Terrorist Attacks, Analyst Sentiment, and Earnings Forecasts*

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Abstract – We examine whether exogenous and extremely negative events such as terrorist attacks and mass shootings influence the sentiment and forecasts of sell-side equity analysts. We find that analysts who are local to these attacks issue forecasts that are relatively more pessimistic than the consensus forecast. This effect is stronger when the analyst is closer to the event and located in a low-crime region. Impacted analysts are also relatively more pessimistic around the one- and two-year anniversaries of the attacks. Collectively, these findings indicate that exposure to extreme negative events affects the behavior of information intermediaries and the information dissemination process in financial markets.

Keywords: Analyst sentiment, forecast accuracy, extreme events, terrorist attacks.

JEL classification: G14, G40.

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1 Introduction

Earnings forecasts of sell-side analysts are a useful source of information for investors.[1] However, the analyst literature in finance and accounting suggests that investors should use this information cautiously since analyst forecasts can be biased (e.g., Klein (1990); De Bondt and Thaler (1990); Zhang (2006); Williams (2013); Dehaan et al. (2017)). In particular, analysts may be systematically optimistic or subject to the attribution and overconfidence biases (e.g., Easterwood and Nutt (1999); Hilary and Menzly (2006); Bergman and Roychowdhury (2008); Walther and Willis (2013)). Analysts' biased forecasts could also reflect their career incentives (e.g., Lim (2001); Hong and Kubik (2003); Ke and Yu (2006); Firth et al. (2013)).

In this paper, we extend this growing analyst bias literature and examine whether exposure to extremely negative events that are exogenous and unrelated to financial markets shock analysts' "sentiment" and influence their earnings forecasts. Our study is motivated by the psychology literature, which finds that people exposed to extreme negative events, such as terrorist attacks and mass shootings (henceforth, "terrorist attacks" or "attacks"), become more pessimistic in their risk assessments in unrelated domains (e.g., Lerner and Keltner (2001); Lerner et al. (2003)). The impact of these events is stronger among individuals located closer to the event.[2]

Motivated by these earlier findings, we posit that sell-side equity analysts located near terrorist attacks will issue relatively more pessimistic earnings forecasts following these events, compared with non-local analysts that issue forecasts for the same firm.[3] Further, analysts for who the extreme negative events are more salient will exhibit stronger reactions. And systematic forecast shifts could have an impact on their forecast accuracy.

To test these hypotheses, we obtain the dates and locations of terrorist attacks and mass shootings from the Global Terrorism Database (GTD) and Mother Jones' Magazine mass shooting database for the 1994–2016 period. We estimate a series of regression models where the dependent variable compares the one-quarter ahead earnings forecast of analyst i for company j at time t and the existing consensus forecast for the same firm at that particular time. Our key independent variable is $Exposure$, a dummy variable that indicates whether analyst i is affected by the attack. In particular, it is equal to one if the distance between the location of an analyst and the location of the attack is less than 100 miles and if the forecast is issued during

[1] See Kothari (2001); Ramnath et al. (2008); Zhang (2008); Chen et al. (2010); Grinblatt et al. (2016), among others.

[2] See, for example, Vlahov et al. (2002); Galea et al. (2002); Hughes et al. (2011).

[3] Given the known optimism bias among analysts (e.g. Lin and McNichols (1998); Hong and Kubik (2003); Firth et al. (2013)), the forecasts may still remain optimistic.

the 30-day period following the attack, and zero otherwise.[4] Our key prediction is that the coefficient estimate on *Exposure* will be positive and statistically significant, indicating that analysts who are more exposed to these extreme and negative events are relatively more likely to issue pessimistic forecasts compared to the consensus.

In our regression specifications, we include controls for several analyst and brokerage characteristics, as well as various fixed effects. Specifically, we augment our models with analyst fixed effects to exclude the possibility that our results are driven by analysts who are systematically pessimistic. We include time (year-quarter) fixed effects to remove any time trends and firm fixed effects to control for common information about firm earnings that could be available to all analysts.

The empirical results are consistent with our hypotheses. We find that affected analysts are 8.70% more likely to issue forecasts that are below the consensus. We obtain similar results when we estimate logit and probit models. These findings are consistent with our view that proximity to a terrorist attack can negatively affect analysts' sentiment, which in turn can induce them to issue relatively more pessimistic forecasts.

Next, we examine whether events that are potentially more salient influence analyst sentiment more strongly. We use two proxies to measure event salience. First, we use the distance between an analyst and the event. We conjecture that analysts who are located closer to an event will be affected more strongly than analysts located farther away. Second, we utilize state-level data on murder rates. This choice is motivated by the evidence in the psychology literature, which suggests that individuals exhibit a stronger emotional reaction to violence when they have lower prior exposure to such stimuli (e.g., Anderson and Dill (2000)).[5] Consistent with these studies, we hypothesize that analysts located in states with lower murder rates will issue relatively more pessimistic forecasts than analysts located in states with higher murder rates.

Consistent with this conjecture, we find that analysts located within a 100-mile radius are 8.50% more likely to issue pessimistic forecasts than analysts who are more than 100-miles away. Further, we find that treated analysts in low murder-rates states are 9.20% more likely to issue pessimistic forecasts than treated analysts in high murder-rate states. These results suggest that sentiment-related biases are stronger if the extreme event is more salient.

To gather additional support for our salience conjecture, we examine analyst forecasts around event anniversaries. Various ceremonies are often held around the same date and location of

[4] We use hand-collected data to measure the distance between the locations of the terrorist attacks and the locations of the brokerage houses where analysts are employed.

[5] To conduct this test, we use state-level data on murder rates obtained from the FBI's Uniform Crime Reporting (UCR) Program.

terrorist attacks to commemorate the victims; thus, we examine whether affected analysts become more pessimistic around the anniversaries of terrorist attacks. This hypothesis is based on the observation that anniversary ceremonies can remind local individuals of the negative sentiment they experienced following an attack. Remembering these negative and extreme events could affect their current sentiment (Shahrabani et al., 2009).

In line with our hypothesis, we find that treated analysts are more pessimistic around the one- and two-year anniversaries of terrorist attacks. Analyst pessimism diminishes over time and becomes statistically insignificant after three years. These anniversary findings provide additional support for our main conjecture and suggest that memories of terrorist attacks affect analyst sentiment and make their forecasts relatively more pessimistic. These results also allow us to rule out alternative explanations for our findings, as it is hard to imagine what other economic events would occur exactly on the anniversary of terrorist events and influence analyst behavior.

We also study if terrorist attacks can influence the forecast accuracy of affected analysts. It is difficult to hypothesize *ex-ante* whether treated analysts would be more or less accurate after an event. On the one hand, the limited attention literature suggests that analysts near terrorist attacks and mass shootings may be more distracted. Since attention is a scarce resource, analysts could limit the amount of time they spend on their individual forecasts (Hirshleifer and Teoh, 2003; Peng and Xiong, 2006; Hong and Stein, 2007; DellaVigna and Pollet, 2009), resulting in more inaccurate forecasts (Dong and Heo, 2016). On the other hand, due to treated analysts' higher pessimism levels, they may issue forecasts that are systematically lower than the consensus. Since prior studies suggest that relatively more pessimistic analysts (i.e., relatively more conservative analysts) provide more efficient forecasts, treated analysts, on average, could be more accurate (Hugon and Muslu, 2010; Jiang et al., 2016).

We find that treated analysts are more accurate than the average analyst. This effect is also significant in economic terms. For instance, the coefficient on *Exposure* is larger than the coefficient on *All Star*, which suggests that the impact of extreme events on forecast accuracy is at least as large as the improvement in accuracy that can be attributed to being an all-star analyst.

In the next set of tests, we investigate if investors regard as probable that treated analysts are more accurate. Since previous studies suggest that earnings forecasts are a potential useful source of information for investors, we analyze whether there is a stronger price reaction to treated analysts' forecast revisions. We find that investors do not anticipate for treated analysts to be more accurate, as their forecast revisions do not lead to stronger market reactions.

These results are robust to an alternative dependent variable definition, several sub-sample tests, and the inclusion of various fixed effects. Specifically, our conclusions are unchanged if we (i) use a continuous dependent variable, (ii) exclude the 9/11 attacks from our sample (the most significant events during our time period), (iii) exclude all analysts who reside in the state of New York (about 50% of the analysts), (iv) restrict our sample to sunny and cloudy months, and (v) perform sensitivity analysis in our 30-day post-attack window. We also perform a placebo test, where we randomize the location of the terrorist attacks, and we do not find any significant results.

In additional tests, we ensure our results are robust to several alternative explanations and confirm that our findings reflect the impact of attack-induced analyst pessimism. First, we examine whether pre-existing trends in analyst pessimism influence our findings. We find that prior to the attacks, affected analysts do not differ in their forecasts. Second, we test whether analyst pessimism is driven by the current economic conditions in their home state, which in a few cases might also be impacted by terrorist attacks. We repeat our analysis using a state's per capita Gross State Product (GSP) and unemployment rate as control variables. Our findings are robust to the inclusion of these variables.

Our next test analyzes whether treated analysts issue pessimistic forecasts because they have superior information and have a better understanding of how terrorist events affect some firms, as opposed to an adverse effect on their sentiment. We do so by recognizing that terrorist attacks could have differential impact across industries. For example, earnings of airlines may be more sensitive to attacks, relative to other sectors like agriculture. It is possible that affected analysts, who directly observe the effect of these attacks, are better able to understand how these attacks could influence some companies more than others and adjust their forecasts appropriately. If our results are driven by analysts' superior information rather than their attack-induced pessimism, our findings should be concentrated among companies with operations that are more likely to be affected by terrorist attacks. We do not find support for this alternative hypothesis. In fact, treated analysts are more likely to issue pessimistic forecasts for firms in industries that are less sensitive to terrorist attacks.

Further, a possible explanation as to why treated analysts are more accurate could be that they issue more bold forecasts, regardless of the direction (upward or downward), which are known to be more accurate (Clement and Tse, 2005). However, if their greater accuracy is driven by attack-induced pessimism, they would be more likely to issue downward bold revision forecasts but not upward bold revision forecasts. We find support for this latter hypothesis. In particular, treated analysts are less likely to issue bold forecasts, on average. They are also more likely to issue downward bold revision forecasts but not upward bold revision forecasts.

