicator variable equal to one for analysts' forecasts during the quarter following the Super Bowl and that reside within the city (CSA) that has lost (won) the game. Column 1 (2) excludes forecasts of analysts in cities that have lost (won) the Super Bowl. We vary our FE structure in Column (3) by including a by-year fixed effects structure. Definitions of variables are shown in the Appendix. Standard errors are clustered by analysts' residing cities and reported in the parentheses expected Column 1. The intercepts are included but not reported. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level respectively.

	Forecast Optimism		
	(1)	(2)	(3)
	excl. Loser	excl. Winner	FE StructurexYear
Super Bowl Winner	0.2208***		0.1863***
	(0.0545)		(0.0501)
Super Bowl Loser		-0.3696**	-0.4709**
		(0.1573)	(0.2014)
Analyst fixed effect?	Y	Y	N
Analyt-by-year fixed effect?	N	N	Y
Broker fixed effect?	Y	Y	Y
Year fixed effect?	Y	Y	N
Firm fixed effect?	Y	Y	N
Firm-by-year fixed effect?	N	N	Y
CSA fixed effect?	Y	Y	N
CSA-by-year fixed effect?	N	N	Y
Controls included?	Y	Y	Y
N	302,992	300,952	290,888
Adj. R-squared	0.116	0.118	0.344
Cluster (Number)	CSA (77)	CSA (77)	CSA (75)

DATA APPENDIX

Forecast Data

We start by deriving information on analysts' working locations from BrokerCheck. The database has been used in prior research to identify analysts' locations (Bourveau & Law 2021). We merge the IBES recommendation file with the EPS file to obtain brokerage company names and analyst initials and last names.[16] We use the IBES brokerage translation file to convert brokerage numeric codes into brokerage names. Since 2007 the translation file is no longer updated, thus we apply a two-step procedure to verify brokerage names and change them accordingly if necessary. First, we compare the full name of the broker translation file to the brokerage name abbreviation of the recommendations file (ESTIMID) to account for brokerage mergers (Wu & Zang 2009). Second, by using a combination of the target firm's name, the name of the analyst, and the forecast announcement date, we use earnings conference call participation lists from Refinitiv (former Thomson Reuters) to verify and update the brokerage association.

FINRA Data

We scrape data of analysts' professional experience, and employment history including geographic location and duration of their employment from BrokerCheck. We match location data to IBES by using the analyst's last name, initials, brokerage affiliation, and working history. This method provides us with the working location of 5,100 analysts. Next, we use Google's Geocode API to obtain the latitude and longitude of analysts' employment city and match it to the respective combined statistical area (CSA) using county the federal information processing standard code

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[16] The analyst codes are the same in both I/B/E/S files, the broker codes are not: https://wrds-www.wharton.upenn.edu/pages/support/support-articles/ibes/earnings-forecast-data-estimators-and-analysts-vs-recommendation-data-estimators-and-analysts/ . Thus, we merge both files by analyst code and apply a conservative matching procedure. We drop observations for brokerage firms that provide less than 15 EPS forecasts in our sample period. We drop observations if there are less than 20 matches between the eps and recommendations file.

(fips). We use CSA to match whether the analysts reside in a city, whose team participates in the Super Bowl.[17] We combine the panel with control variables and drop forecasts of firms within the year that sponsor the Super Bowl, NFL teams, or the halftime show.

Conference Call Data

We use the conference call transcripts from Refinitiv (former Thomson Reuters) in the period from 2002 to 2021. First, we divide each transcript into the management presentation and Q&A section and clean the transcripts. Second, we separate the Q&A section into individual statements and aggregate statements per participant for each call. We can disentangle analysts and corporate insiders by position (department) and company name. Using Loughran & McDonald's dictionary and retaining stop words, in order to account for negations in the three preceding words (Loughran & McDonald 2011), we count the total number of words, the number of positive words, and the number of negative words. We use these results to compute our textual analysis variables for earnings conference calls. We conservatively match analysts' forecasts to earnings conference calls by using the target firm's Compustat identifier (GVKEY), fiscal year-quarter, analyst's last name, and brokerage house name.