These findings contribute to several strands of sell-side analysts and terrorism related literature in finance, accounting, and economics. First, we extend the literature that analyzes the economic implications of terrorist attacks. Previous studies examine both the micro- and macro-economic implications of terrorist attacks.[6] In particular, Dai et al. (2018) suggest that CEOs employed by firms located near terrorist attacks receive a terrorist attack premium. Wang and Young (2019a) find that following a terrorist attack, retail investors reduce their stock market participation and trading activity. Even the aggregate risk aversion is inversely related to terrorist activity, where flows to risky assets decrease as the number of terrorist attacks increase (Wang and Young, 2019b). We extend this literature and show that terrorist attacks can affect financial markets through its impact on sell-side equity analyst sentiment, and subsequently, their forecasts.

Second, we complement the literature that examines whether analyst forecasts are affected by market-driven sentiment (Hribar and McInnis, 2012) or behavioral biases, such as representativeness (De Bondt and Thaler, 1990), conservatism (Zhang, 2006), availability (Bourveau and Law, 2016), overconfidence (Hilary and Menzly, 2006), depression (Dehaan et al., 2017), and limited attention (Dong and Heo, 2016). Our economic setting allows us to identify the impact of analyst mood on forecasting behavior more precisely. In particular, we are able to compare forecasts issued by analysts located close to a terrorist attack with the forecasts of analysts located farther away, for the same firm and at the same time.

In a related paper, Bourveau and Law (2016) demonstrate that analysts who just experienced a life-threatening weather event, Hurricane Katrina, become more risk averse because they associate tasks involving risk and uncertainty with their recent experience of the natural disaster. Consequently, affected analysts are more pessimistic than other analysts who did not experience the storm. Our work differs from this study in several ways. First, we identify an alternative channel through which non-economic events can affect analyst forecasts. Specifically, we document a sentiment-based mechanism, whereas Bourveau and Law (2016) rely on the availability heuristic. Our evidence suggests that analysts are still willing to take risks since they are more likely to issue downward (i.e., pessimistic) bold forecasts (Sapienza, 2010). Second, our empirical methodology provides a more robust setting to examine whether extreme negative events can affect analysts sentiment, and subsequently, their behavior. Our sample contains more than 90 events that span 22 years. Therefore, our results are immune to the

[6]For example, see Abadie and Gardeazabal (2003); Blomberg et al. (2004); Drakos (2004); Eckstein and Tsiddon (2004); Eldor and Melnick (2004); Barry Johnston and Nedelescu (2006); Siems and Chen (2007); Arin et al. (2008); Brounen and Derwall (2010); Karolyi and Martell (2010); Becker et al. (2011); Chesney et al. (2011); Llussá and Tavares (2011); Bandyopadhyay et al. (2013); Ahern (2018), among others.

potential biases and noise associated with a single treatment event. In particular, we are able to show that our findings are not driven by a specific time period or a particular set of treated analysts.

Further, our economic setting allows us to separate the economic-based effects from sentiment-based effects.[7] Because the direct economic costs for most of the attacks in our sample are quite small, such economic motives are less likely to be relevant.[8] Additionally, we are able to perform cross-sectional tests and illustrate more precisely the subtle ways that sentiment-inducing events influence analysts' behavior. For example, we show that the effects are stronger for more salient events or when analysts reside in low crime-rate states.

In another related study, Dehaan et al. (2017) study whether unpleasant weather, such as clouds, wind, and rain, can affect how market participants respond to information. They focus on sell-side equity analysts and analyze if local unpleasant weather can affect their response to earnings announcements. Our results complement these findings by showing that analysts also become pessimistic after terrorist attacks. The distinction between weather-induced pessimism and attack-induced pessimism is important as the psychology literature suggests that weather-related events and attack-related events can have different effects on individuals' mood (Peek and Sutton, 2003). For example, the nature of terrorism is clandestine and criminal and the goal of the perpetrator is to shock and terrify the masses (Juergensmeyer, 2017). Therefore, they typically have both short- and long-term consequences on a person's mental and physical health (Peek and Sutton, 2003). In contrast, unpleasant weather is unlikely to generate lasting psychological consequences (Howarth and Hoffman, 1984; Peek and Sutton, 2003; Denissen et al., 2008).

Beyond the analyst literature, our paper complements studies that examine the effects of significant "life events" on financial decisions. Recent work shows that traumatic early-life experiences have permanent effects on the decisions of corporate managers and sell-side analysts (Clement and Law, 2014; Bernile et al., 2017). In addition, extreme negative events experienced later in life exert a short-term effect on the decisions of mutual fund investors and corporate managers (Wang and Young, 2019b; Antoniou et al., 2017). We extend this literature by showing that terrorist attacks and mass shootings have a short-term impact on analyst forecasts.

Lastly, we contribute to the literature that analyzes whether market participants can display

[7]The direct economic cost of Hurricane Katrina was very large, especially for the residents of Louisiana; thus, it is possible that economic motives play a role in this setting. For example, Lim (2001) shows that, in equilibrium, analysts may issue optimistic forecasts to gain management access in the long term, accepting an immediate cost due to lower accuracy. If Louisiana-based analysts experienced a shock to their wealth due to hurricane Katrina and became more risk averse, then the immediate cost of optimism may increase, thus inducing these analysts to become less optimistic.

[8]The only events in our sample that are comparable to Hurricane Katrina in terms of economic costs are the 9/11 attacks. However, our results are robust to dropping the 9/11 events from the sample.

behavioral biases. For example, Goetzmann et al. (2014) show that weather-induced mood influences the decisions of institutional investors. Shu et al. (2017) suggest that bereavement due to parental loss influences the trades and profitability of mutual fund managers. We show that exposure to extreme negative events influences the behavior of relatively-sophisticated information intermediaries, and thus, affects the information dissemination process in financial markets.

The rest of the paper is organized as follows. In Section 2, we develop our main testable hypotheses. In Section 3, we describe the data sources and define the key variables. In Section 4, we discuss the main empirical findings and, in Section 5, we presents results from various robustness tests. Section 6 examines potential alternative explanations for our findings and Section 7 concludes with a brief summary.

2 Hypotheses Development

The affect heuristic (Slovic et al., 2007) suggests that salient events not only have negative effects on people's sentiment, but that they can also spillover and lead to pessimistic assessments of risks in unrelated domains. For example, experimental evidence in psychology shows that, individuals who read a sad newspaper article are subsequently more likely to assign a higher probability to unrelated negative future events (Johnson and Tversky, 1983). Consistent with these findings, recent studies show that terrorist attacks and mass shootings can influence the general risk perceptions of individuals (Benzion et al., 2009), since they exert a strong negative impact on their sentiment (e.g., Galea et al. (2002); Lerner et al. (2003); Fischhoff et al. (2005); Hughes et al. (2011)). The impact of these extreme negative events on individual sentiment is stronger when a person is closer to an event (e.g., Fischhoff et al. (2005); Benzion et al. (2009); Shahrabani et al. (2009)).

Motivated by this evidence in the psychology literature, we conjecture that:

H1: *Sell-side equity analysts located closer to a terrorist attack will issue more pessimistic earnings forecasts for a firm, compared to the prevailing consensus for the same firm at the same time.*

It is important to mention that, *ex-ante*, it is not clear whether analysts should be affected by non-economic, extreme negative attacks, such as terrorist events. Sell-side analysts are a relatively sophisticated group of market participants who should be well informed about firm fundamentals and should be immune to sentiment effects (Hribar and McInnis, 2012).

Our second hypothesis focuses on event salience. Specifically, we investigate whether attacks that are more salient lead to more pessimistic forecasts. Our first proxy for event salience is the geographical distance between an analyst and the terrorist event. We conjecture that analysts located closer to the event will be affected more strongly compared to analysts located farther away.

The second proxy is the state-level murder rate. This choice is based on the evidence in the psychology literature, which finds that people exhibit stronger emotional reactions to violence when they have limited prior exposure to such stimuli (e.g., Anderson and Dill (2000); Krahé et al. (2011)). In line with these findings, we hypothesize that analysts who are located in states with lower murder rates will react more strongly to the attacks and will issue relatively more pessimistic forecasts than affected analysts who are located in states with higher murder rates.

These insights motivate our second conjecture:

H2: *Affected analysts will issue more pessimistic earnings forecasts when they are located closer to extreme events, especially if they are located in regions with lower murder rates.*

In our next hypothesis, we refine the salience conjecture further. This insight is based on the observations that anniversary ceremonies are often held around the same date and location of terrorist attacks to commemorate the victims.[9] These ceremonies are likely to remind local individuals of the extreme negative emotions they experienced due to the attacks, and consequently, may exert a negative influence on their sentiment (e.g., Shahrabani et al. (2009)).[10] In a similar manner, local analysts may experience a negative shock to their sentiment around the anniversaries of terrorist attacks and become pessimistic. Specifically, we conjecture that:

H3: *Treated analysts will issue more pessimistic earnings forecasts around the anniversaries of terrorist attacks.*

In our fourth hypothesis, we examine whether terrorist attacks affect the forecast accuracy of treated analysts. It is difficult to posit *ex-ante* whether treated analysts would become more or less accurate after a terrorist attack. It is possible that analysts near terrorist attacks and mass shootings become more distracted. Since attention is a scarce resource, they could allocate less time to analyzing firm information when issuing their forecasts. As a result, the forecasts of affected analysts may deviate significantly from the consensus, potentially leading to less accurate forecasts (Hirshleifer and Teoh, 2003; Peng and Xiong, 2006; Hong and Stein, 2007; DellaVigna and Pollet, 2009; Dong and Heo, 2016).

Alternatively, if a terrorist attack affects an analyst's mood by increasing her pessimism,

[9] See, for example, http://edition.cnn.com/2002/US/09/11/ar911.memorial.newyork/, http://edition.cnn.com/2010/US/11/05/texas.fort.hood.anniversary/, http://www.usatoday.com/story/news/nation/2013/12/14/newtown-sandy-hook-shooting-anniversary/4022649/, http://edition.cnn.com/2014/04/15/us/boston-marathon-bombing-anniversary/.

[10] For a review of the psychological literature on the retrieval of emotional memories, see Buchanan (2007).

then she would issue forecasts that are systematically below the consensus. On average, this systematic downward bias could lead to more accurate forecasts (Hugon and Muslu, 2010; Jiang et al., 2016).[11] To examine these possibilities, our fourth hypothesis posits that:

H4: *Pessimism induced by terrorist attacks influence the forecast accuracy of treated analysts, but the direction of this impact cannot be predicted ex-ante.*

3 Data and Methods

In this section, we describe our datasets and empirical methodology. We use several data sources, including the Global Terrorism Database, Mother Jones, Thomson Reuters' Institutional Brokers Estimate System, Center for Research in Security Prices (CRSP) and COMPUSTAT. To test our hypotheses, we use OLS, logit, and probit regressions and include controls for a number of analyst and brokerage characteristics.

3.1 Terrorist Attacks and Mass Shootings Data

We obtain data on terrorist attacks and mass shootings that occurred in the U.S. from January 1994 to December 2016. Specifically, we collect data on terrorist attacks from the Global Terrorism Database (GTD).[12] It is an open-source database that contains systematic data on terrorist attacks (START 2016).[13] We acquire data for mass shootings from Mother Jones,[14] a nonprofit magazine that documents mass shootings in the U.S. For each one of the events during this time period, we obtain their location and date.

Since the GTD includes information on terrorist attacks around the world, we eliminate any event that has occurred outside of the U.S. Further, we consider only events that caused human casualties. From the resulting list, we eliminate duplicate events that appear in both datasets.[15] We also exclude events for which there are no affected analysts around the attack period.

[11] Existing studies suggest that the forecasts of relatively more conservative analysts (i.e., relatively more pessimistic analysts) tend to be more accurate. For instance, Hugon and Muslu (2010) find that conservative analysts provide more efficient forecasts. Likewise, Jiang et al. (2016) show that conservative analysts, who are less likely to "hype a stock," produce forecasts that are more accurate.

[12] The data are available at https://www.start.umd.edu/gtd/.

[13] To consider an event a terrorist attack and to distinguish it from common criminal activities, we apply the following three criteria as they appear in the GTD: "(i) The act must be aimed at attaining a political, economic, religious, or social goal; (ii) There must be evidence of an intention to coerce, intimidate, or convey some other message to a larger audience (or audiences) than the immediate victims; and (iii) The action must be outside the context of legitimate warfare activities, i.e., the act must be outside the parameters permitted by international humanitarian law (particularly the admonition against deliberately targeting civilians or non-combatants)." *Source:* https://www.start.umd.edu/gtd/faq/.

[14] The data are available at https://www.motherjones.com/politics/2012/12/mass-shootings-mother-jones-full-data/.

[15] Some terrorist events were mass shootings, and thus, are classified as both terrorist events and mass shootings. However, the overlap between both datasets is small (less than 10 events).

Table A1 lists the 91 events during the 1994-2016 period that are included in our final sample. Figure A1 shows their geographical distribution. The attacks do not exhibit any obvious regional clustering.[16]

3.2 Analyst Forecasts

We obtain information on quarterly analyst forecasts for U.S. firms traded on the NYSE, AMEX, or NASDAQ from Thomson Reuters' Institutional Brokers Estimate System (I/B/E/S). We exclude from our sample forecasts for firms that have missing price information in the Center for Research in Security Prices (CRSP) database. We drop forecasts made by unidentified analysts (i.e., forecasts with an analyst identifier equal to zero) and forecasts for stocks with reported earnings measured in a currency other than U.S. dollars. Similar to Easton and Sommers (2007), Malmendier and Shanthikumar (2014), and Jiang et al. (2016), our sample period starts in 1994, where I/B/E/S data accuracy improves, and extends until 2016.

We follow the analyst literature and filter for potential entry errors by excluding forecasts with an absolute forecast error greater than one (Lim, 2001; Bernhardt et al., 2006). To mitigate the influence of outliers, we use forecasts for firms with an average share price greater than $1 (Chen and Jiang, 2006; Cen et al., 2013; Malmendier and Shanthikumar, 2014). We also eliminate forecasts for firms that are covered by less than five analysts (Hilary and Hsu, 2013) to ensure that our consensus measurement is not influenced by firms that are covered by a small number of analysts. Further, we keep forecasts with a maximum (minimum) horizon of 100 (2) days from the earnings announcement to minimize the effect of stale forecasts and potential information leakage (Jegadeesh et al., 2004; Jackson, 2005).

To identify the location of each analyst, we follow Jiang et al. (2016) and use the coordinates of the city center in which the analysts' branch office is based as the analyst location. We obtain the latitude and longitude coordinates from the Gazetteer Files available from the U.S. Census Bureau.

Our final sample consists of 24,203 forecasts issued by 2,631 analysts for 2,290 firms during the 1994-2016 period. Figure A2 illustrates the distribution of these forecasts across different states. Consistent with the findings in Malloy (2005), 51.20% of the analysts in our sample are located in the state of New York and their forecasts constitute 58.80% of the total number of forecasts.

[16] Alaska and Hawaii are not included in our sample because they did not have any terrorist attacks or mass shootings during the 1994-2016 time period.

3.3 Equity Data

We also use CRSP and COMPUSTAT datasets. From CRSP, we obtain monthly stock prices, returns, and shares outstanding from January 1994 to December 2016. We restrict our sample to only include common shares by keeping the observations with share codes of 10 or 11. From COMPUSTAT, we obtain the location of each company's headquarters.

3.4 Variable Definitions and Econometric Models

To examine whether affected analysts are more likely to issue relatively more pessimistic forecasts following a terrorist attack, we use an ordinary least squares (OLS) model. This model allows us to include a large number of fixed effects without raising an incidental parameters issue. Our conclusions remain unchanged if we use a logit or a probit estimator. Our OLS model takes the following form:

$$Pessimism_{i,j,t} = c + \beta\ Exposure_{i,t} + \gamma\ X_{i,j,t} + \delta_{analyst} + \alpha_{firm} + \zeta_{time} + \varepsilon_{i,j,t} \quad (1)$$

where i indexes analyst, j indexes firm, and t indexes time (quarter). $Pessimism_{i,j,t}$ is a dummy variable equal to one if the forecast of analyst i is less than the consensus forecast of analysts who cover the same firm j within a 30-day window after an attack, and zero otherwise.[17] The consensus forecast is equal to the average value of the latest forecasts issued by all unaffected analysts during the same 30-day period.[18]

Our main variable of interest, $Exposure_{i,t}$, is a dummy variable equal to one if an analyst is located within a 100-mile radius of an attack and if she issued a forecast during the 30-day period following the terrorist attack, and zero otherwise. We calculate the distance between the terrorist attacks and the analyst locations using the Haversine formula (Vincenty, 1975).

We control for a number of analyst and brokerage characteristics, indicated in equation (1) as $X_{i,j,t}$. Specifically, *Forecast Horizon* is the number of days between the forecast date of analyst i for company j and the earnings announcement date of company j during the same time period t. *Companies* is the number of companies analyst i follows in year t. *Firm Experience* is the number of years analyst i has covered firm j. *General Experience* is the number of years since analyst i's forecast for company j at time t and the first forecast by analyst i for any company in the I/B/E/S database. To reduce the effect of outliers, we take the natural logarithm of *Firm Experience* and *General Experience*. *Broker Size* is the number of analysts employed

[17] In section 5.1, we show that our results are robust to using *Relative Rank*, an alternative continuous dependent variable.

[18] In our empirical analysis, we only compare forecasts within the same fiscal quarter.

by analyst i's brokerage at time t. We include *Female*, a dummy variable equal to one if analyst i is female, and zero otherwise.[19] *All Star* is a dummy variable equal to one if analyst i is ranked as first, second, third, or runner-up in the Institutional Investor magazine in the previous year, and zero otherwise.[20] We use the *All Star* indicator variable to capture an analyst's ability and reputation.

In our specification, we also include the variable *Distance*, defined as the natural logarithm of the distance between analyst i and firm's j location.[21] An analyst's distance from a specific firm may affect their propensity to issue pessimistic forecasts, as analysts who work near the firms they cover tend to be more accurate (Malloy, 2005). Since analysts tend to specialize in certain industries, we add *Industry*, which is the number of two-digit SIC codes analyst i covers at time t. Lastly, we control for the lagged absolute value of the forecast error (LAFE), which is analyst i's absolute forecast error for company j at time $t-1$, to capture the effect of her previous forecast accuracy on the current earnings forecast. Overall, our set of controls aligns with studies by Clement and Tse (2003, 2005), Cohen et al. (2010), and Walther and Willis (2013).

In addition to these control variables, we include analyst, firm, and time fixed effects, denoted as $\delta_{analyst}$, α_{firm}, and ζ_{time}, respectively. The analyst fixed effects capture any systematic variation in pessimism among analysts. The firm fixed effects control for any firm-specific, time invariant, unobservable variables that could be driving our results. The time fixed effects are used to remove any time trends.

3.5 Summary Statistics

We report summary statistics for our sample in Table 1. Panel A contains information on the number of forecasts, analysts, brokerage houses, and stocks that are included in our dataset. We also provide information regarding the number of affected analysts per period and the number of forecasts they issued.[22] As expected, the number of affected forecasts is always lower than the number of total forecasts. However, it is greater than the number of affected analysts, as some analysts tend to give forecasts for two or more firms during the 30-day period following an attack. During our sample period, 34.41% of the analysts are treated and 39.57% of the forecasts are issued by them.

[19]Kumar (2010) shows that an analysts' gender can affect their forecasts.

[20]The data on analyst gender and all-star status are those used in Kumar (2010) and Jiang et al. (2016). We update their data for our sample period using their method.

[21]We obtain the coordinates of firms by matching their ZIP codes with the Gazetteer Files from the U.S. Census Bureau. We drop from our sample firms with missing ZIP codes. To calculate the distance between the firms and the analysts, we use the Haversine formula (Vincenty, 1975).

[22]Since there were no attacks during the years 2003, 2004, and 2007, we do not include them in our sample. A list of attacks, their date and location can be found in Table A1.