Weather Data

To identify analysts' exposure to sunshine, we use the hourly sky cover index from the ISD databases that take values from one to five (one = clear, two = few clouds, three = scattered clouds, four = broken cloud cover, and five = overcast) (Chen et al. 2022). We average the hourly data per day for observations between 6 a.m. and 6 p.m. and match daily observations to the analyst's location by using longitude and latitude data for a 50-mile radius. We use the average of the daily

[17] Only Los Angles has two NFL's within the same CSA and both teams never participate in the Super Bowl at the same time. Our robustness test shows the same results if we use the city of analysts' residence.

index for a 7-day window prior to the analysts' forecast as our proxy for sunshine. We match analysts' offices based on longitude and latitude coordinates to the weather data.

Management Guidance Data

We use management earnings guidance data on quarterly (pdicity = QTR) earnings per share (EPS) forecasts from IBES. We use the indicator (range_desc) to determine if it is a point or range forecast and calculate the range as the absolute value of the lower and upper bound. We match management guidance based on the ticker of the company and the issuing date.

GDELT Data

We use data from the Global Database of Events, Language, and Tone (GDELT) that in essence, monitors every 15 minutes every news outlet worldwide. Each article is processed to identify all events, counts, quotes, people, organizations, locations, themes, emotions, relevant imagery, video, and embedded social media posts and placed into a global context. We use news published in the U.S. between April 2015 and September 2021. We only include articles from outlets that can be matched to local cities via their names (i.e., Chicago Tribune) and that are not considered to report nationally (i.e., New York Times). This ensures, that the author of the article likely resides in the treated metropolitan area. Further, we hand-check the websites of news publishers (*SourceCommonName*) for their office locations. We exclude articles that cannot be classified as predominantly positive or negative and articles under 400 words as these have limited information value (e.g., the title could already set the tone of the article). For classifying the tone of each article we deploy the tone measure that is provided by the GDELT database score. The score is measured by the share of positive and negative words in the document as a whole. Positive and negative words are identified by a model that is pre-trained on the specific GDELT data and the score ranges from -100 (extremely negative) to +100 (extremely positive).

Twitter Data

To verify the mood measure in the private context we use the Twitter APIv2 to scrape tweets to generate a measure of local private mood. To identify local tweets we limit our sample to tweets with a geotag (place_type = city). Further, we exclude retweets to avoid measuring reactions on tweets, not originated in the local area, and "nullcasted" tweets as well as tweets of verified accounts to make sure that the tweets are not prewritten.[18] To carve out the shock on the mood of the local community apart from the event itself we exclude tweets with the annotation NFL.[19] We classify the sentiment of each tweet by a RoBERTa-base model trained on approx. 124 Mil. tweets from January 2018 to December 2021, and fine-tuned for sentiment analysis with the TweetEval benchmark.

[18] For information on the Query Choices, see: https://developer.twitter.com/en/docs/twitter-api/data-dictionary/object-model/place .

[19] The annotation code for the NFL we used is context:11.689566306014617600. For further information see: https://developer.twitter.com/en/docs/twitter-api/annotations/overview

APPENDIX B FULL-YEAR EPS FORECASTS

Table B1: Super Bowl and Analysts Optimism

Note: This table provides summary statistics of the main variables used in the subsequent regression analyses. The number of observations for each variable corresponds to the number of observations in the main regression (after dropping singletons).

	N	Mean	SD	p25	Median	p75
Forecast Optimism	1,423,898	-.171	2.706	-1	0	1
Super Bowl Loser	1,423,898	.003	0.051	0	0	0
Super Bowl Winner	1,423,898	.005	0.068	0	0	0
Super Bowl before	1,423,898	.002	0.042	0	0	0
Year before	1,423,898	.09	0.287	0	0	0
# Firms	1,423,898	14.677	7.367	10	14	19
Company Experience	1,423,898	4.262	3.451	2	3	6
Days to Consensus	1,423,898	2.646	0.683	2.197	2.773	3.135
Distance Analyst & Firm	1,423,898	6.13	1.699	5.448	6.614	7.304
Sunshine	1,423,898	-1.832	0.696	-2.314	-1.846	-1.338

Table B2: Super Bowl Participants and Treated Analysts

Note: This table reports the attending cities (teams) at the Super Bowl and how many forecasts and analysts are treated per year.