Table 1 also shows the descriptive statistics for the variables in our main specification. We find that analysts in our sample have 6.71 years of *General Experience*, a little more than 2 years of *Firm Experience*, and follow stocks in about 3 industries. *Female* and *All Star* analysts constitute 13% and 14% or our sample, respectively.

4 Main Empirical Results

In this section, we test our main conjectures. In particular, we analyze whether analysts who have been exposed to a terrorist attack are more likely to issue relatively more pessimistic forecasts. We also examine if this effect is stronger when an event is considered to be more salient. Specifically, we investigate whether this effect diminishes as an analyst's distance from an attack increases and if the effect is stronger in states that have lower homicide rates. In addition, we test if treated analysts are relatively more pessimistic around the anniversaries of these attacks and if this attack-induced pessimism can affect their forecast accuracy. We then investigate the market's reaction to treated analysts' forecast revisions.

4.1 Terrorist Attacks and Analyst Pessimism

We present our baseline results in Table 2. We report the results from the OLS models in columns (1) to (5) and results from logit and probit regressions in the subsequent columns. For the OLS specifications, we include analyst, time, and firm fixed effects sequentially.

Consistent with our main hypothesis (H1), we find that affected analysts (i.e., analysts who are local to terrorist attacks and issue a forecast during the 30-day period following the event) are relatively more pessimistic. As shown in column (5), treated analysts are 8.70% more likely to issue a forecast below the consensus than untreated analysts. Not only is this effect statistically significant at the 1% level, but it is also economically meaningful, representing approximately 17.6% (i.e., 0.087/0.494) of the standard deviation of our *Pessimism* variable. Our first hypothesis is also supported by the results from the logit and probit regression models. Examining the estimates of our control variables, we find that $Horizon$ is negatively related to pessimism, in line with the results in Malloy (2005) and Cowen et al. (2006).

The findings in the section provide strong support for our first hypothesis (H1): affected analysts who are exposed to terrorist attacks are more likely to issue pessimistic forecasts. It is important to mention that the consensus forecast could be biased either upward or downward relative to firm fundamentals (So, 2013). Since in our setting we are using analysts' consensus as our benchmark, it is possible that treated analysts are more pessimistic relative to other analysts but not relative to firm fundamentals. Similarly, they could be more pessimistic to both benchmarks. Nonetheless, both of these results suggest that terrorist attacks are associated with downward biased analyst forecasts, albeit to different degrees.

4.2 Event Salience and Analyst Pessimism

Our second hypothesis (H2) states that more salient events will generate more pessimistic forecasts. To test this conjecture, we use two measures of salience. First, we use the geographical distance between an analyst and an event. We expect that analysts who are located closer to the attack will be more pessimistic than analysts who are located farther away from the event location. The results, shown in Table 3, indicate that analysts who reside within a 100-mile radius from the event are 8.50% more likely to issue a pessimistic forecast. In contrast, analysts that reside outside of this radius do not issue pessimistic forecasts. We find similar results using logit and probit regressions in columns (6) to (15). Additionally, the pessimism levels of analysts inside and outside the 100-mile radius are consistently statistically different at the 1% level.[23]

As our second salience proxy, we utilize the general level of murder rates in an analyst's home state. We collect information on the murder rates of each state from the FBI's Uniform Crime Reporting Program (UCR).[24] We divide each state's murder rate by its respective population to obtain a per-capita level of murder activity. The dummy variable *Crime* is equal to one if the analyst is located in a state with a murder rate that is below the median in a given year. We re-estimate our models by interacting *Exposure* with *Crime*, where we expect to find a positive coefficient on the interaction term.

The results in Table 4 are in line with our conjecture. We find that analysts who are located in states with low murder rates are 9.20% more likely to issue pessimistic forecasts than treated analysts who reside in states with high murder rates. In addition, these results indicate that the aggregate effect of being treated and living in a low crime state is 12.90% (i.e., $0.038 - 0.001 + 0.092$). As shown by the last two columns, these findings are robust to using logit and probit models.

Collectively, the results in this section support our second hypothesis (H2) and show that events that are likely to be perceived as more salient generate more pessimistic earnings forecasts.

[23]The average forecast horizons of analysts who reside within and outside a 100-mile radius of the attack locations during the 30-day period following the events are very similar, 37.04 and 37.30 days, respectively. These two values are not statistically different, suggesting that local analysts are unlikely to be more pessimistic because they systematically delay the timing of their forecasts.

[24]The UCR defines criminal homicide, meaning murder and nonnegligent manslaughter, as "the willful (non-negligent) killing of one human being by another."

4.3 Anniversaries of Terrorist Attacks and Analyst Pessimism

In this section, we test our third hypothesis (H3) and examine whether affected analysts become more pessimistic around the anniversaries of terrorist attacks. To test this conjecture, we re-estimate our baseline specification one, two, and three years after the attacks. Further, since the state of New York has experienced several events, including a 9/11 attack, we exclude analysts located in this state and examine whether our anniversary results hold.

Table 5, Panels A and B report the results for the first anniversaries. We find that after one year, affected analysts are 8.10% more likely to issue a pessimistic forecast. This effect is lower than the effect during the year of the attack, which is expected since the shock to the sentiment of an analyst around the anniversary of the event is likely to be weaker. Similarly, Panel B suggests that the results are robust to excluding NY analysts from the sample.

In Panels C and D, we conduct the same analysis for the second anniversaries. We find a significant anniversary effect, as the *Exposure 2 Yr. Anniversary* is positive and statistically significant throughout all specifications. In Panel C, the *Exposure 2 Yr. Anniversary* coefficient is even stronger than the *Exposure 1 Yr. Anniversary* coefficient. A possible explanation for this finding is that in 2003, the Lower Manhattan Development Corporation launched an international competition (the World Trade Center Site Memorial Competition) to encourage individuals or teams to submit proposals to design the memorial.[25] The awareness created by this event could have made NY analysts relatively more pessimistic. As shown by Panel D, when we drop analysts located in NY, analysts' pessimism decreases monotonically starting the year of the event until two years after.

Panels E and F show that after three years, the *Exposure 3 Yr. Anniversary* is not statistically significant. This evidence indicates that after three years, terrorist events no longer affect analyst sentiment.[26]

The anniversary effects are evident in Figure 1a, as treated analysts tend to be more pessimistic 30 days following the attacks, as well as during the first and second anniversaries. Importantly, treated analysts are not consistently pessimistic throughout the year, suggesting that the effect is likely to be driven by analysts remembering these terrorist attacks. For instance, the 1-year anniversary effect tends to be greater than the pessimism levels during the previous and following quarters. Treated analysts' pessimism during the 30 days following the

[25] *Source:* https://www.cnn.com/2013/07/27/us/ground-zero-memorial-and-rebuilding-fast-facts/

[26] It is difficult to predict *ex-ante* how long it should take for the impact of the extreme, negative event to disappear. Our results are consistent with studies that analyze how sudden deaths can affect family members. For instance, a Harvard Medical School study suggests that the spouses of people who died suddenly or with little warning tend to mourn for about two to four years. *Source:* https://www.nytimes.com/1988/03/29/science/study-of-normal-mourning-process-illuminates-grief-gone-awry.html.

second anniversaries is also higher than the effects leading up to the second anniversary. Overall, these findings support our third hypothesis (H3) and show that treated analysts become more pessimistic during the anniversaries of attacks.

4.4 Terrorist Attacks and Forecast Accuracy

However, whether biases improve forecast accuracy or make analysts less accurate is not clear. Next, we test our fourth hypothesis (H4), which examines whether the attack-induced pessimism affects analyst accuracy.

To test this conjecture, we create a performance measure similar to Clement (1999). Specifically, we calculate the proportional median absolute error (PMAFE) to compare an analyst's absolute forecast error to the median absolute forecast error of other analysts following the same firm during the same time period. Specifically, PMAFE is calculated as follows:

$$PMAFE_{i,j,t} = \frac{AFE_{i,j,t} \ - \ \widehat{AFE_{j,t}}}{\widehat{AFE_{j,t}}}, \tag{2}$$

where $AFE_{i,j,t}$ is the absolute forecast error for analyst i, firm j, at time t and $\widehat{AFE_{j,t}}$ is the median absolute error for firm j at time t.[27] An advantage of using this measure, as Clement (1999) suggests, is that it accounts for firm × time fixed effects. A negative value of PMAFE suggests that an analyst has a better than average performance while a positive value suggests that an analyst has worse than average performance.

The results from the forecast accuracy regressions in Table 6 indicate that affected analysts are more accurate than the average analyst. This finding provides novel evidence that in some cases, behavioral biases can induce an improvement in performance.[28] Specifically, our results show that exogenous events, such as terrorist attacks and mass shootings, improve the forecast accuracy of affected analysts. The effect on accuracy is not only statistically significant but also economically significant, since the *Exposure* coefficient is larger than the coefficient estimate on *All Star* indicator. We also find that analysts with shorter horizons are more accurate. These results are in line with the findings in the analyst literature (Malloy, 2005; Clement and Tse, 2005; Kumar, 2010; Jiang et al., 2016).

Collectively, our results show that exposure to terrorist attacks affect analyst forecast accuracy. Treated analysts issue forecasts that are more accurate. These findings are inconsistent with the limited attention literature, which predicts that analysts who are more distracted

[27] See Clement (1999) for more details on this measure.

[28] Most existing studies find that behavioral biases either do not affect or worsen an analyst's forecast accuracy (Hilary and Menzly, 2006; Dehaan et al., 2017).

would issue forecasts that are systematically farther away from the consensus and have a lower forecast accuracy.

4.5 Market's Reaction to Forecast Revisions

Since the earnings forecasts of analysts can be a useful source of information for investors, we examine whether investors anticipate, or regard as probable, that treated analysts are more accurate. For this test, we follow the methodology of Hirshleifer et al. (2019) and regress a firm's returns on $Forecast\ Revision \times Exposure$. The dependent variable in the regression is a firm's three-day market adjusted excess return centered on the forecast revision date. The main independent variable is $Forecast\ Revision$, which is a measure of the difference between analyst i's current forecast for firm j at time t and the forecast issued immediately before the current forecast, scaled by the standard deviation of forecasts of all analysts who follow firm j in time t. We control for Friday and fourth quarter effects, in addition to the covariates in equation (1).[29]

The estimates in Table 7 show that the coefficient on $Forecast\ Revision$ is positive and statistically significant in all columns, except when we include controls interacted by $Forecast\ Revision$. This evidence indicates that the market reaction around the forecast revision is correlated with the signed magnitude of the forecast revision. However, the interaction term, $Forecast\ Revision \times Exposure$ is not statistically significant in our strictest specifications. This finding suggests that the forecasts revisions of exposed analysts do not generate stronger market reactions, meaning that investors do not anticipate for exposed analysts to be more accurate.[30]

5 Robustness Tests

Our baseline results indicate that following a terrorist attack, affected analysts tend to issue more pessimistic forecasts than analysts who have not been impacted by the event. In this section, we examine the robustness of these results using a continuous measure of pessimism

[29] The strictest regression specification includes Analyst × Firm fixed effects. We are unable to include Analyst × Day fixed effects as they absorb our main independent variable, $Exposure$.

[30] Malmendier and Shanthikumar (2014) suggest that large investors are more likely to follow analysts' forecasts, while small investors tend to follow analysts' recommendations. We use a small sample of institutional trading data to test whether large investors are more likely to react to treated analysts' forecast revisions by analyzing their trading behavior on the revision date of pessimistic forecasts. In untabulated results, we find that after an analyst issues a pessimistic forecast for a certain firm, local institutional investors sell 4.6% more of their holdings relative to nonlocal institutional investors. Consistent with Malmendier and Shanthikumar (2014), this evidence suggests that institutional investors pay more attention to the pessimistic forecasts of sell-side analysts. Of course, this evidence does not rule-out the possibility that retail or small investors also follow treated analysts' pessimistic forecasts. Unfortunately, we do not have access to retail trading data to test this hypothesis directly.

and alternative sample and regression specifications.

5.1 Alternative Dependent Variable

The main dependent variable in our analysis, *Pessimism*, is a dummy variable equal to one when an analyst issues a forecast that is less than the consensus forecast of all unaffected analysts who cover the same firm during the same 30-day window following the attack date, and zero otherwise. As an alternative dependent variable, we use a continuous measure of pessimism, *Relative Rank*. Since this alternative variable is constructed on the basis of how an analyst's pessimism ranks in the distribution of all forecasts for a certain firm during the same time period, it could be less sensitive to outliers. To construct *Relative Rank*, we follow Hong and Kubik (2003) and compute analyst i's forecast error (FE) for firm j at time t.[31] We sort all forecasts for firm j at time t based on this value.[32] A lower ranking value reflects that analyst i is relatively more pessimistic.[33]

Table 8, Panel A provides evidence that our results are robust to using *Relative Rank* as the dependent variable. The coefficient in the strictest specification is -0.378 (t-statistic = -6.56), suggesting that analysts who have been exposed to an attack are relatively more pessimistic and have a lower ranking.

5.2 Excluding 9/11 Attacks

The most significant events in our sample are the attacks that occurred on September 11, 2001. To ensure that our findings are not solely driven by these attacks, we exclude them from our sample and re-estimate our baseline specifications. The results in Table 8, Panel B show that our main independent variable, *Exposure*, remains positive and statistically significant throughout all regression specifications. This evidence indicates that our main effect is not driven by the 9/11 attacks.

5.3 Excluding New York Analysts

About 51.20% of the analysts in our sample are located in the state of New York. To confirm that our results are not driven by analysts located in this state or by attacks that occur in this area, we exclude all analysts who work in the state of New York and repeat our baseline analysis.

[31] The forecast error FE is defined as $\frac{Forecasted\ Earnings_{i,j,t}\ -\ Actual\ Earnings_{j,t}}{Stock\ Price_{j,t}}$. The stock price is measured at the end of the previous month in which the forecast is issued.

[32] Hong and Kubik (2003) rank analysts using AFE instead of FE. However, since we want to analyze an analyst's relative pessimism, it is important for us to know whether the forecast error is above or below the actual earnings estimate.

[33] If two or more analysts were equally pessimistic, we assign the midpoint value of the ranks to all those analysts (Hong and Kubik, 2003).

Table 8, Panel C shows that even though the statistical significance of the coefficient *Exposure* is reduced, it remains statistically significant. This evidence suggests that our findings are not generated by the high concentration of equity analysts in the state of New York.

5.4 Forecasts during Sunny and Cloudy Months

Recent research has examined whether cloud cover can affect investor mood (e.g., Chang et al. (2008); Bassi et al. (2013); Goetzmann et al. (2014)). Similarly, Dehaan et al. (2017) use wind and rainfall, along with cloud cover, to show that unpleasant weather can induce analyst pessimism. To ensure that our results are distinct from weather-induced pessimism, we re-estimate our baseline specification during Sunny (three months with low cloud cover) and Cloudy months (three months with high cloud cover). We collect cloud cover data from the Comparative Climatic Data from the National Centers for Environmental Information (NCEI), which is overseen by the National Oceanic and Atmospheric Administration (NOAA). The estimates in Table 8, Panel D show that our results hold during sunny and cloudy months, suggesting that our findings are unlikely to be driven by weather-induced pessimism.

5.5 Event Window Sensitivity

In our empirical analysis, we use a 30-day window to analyze whether terrorists become more pessimistic after a terrorist attack. We perform sensitivity analysis on this time-frame and examine if our results are robust to smaller windows. Table 8, Panel E presents results for analysts who issued forecasts five days after an event and are located within 100 miles. We find that even if the number of observations is significantly reduced, treated analysts are more likely to issue pessimistic forecasts. The magnitude of the estimates are also larger, suggesting that the effect is stronger when the forecast issue date is closer to the attack date. In untabulated results, we also find that our results are robust to the choice of a three-day event window.

5.6 Placebo Tests

To further ensure that we are capturing the effect of terrorist attacks on analysts' mood, we conduct a placebo test. In particular, for each terrorist attack, we randomize the location. We expect the *Exposure* coefficient to be statistically insignificant. Consistent with this expectation, the results in Table 8, Panel F show that the *Exposure* coefficient estimate is not significant when we randomize attack locations.

5.7 Firm Characteristics

In this section, we examine whether treated analysts' pessimistic forecasts are driven by certain firm characteristics. It is likely that pessimistic forecasts are potentially more likely to be issued for smaller and relatively more illiquid stocks. In Table A2, we report the average characteristics of firms for which treated analysts issue pessimistic forecasts and compare them to the average characteristics of firms for which they issue non-pessimistic forecasts. As shown by the *Diff.* column, none of the differences are statistically significant. This evidence suggests that the pessimistic forecasts are unlikely to be driven by systematic differences in firm characteristics.

5.8 Firm × Time Fixed Effects

Our baseline specification includes firm, time, and analyst fixed effects. For additional robustness, we modify our specification to include firm × time fixed effects and analyst fixed effects. Firm × time fixed effects are useful to control for common information about firm earnings that is available to all analysts. In untabulated results, we find that our results are robust to the inclusion of these fixed effects.

6 Alternative Explanations: Pessimism or Other Factors?

We conduct several tests to examine the robustness of our findings and entertain alternative explanations for our results. First, we study whether analysts are pessimistic before an attack. Second, we analyze whether analyst pessimism is induced by omitted economic variables. We also investigate whether certain analysts are more pessimistic because they have superior information and understand that some companies could be more sensitive to terrorist attacks. Last, we test if treated analysts are more accurate not due to increased pessimism but because they are more likely to issue bold forecasts.

6.1 Time Trend in Pessimism

A potential concern with our results is that we are capturing a pre-existing trend in analyst pessimism rather than the impact of terrorist attacks. Specifically, analysts could already be pessimistic before the attack as opposed to becoming pessimistic after the event. Ruling out the existence of this trend is important for our analysis because our hypothesis states that the differences in analyst pessimism arise due to their exposure to terrorist events and not due to other variables that could have affected their pessimism *ex-ante*.

Figure 1b provides a visual representation of analysts' pessimism starting 90 days before the attack until 90 days after the attack. The graph shows that prior to the attacks, analysts are not pessimistic. This evidence suggests that the pre-existing pessimism hypothesis is not supported. However, after the attack, treated analysts are relatively more pessimistic for about 30 days. After this time period, their pessimism gradually decreases for another month until it disappears three months after the attack.

To ensure that the potential differences in pessimism levels of treated and untreated analysts are not statistically significant, we include an indicator variable, $Exposure_{-90 \text{ to } -1 \text{ days}}$, that equals one if an analyst issues a forecast 90 days prior to an attack and is located within 100 miles. The results in Table 9, Panel A show that the lagged variables are statistically insignificant, suggesting that prior to the attacks, there are no significant differences between treated and untreated analysts. On the other hand, the $Exposure_{0 \text{ to } 30 \text{ days}}$ coefficient is positive and statistically significant at the 1% level. This evidence indicates that prior to an attack, there are no significant differences in the pessimism levels of treated and untreated analysts; however, after an attack occurs, the sentiment of treated analysts changes and they become relatively more pessimistic.

Taken together, the evidence in Figure 1b and Table, 9 Panel A indicates that the differences in pessimism levels only exist following the terrorist attacks. Thus, some pre-existing trend in analyst pessimism does not explain our findings.

6.2 Terrorist Events and State-Level Macroeconomic Conditions

Another possible alternative explanation for our findings could be that terrorist events are related to the macroeconomic environment of the state in which they occur, which could subsequently affect analysts' risk attitudes and increase their likelihood of issuing pessimist forecasts. To control for this possibility, we re-estimate our baseline specification and include each state's per capita Gross State Product (GSP) and unemployment rate as control variables.[34] The estimates reported in Table 9, Panel B indicate that the coefficient on *Exposure* remains positive and statistically significant at the 1% level across all model specifications. The *GSP* coefficient is positive and statistically significant in column (5). However, the *Unemployment* coefficient is statistically insignificant when we include analyst, time, and firm fixed effects. These findings suggest that even when we account for a state's economic environment, treated analysts are more likely to issue pessimistic forecasts.

[34] We collect state-level GDP data from the U.S. Bureau of Economic Analysis (BEA) and unemployment data from the Bureau of Labor Statistics (BLS). The time period extends from 1994 to 2016.