Season	Winner City	Loser City	#Forecasts	#Analysts	#Winner Forecasts	#Winner Analysts	#Loser Forecasts	#Loser Analysts
2000	STLOUIS	NASHVILLE	21,213	908	177	44	3	1
2001	BALTIMORE	NEWYORK	27,906	1,030	52	24	1,427	339
2002	BOSTON	STLOUIS	29,135	1,065	27	8	195	43
2003	TAMPA	OAKLAND	33,969	1,122	4	2	148	44
2004	BOSTON	CHARLOTTE	41,781	1,250	73	18	31	12
2005	BOSTON	PHILADELPHIA	44,91	1,349	67	22	15	7
2006	PITTSBURGH	SEATTLE	49,108	1,432			4	2
2007	INDIANAPOLIS	CHICAGO	52,657	1,521			122	43
2008	NEWYORK	BOSTON	62,769	1,522	2,212	577	95	27
2009	PITTSBURGH	GLENDALE	63,646	1,525				
2010	NEWORLEANS	INDIANAPOLIS	67,748	1,725	51	13		
2011	GREENBAY	PITTSBURGH	76,09	1,887				
2012	NEWYORK	BOSTON	84,569	1,954	3,183	769	127	38
2013	BALTIMORE	SANFRANCISCO	83,62	1,966	190	54	356	103
2014	SEATTLE	DENVER	86,704	1,971	3	3	113	14
2015	BOSTON	SEATTLE	90,844	1,944	173	45		
2016	DENVER	CHARLOTTE	86,11	1,881	139	15	6	2
2017	BOSTON	ATLANTA	82,095	1,775	139	48	103	26
2018	PHILADELPHIA	BOSTON	80,952	1,718	34	11	147	43
2019	BOSTON	LOSANGELES	80,093	1,682	137	40	98	24
2020	KANSAS CITY	SANFRANCISCO	96,904	1,627	35	2	696	81
2021	TAMPA	KANSAS CITY	81,075	1,602	7	2	11	2
			1,423,898		6,703		3,697	

Table B3: Super Bowl and Analysts Optimism

Note: This table reports the regression estimates using OLS. The dependent variable is Relative Forecast Optimism (Bourveau & Law 2021) defined as the analyst's forecast of firm's full-year earnings minus the closest consensus forecast before the forecast, divided by the standard deviation of the consensus forecast. Super Bowl Loser (Winner) is an indicator variable equal to one for analysts' forecasts during the quarter following the Super Bowl and that reside within the city (CSA) that has lost (won) the game. Before Super Bowl is an indicator variable that takes the value of one for days after the Conference Champion Game and prior to the Super Bowl for analysts in winner/loser cities (CSA). Definitions of variables are shown in the Appendix. Standard errors are clustered by analysts' residing cities (CSA) and reported in the parentheses. The intercepts are included but not reported. ***,**, and * indicate statistical significance at the 1%, 5%, and 10% level respectively.

	Forecast Optimism		
	(3)	(4)	(5)
	Base Model	Before	Both
Super Bowl Loser	-0.7190***		-0.7174***
	(0.2228)		(0.2239)
Super Bowl Winner	0.1213*		0.1250*
	(0.0703)		(0.0712)
Year Before		0.0123	0.0084
		(0.0153)	(0.0152)
Super Bowl Before (W)		0.2218***	0.2235***
		(0.0687)	(0.0617)
Super Bowl Before (L)		0.1972**	0.1692*
		(0.0794)	(0.0896)
Analyst fixed effect?	Y	Y	Y
Broker fixed effect?	Y	Y	Y
Year fixed effect?	Y	Y	Y
Firm fixed effect?	Y	Y	Y
CSA fixed effect?	Y	Y	Y
Controls included?	Y	Y	Y
N	1,423,898	1,423,898	1,423,898
Adj. R-squared	0.0875	0.0875	0.0877
Cluster	CSA (88)	CSA (88)	CSA (88)