6.3 Do Affected Analysts Have Superior Information?

In the next set of tests, we examine whether treated analysts issue pessimistic forecasts because they have a better understanding of how terrorist events affect some industries more than others. For example, companies that belong to the airline industry could be more sensitive to terrorist attacks than companies that belong to the agricultural industry. As a result, analysts may issue information-driven pessimistic forecasts for highly sensitive companies. If we find support for this alternative story, it would suggest that our results may be driven by treated analysts' superior information instead of their attack-induced pessimism.

To determine whether our results reflect treated analysts' superior information or sentiment-induced pessimism, we first estimate the sensitivity of each industry to terrorist attacks. We use two interaction terms to condition our main independent variable, *Exposure*, on whether a specific company operates in a high- or low-sensitivity industry: $Exposure \times Industry_{\text{Low}}$ and $Exposure \times Industry_{\text{High}}$. If our findings are driven by the information channel, then the coefficient of the interaction term, $Exposure \times Industry_{\text{Low}}$, would be lower than the coefficient for the interaction term, $Exposure \times Industry_{\text{High}}$, suggesting that treated analysts are more likely to issue pessimistic forecasts for firms that are more sensitive to terrorist attacks.

To estimate the sensitivity of each industry to terrorist attacks, we regress the daily excess returns of the 48 Fama-French industries on the market excess returns and a dummy variable that equals one when an attack occurs.[35] We use a rolling 12-month window to calculate the betas. The industries with a lower beta (i.e., bottom half) are labeled as low sensitivity industries and industries with a higher beta (i.e., top half) are labeled as high sensitivity industries.

The results in Table 10 do not support the superior information hypothesis. The coefficients, $Exposure \times Industry_{\text{Low}}$ and $Exposure \times Industry_{\text{High}}$, are both statistically significant. Further, the coefficient of the interaction term, $Exposure \times Industry_{\text{Low}}$, is systematically higher than the coefficient for, $Exposure \times Industry_{\text{High}}$. More importantly, the difference between the $Exposure \times Industry_{\text{Low}}$ and $Exposure \times Industry_{\text{High}}$ coefficients is positive and statistically significant throughout all the specifications. This finding indicates that treated analysts are less likely to issue pessimistic forecasts for industries that are more sensitive to these events, providing support for the sentiment-induced channel as opposed to the superior information hypothesis.

[35] If an event takes place during the weekend, we consider the attack date to be the next available trading day.

6.4 Pessimism Induced Accuracy or Bold Forecasts?

A possible explanation for the higher accuracy of treated analysts could be that they are more likely to issue both positive and negative bold forecasts, which are known to be associated with greater forecasts accuracy (Clement and Tse, 2005). However, if their greater accuracy is driven by sentiment-induced pessimism due to the attacks, then they are more likely to issue downward bold revision forecasts but not upward bold revision forecasts.

To test for these possibilities, we first analyze whether treated analysts are more likely to issue bold forecasts. Our first dependent variable is *Bold Revision*, a dummy variable equal to one if an analyst issues a forecast that is either above or below the prior consensus as well as her previous forecast, and zero otherwise. Similar to our baseline specification, we regress *Bold Revision* on *Exposure* and several control variables, identical to those used in equation (1). Table 11, columns (1) and (2) show that the coefficient on *Exposure* is negative and statistically significant, suggesting that analysts who are exposed to the terrorist attacks are less likely to issue bold forecasts. This evidence suggests that treated analysts are not more accurate because they systematically issue bold forecasts.

We then test whether they are more likely to issue downward bold forecasts but less likely to issue upward bold forecasts. In columns (3) and (4), the dependent variable is *Downward Bold Revision*, a dummy variable equal to one if an analyst issues a forecast below the prior consensus and her previous forecast, and zero otherwise. In columns (5) and (6), the dependent variable is *Upward Bold Revision*, a dummy variable equal to one if an analyst issues a forecast above the prior consensus and her previous forecast, and zero otherwise.

Our results show that affected analysts are more likely to issue downward bold revisions but not upward bold revisions. For instance, the *Exposure* coefficient in column (4) is 0.040 (t-statistic = 1. 90), while the *Exposure* coefficient in column (6) is -0.488 (t-statistic = -27.56). These results also rule-out an alternative explanation where treated analysts are more likely to wait until after management guidance to revise their forecasts. If this were the case, they would be more likely to issue both downward and upward bold forecasts.

Overall, the findings from this section suggest that analysts issue more pessimistic forecasts due to the pessimism induced by the attacks. Consistent with the evidence in prior studies, this sentiment-induced pessimism makes analysts more accurate (Hugon and Muslu, 2010; Jiang et al., 2016).

7 Summary and Conclusions

This paper examines the effects of terrorist attacks and mass shootings on the earnings forecasts of sell-side analysts. Specifically, we study whether analysts who are located near such events tend to experience a negative shock to their sentiment, which can potentially generate a pessimistic bias in their earnings expectations.

Consistent with our hypothesis, we find that analysts who are located near major terrorist attacks in the U.S. issue more pessimistic forecasts (relative to the consensus) in the period following the attacks. These effects are stronger when the event is considered to be more salient. In particular, attack induced analyst pessimism is greater when an analyst is located closer to an attack and when the state where an analyst is located has a lower crime rate. We also find that affected analysts become more pessimistic than the consensus around the anniversaries of these attacks. Interestingly, treated analysts are more accurate following an attack. Our market reaction tests suggest that investors do not anticipate for treated analysts to be more accurate, as their forecast revisions do not lead to stronger market reactions.

Collectively, these results complement the evidence from the existing literature on analysts' behavioral biases. Our main contribution is to show that the attack-induced pessimism of treated analysts affects their forecasts and the information dissemination process in financial markets. In future research, it would be interesting to examine whether the decisions of other market participants are also affected by exposure to these types of extreme negative events.

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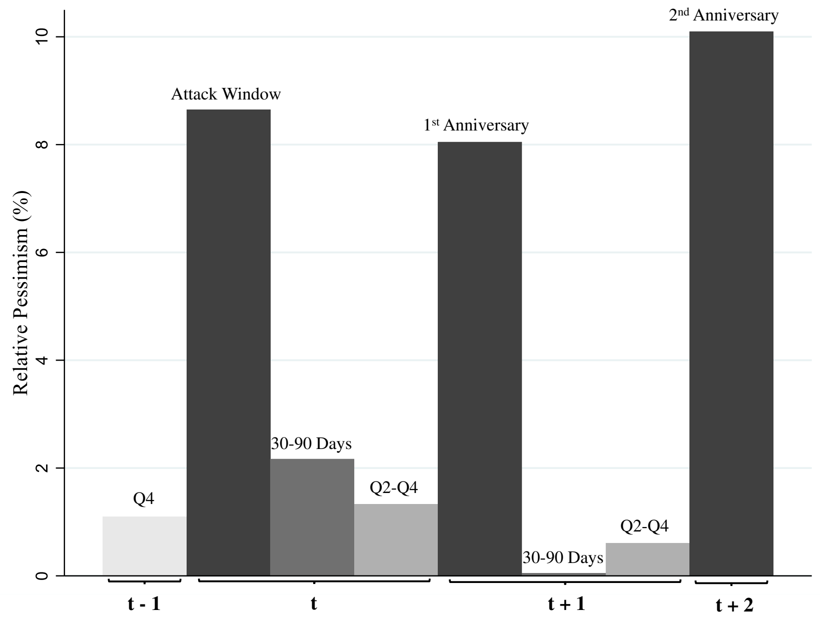
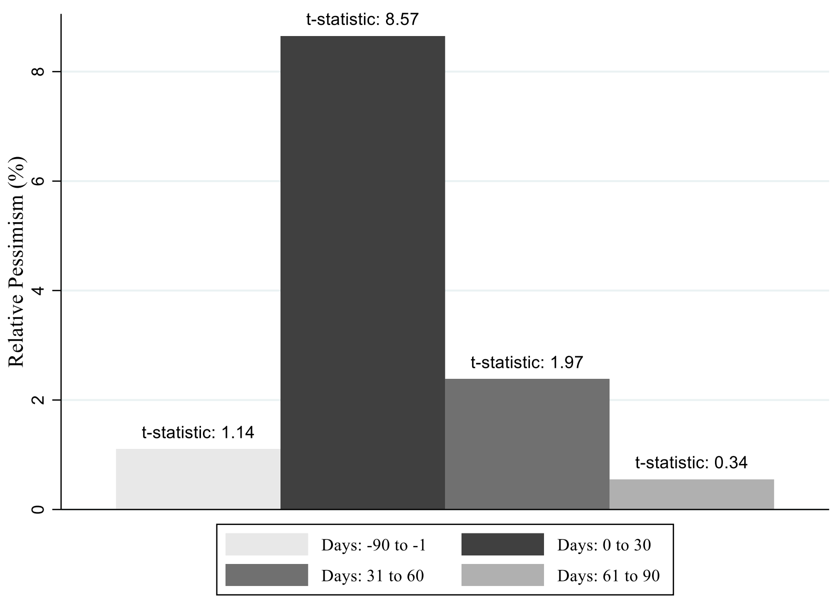
Figure 1
Time Series Trend in Treated Analysts' Pessimism

The figure in Panel A plots analysts' pessimism around the attack window as well as during the first and second anniversaries. The first quarter of every year is divided into the initial 30-day and subsequent 60-day intervals. The following quarters (i.e., quarters two to four) are combined into a single time period. The figure in Panel B graphs analysts' pessimism around the event window. It plots the pessimism-level starting 90 days before the attack until 90 days following the attack. These are nonoverlapping intervals with a 90-day length prior to the attack and a 30-day length after the attack.



(a) Around Attack Anniversaries



(b) Around Attack Window

Table 1
Summary Stastics

This table presents summary statistics for the main variables used in the empirical analysis. The sample is for the 1994-2016 period and includes stocks with at least one affected analyst. Panel A provides sample information for each year of our sample. Panel B presents statistics of the variables we consider in our specifications. *Forecast Horizon* is the number of days between an analysts' forecast date for a specific company and the corresponding company's earnings announcement. *Companies* is the number of companies an analyst follows during a specific year. *Firm Experience* is the number of years an analyst has covered a certain firm. *General Experience* is the number of years since an analyst issued a forecast for a company and the first forecast of the analyst available in the I/B/E/S database. *Broker Size* is the number of analysts employed by an analyst's brokerage firm. *Female* is a dummy variable equal to one if analyst i is female. *All Star* is a dummy variable equal to one if an analyst is ranked as first, second, third, or runner-up in the Institutional Investor magazine in the previous year. *Distance* is the natural logarithm of the distance between an analyst and the firm for which she issued a forecast. *Industry* is the number of two-digit SIC codes followed by an analyst. *AFE* is an analyst's absolute forecast error for a certain company at time t.

Panel A: Distribution of Sample Across Years

Year	Forecasts	Analysts	Brokerage Houses	Stocks	Affected Analysts	Affected Forecasts
1994	511	236	62	191	166	389
1995	345	193	55	126	147	265
1996	4	4	4	3	1	1
1997	118	87	34	72	74	101
1998	218	162	55	100	93	125
1999	125	86	42	26	16	28
2000	15	11	5	9	5	8
2001	5,370	1,352	125	682	792	3,141
2002	159	125	60	32	18	29
2003	-	-	-	-	-	-
2004	-	-	-	-	-	-
2005	750	453	93	208	51	184
2006	1,389	732	127	264	70	220
2007	-	-	-	-	-	-
2008	433	286	80	172	56	107
2009	136	91	50	39	13	37
2010	907	474	117	256	82	249
2011	291	171	68	62	19	67
2012	3,311	827	123	768	401	1,177
2013	659	318	88	130	39	144
2014	9,047	797	120	1297	455	5,586
2015	322	173	67	84	29	87
2016	593	215	67	143	42	173

Panel B: Summary Statistics

	Obs.	Mean	Stdv.	10th Pctl.	Median	90th Pctl.
Forecast Horizon	24,703	37.17	29.49	5.00	28.00	90.00
Companies	24,703	10.83	9.93	2.00	8.00	25.00
Firm Experience	24,703	2.20	3.65	0.00	0.00	7.00
General Experience	24,703	6.71	5.43	0.00	6.00	13.00
Brokerage Size	24,703	16.62	14.14	2.00	13.00	32.00
Female	24,703	0.13	0.33	0.00	0.00	1.00
All Star	24,703	0.14	0.34	0.00	0.00	1.00
Distance	24,703	1,051.66	864.20	26.23	841.19	2,481.67
Industry	24,703	3.89	2.71	1.00	3.00	7.00
AFE	24,703	0.01	0.05	0.00	0.00	0.01

Table 2
Terrorist Events and Analyst Pessimism: Baseline Estimation

This table presents estimates from regressions of the *Pessimism* variable on a vector of analyst and brokerage level covariates. Columns (1) to (5) present the results for the OLS regressions while the logit and probit specifications can be found in the following columns, respectively. Column (1) does not include any fixed effects. However, column (2) only includes analyst-level fixed effects and column (3) only includes time fixed effects. Column (4) incorporates analyst and time fixed effects, while column (5) also incorporates firm fixed effects. The logit and probit regressions do not include any fixed effects. *Exposure* is a dummy variable equal to one if the distance between the location of an analyst and the location of the attack is less than 100 miles and if the forecast is issued during the 30-day period following the terrorist attack. The set of covariates is constant throughout all the specifications. *Forecast Horizon* is the number of days between an analysts' forecast date for a specific company and the corresponding company's earnings announcement. *Companies* is the number of companies an analyst follows during a specific year. *Firm Experience* is the number of years an analyst has covered a certain firm. *General Experience* is the number of years since an analyst issued a forecast for a company and the first forecast of the analyst available in the I/B/E/S database. *Broker Size* is the number of analysts employed by an analyst's brokerage firm. *Female* is a dummy variable equal to one if analyst i is female. *All Star* is a dummy variable equal to one if an analyst is ranked as first, second, third, or runner-up in the Institutional Investor magazine in the previous year. *Distance* is the natural logarithm of the distance between an analyst and the firm for which she issued a forecast. *Industry* is the number of two-digit SIC codes followed by an analyst. Lagged AFE (LAFE) is an analyst absolute forecast error for a certain company at time $t-1$. Heteroskedasticity robust t-statistics are presented in parentheses and are clustered at the firm-year level.

	Dependent Variable: Pessimism						
	(1)	(2)	(3)	(4)	(5)	Logit	Probit
Exposure	0.152	0.140	0.133	0.120	0.087	0.144	0.144
	(21.61)	(15.52)	(18.46)	(12.90)	(8.57)	(19.86)	(19.85)
Forecast Horizon	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(-5.17)	(-5.01)	(-5.12)	(-5.19)	(-5.41)	(-5.34)	(-5.32)
Companies	0.000	0.000	0.000	0.000	0.000	0.001	0.001
	(0.81)	(-0.43)	(-0.14)	(-0.39)	(-0.23)	(1.10)	(1.09)
Firm Experience	-0.008	-0.013	-0.010	-0.014	0.009	-0.006	-0.006
	(-2.06)	(-2.80)	(-2.50)	(-2.91)	(1.62)	(-1.38)	(-1.40)
General Experience	0.006	-0.004	-0.007	-0.013	-0.021	0.006	0.006
	(1.64)	(-0.64)	(-1.49)	(-0.94)	(-1.42)	(1.49)	(1.50)
Broker Size	-0.002	-0.002	0.000	0.000	0.001	-0.002	-0.002
	(-5.75)	(-4.80)	(-0.13)	(0.35)	(1.17)	(-5.25)	(-5.27)
Female	0.007		0.011			0.010	0.010
	(0.73)		(1.12)			(1.01)	(1.01)
All Star	0.021	0.014	0.009	0.004	-0.002	0.022	0.022
	(2.13)	(0.89)	(0.81)	(0.26)	(-0.14)	(2.15)	(2.17)
Distance	-0.001	0.000	-0.001	0.000	0.003	-0.001	-0.001
	(-0.36)	(0.08)	(-0.64)	(0.06)	(0.95)	(-0.27)	(-0.28)
Industry	0.004	0.002	0.002	0.002	0.001	0.004	0.004
	(2.15)	(0.79)	(1.13)	(0.47)	(0.39)	(2.06)	(2.07)
LAFE	-0.067	-0.116	-0.008	-0.088	-0.135	-0.067	-0.067
	(-0.85)	(-1.38)	(-0.10)	(-1.01)	(-0.91)	(-0.80)	(-0.81)
Analyst FE	No	Yes	No	Yes	Yes	No	No
Time FE	No	No	Yes	Yes	Yes	No	No
Firm FE	No	No	No	No	Yes	No	No
N	24,703	24,153	24,703	24,153	23,795	23,795	23,795
Adj./Pseudo R Sq.	0.027	0.056	0.034	0.060	0.085	0.019	0.019

Table 3
Geographical Proximity to Terrorist Events

This table tests whether an analyst's pessimism decreases as her geographical distance from the attack increases. Columns (1) to (5) present the results for the OLS regressions, columns (6) to (10) present the results for the logit regressions, and columns (11) to (15) present the results for the probit regressions. Columns (1) tp (5) include analyst, time, and firm fixed effects. The logit and probit regressions do not include any fixed effects. *Exposure* is a dummy variable equal to one if the distance between an analyst and an attack is less than 100 miles and if the forecast is issued during the 30-day period following event. $Exposure_{>100\text{ - }200\text{ mi}}$ is a dummy variable equal to one if the distance between an analyst and an attack is more than 100 but less than 200 miles and if the forecast is issued during the 30-day period following event. $Exposure_{>200\text{ - }300\text{ mi}}$ is a dummy variable equal to one if the distance between an analyst and an attack is more than 200 but less than 300 miles and if the forecast is issued during the 30-day period following event. $Exposure_{>300\text{ - }400\text{ mi}}$ is a dummy variable equal to one if the distance between an analyst and an attack is more than 300 but less than 400 miles and if the forecast is issued during the 30-day period following event. $Exposure_{>400\text{ - }500\text{ mi}}$ is a dummy variable equal to one if the distance between an analyst and an attack is more than 400 but less than 500 miles and if the forecast is issued during the 30-day period following event. The set of control variables is constant throughout all the specifications but suppressed for brevity. *Forecast Horizon* is the number of days between an analysts' forecast date for a specific company and the corresponding company's earnings announcement. *Companies* is the number of companies an analyst follows during a specific year. *Firm Experience* is the number of years an analyst has covered a certain firm. *General Experience* is the number of years since an analyst issued a forecast for a company and the first forecast of the analyst available in the I/B/E/S database. *Broker Size* is the number of analysts employed by an analyst's brokerage firm. *Female* is a dummy variable equal to one if analyst i is female. *All Star* is a dummy variable equal to one if an analyst is ranked as first, second, third, or runner-up in the Institutional Investor magazine in the previous year. *Distance* is the natural logarithm of the distance between an analyst and the firm for which she issued a forecast. *Industry* is the number of two-digit SIC codes followed by an analyst. Lagged AFE (LAFE) is an analyst absolute forecast error for a certain company at time $t-1$. The differences between the *Exposure* and the $Exposure_{>100\text{ - }200\text{ mi}}$ coefficients can be found below the table with their *p-values* in parentheses. Heteroskedasticity robust t-statistics are presented in parentheses and are clustered at the firm-year level.

	Dependent Variable: Pessimism														
	OLS Regressions					*Logit Regressions*					*Probit Regressions*				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Exposure	0.087	0.086	0.085	0.085	0.085	0.144	0.143	0.143	0.143	0.142	0.144	0.142	0.143	0.143	0.142
	(8.57)	(8.44)	(8.23)	(8.23)	(8.13)	(19.86)	(19.54)	(19.19)	(19.13)	(18.88)	(19.85)	(19.54)	(19.18)	(19.11)	(18.87)
$\text{Exposure}_{>100\text{ - }200\text{ mi}}$		-0.011	-0.012	-0.012	-0.012		-0.016	-0.016	-0.016	-0.016		-0.016	-0.016	-0.016	-0.016
		(-0.43)	(-0.46)	(-0.45)	(-0.47)		(-0.98)	(-0.97)	(-0.95)	(-0.99)		(-0.99)	(-0.98)	(-0.96)	(-1.00)
$\text{Exposure}_{>200\text{ - }300\text{ mi}}$			-0.011	-0.010	-0.012			0.001	0.001	0.000			0.001	0.001	0.000
			(-0.44)	(-0.43)	(-0.48)			(0.04)	(0.06)	(0.02)			(0.04)	(0.07)	(0.02)
$\text{Exposure}_{>300\text{ - }400\text{ mi}}$				0.006	0.003				0.010	0.010				0.010	0.010
				(0.18)	(0.10)				(0.41)	(0.38)				(0.41)	(0.38)
$\text{Exposure}_{>400\text{ - }500\text{ mi}}$					-0.040					-0.033					-0.033
					(-0.98)					(-0.92)					(-0.92)
Exposure - $\text{Exposure}_{>100\text{ - }200\text{ mi}}$		0.097	0.097	0.097	0.097		0.144	0.159	0.159	0.159		0.144	0.159	0.159	0.159
		(0.00)	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No	No	No	No	No	No
Time FE	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No	No	No	No	No	No
Firm FE	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No	No	No	No	No	No
N	23,795	23,795	23,795	23,795	23,795	23,795	23,795	23,795	23,795	23,795	23,795	23,795	23,795	23,795	23,795
Adj./Pseudo R Sq.	0.085	0.085	0.085	0.085	0.085	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019

Table 4
Analyst Pessimism and State's Murder Activity

This table examines whether the effect of an attack on an analyst's sentiment is stronger in states with a lower murder activity. To measure the level of murder activity, we divide the number of murders (available from the FBI and reported in the Uniform Crime Reporting Program) with the population of the state, and we compute the average murder rate across states for each year. Columns (1) to (5) present the results for the OLS regressions while the logit and probit specifications can be found in the following columns, respectively. Column (1) does not include any fixed effects. However, column (2) only includes analyst-level fixed effects and column (3) only includes time fixed effects. Column (4) incorporates analyst and time fixed effects, while column (5) also incorporates firm fixed effects. The logit and probit regressions do not include any fixed effects. *Exposure* is a dummy variable equal to one if the distance between the location of an analyst and the location of the attack is less than 100 miles and if the forecast is issued during the 30-day period following the terrorist attack. *Crime* is a dummy variable equal to one if an analyst's state has a murder rate less than or equal to the median murder rate during a given year. The set of covariates is constant throughout all the specifications. *Forecast Horizon* is the number of days between an analysts' forecast date for a specific company and the corresponding company's earnings announcement. *Companies* is the number of companies an analyst follows during a specific year. *Firm Experience* is the number of years an analyst has covered a certain firm. *General Experience* is the number of years since an analyst issued a forecast for a company and the first forecast of the analyst available in the I/B/E/S database. *Broker Size* is the number of analysts employed by an analyst's brokerage firm. *Female* is a dummy variable equal to one if analyst i is female. *All Star* is a dummy variable equal to one if an analyst is ranked as first, second, third, or runner-up in the Institutional Investor magazine in the previous year. *Distance* is the natural logarithm of the distance between an analyst and the firm for which she issued a forecast. *Industry* is the number of two-digit SIC codes followed by an analyst. Lagged AFE (LAFE) is an analyst absolute forecast error for a certain company at time $t-1$. Heteroskedasticity robust t-statistics are presented in parentheses and are clustered at the firm-year level.

	Dependent Variable: Pessimism						
	(1)	(2)	(3)	(4)	(5)	Logit	Probit
Exposure	0.096	0.087	0.084	0.074	0.038	0.143	0.143
	(9.19)	(6.57)	(7.62)	(5.23)	(2.53)	(19.70)	(19.69)
Crime	-0.012	0.002	-0.014	-0.004	-0.001	0.044	0.044
	(-1.32)	(0.09)	(-1.44)	(-0.19)	(-0.04)	(5.70)	(5.70)
Exposure x Crime	0.110	0.099	0.100	0.089	0.092	0.103	0.103
	(7.08)	(5.35)	(5.96)	(4.35)	(4.13)	(8.23)	(8.22)
Forecast Horizon	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(-4.88)	(-4.81)	(-4.87)	(-5.05)	(-5.30)	(-5.06)	(-5.04)
Companies	0.000	-0.001	0.000	-0.001	-0.001	0.000	0.000
	(-0.88)	(-1.32)	(-0.68)	(-0.69)	(-0.56)	(-0.68)	(-0.68)
Firm Experience	-0.006	-0.013	-0.009	-0.014	0.009	-0.004	-0.004
	(-1.64)	(-2.86)	(-2.35)	(-2.94)	(1.61)	(-0.96)	(-1.00)
General Experience	-0.002	-0.014	-0.006	-0.011	-0.020	-0.003	-0.003
	(-0.42)	(-2.28)	(-1.20)	(-0.77)	(-1.30)	(-3.74)	(-0.66)
Broker Size	-0.001	-0.002	0.000	0.001	0.001	-0.001	-0.001
	(-4.35)	(-3.80)	(0.49)	(0.89)	(1.70)	(-3.74)	(-3.74)
Female	0.009		0.012			0.012	0.012
	(0.95)		(1.23)			(1.26)	(1.25)
All Star	0.035	0.028	0.012	0.011	0.004	0.036	0.036
	(3.51)	(1.78)	(1.06)	(0.64)	(0.22)	(3.55)	(3.57)
Distance	0.000	0.000	-0.001	0.000	0.004	0.000	0.000
	(0.02)	(0.11)	(-0.30)	(0.12)	(1.08)	(0.14)	(0.14)
Industry	0.002	0.002	0.002	0.002	0.002	0.002	0.002
	(1.21)	(0.59)	(0.92)	(0.53)	(0.46)	(1.10)	(1.10)
LAFE	-0.049	-0.122	-0.013	-0.097	-0.137	-0.046	-0.047
	(-0.61)	(-1.45)	(-0.17)	(-1.11)	(-0.92)	(-0.57)	(-0.58)
Analyst FE	No	Yes	No	Yes	Yes	No	No
Time FE	No	No	Yes	Yes	Yes	No	No
Firm FE	No	No	No	No	Yes	No	No
N	24,703	24,153	24,703	24,153	23,795	23,795	23,795
Adj./Pseudo R Sq.	0.031	0.057	0.036	0.061	0.086	0.022	0.022

Table 5
Terrorist Attacks, Anniversaries, and Analyst Pessimism

This table analyzes whether the anniversaries of terrorist attacks can affect the forecasts of treated analysts. Panels A, C, and E report the results from the first, second, and third anniversaries, respectively. Panels B, D, and F present the findings from the first, second, and third anniversaries, respectively, while also excluding analysts located in the state of New York. Columns (1) to (5) present the results for the OLS regressions while the logit and probit specifications can be found in the following columns, respectively. Column (1) does not include any fixed effects. However, column (2) only includes analyst-level fixed effects and column (3) only includes time fixed effects. Column (4) incorporates analyst and time fixed effects, while column (5) also incorporates firm fixed effects. The logit and probit regressions do not include any fixed effects. *Exposure* is a dummy variable equal to one if the distance between the location of an analyst and the location of the attack is less than 100 miles and if the forecast is issued during the 30-day period following the terrorist attack. *Exposure* 1 *Yr. Anniversary* is a dummy variable equal to one if the distance between the location of an analyst and the location of the attack is less than 100 miles and if the forecast is issued within a 30-day period following the terrorist attack first anniversary. *Exposure* 2 *Yr. Anniversary* is a dummy variable equal to one if the distance between the location of an analyst and the location of the attack is less than 100 miles and if the forecast is issued within a 30-day period following the terrorist attack second anniversary. The set of control variables is constant throughout all the specifications but suppressed for brevity. *Forecast Horizon* is the number of days between an analysts' forecast date for a specific company and the corresponding company's earnings announcement. *Companies* is the number of companies an analyst follows during a specific year. *Firm Experience* is the number of years an analyst has covered a certain firm. *General Experience* is the number of years since an analyst issued a forecast for a company and the first forecast of the analyst available in the I/B/E/S database. *Broker Size* is the number of analysts employed by an analyst's brokerage firm. *Female* is a dummy variable equal to one if analyst i is female. *All Star* is a dummy variable equal to one if an analyst is ranked as first, second, third, or runner-up in the Institutional Investor magazine in the previous year. *Distance* is the natural logarithm of the distance between an analyst and the firm for which she issued a forecast. *Industry* is the number of two-digit SIC codes followed by an analyst. Lagged AFE (LAFE) is an analyst absolute forecast error for a certain company at time $t-1$. The differences between the main coefficients can be found below the table along with their corresponding *p-values*. Heteroskedasticity robust t-statistics are presented in parentheses and are clustered at the firm-year level.

Panel A: 1 Year Anniversary

	Dependent Variable: Pessimism						
	(1)	(2)	(3)	(4)	(5)	Logit	Probit
Exposure	0.145	0.136	0.134	0.129	0.111	0.139	0.140
	(22.68)	(19.46)	(19.92)	(17.01)	(14.21)	(22.30)	(22.21)
Exposure 1 Yr. Anniversary	0.139	0.123	0.117	0.102	0.081	0.132	0.133
	(22.29)	(16.98)	(18.36)	(13.56)	(10.38)	(21.68)	(21.58)
Exposure - Exposure 1 Yr. Anniv.	0.007	0.013	0.018	0.027	0.030	0.007	0.007
	(0.41)	(0.12)	(0.05)	(0.00)	(0.00)	(0.35)	(0.35)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst FE	No	Yes	No	Yes	Yes	No	No
Time FE	No	No	Yes	Yes	Yes	No	No
Firm FE	No	No	No	No	Yes	No	No
N	52,713	52,258	52,713	52,258	51,930	51,930	51,930
Adj./Pseudo R Sq.	0.023	0.044	0.028	0.048	0.062	0.017	0.017

Panel B:1 Year Anniversary Excluding New York Analysts

	Dependent Variable: Pessimism						
	(1)	(2)	(3)	(4)	(5)	Logit	Probit
Exposure	0.172	0.182	0.170	0.178	0.151	0.166	0.166
	(16.72)	(15.28)	(14.94)	(13.28)	(10.32)	(15.58)	(15.90)
Exposure 1 Yr. Anniv.	0.141	0.151	0.140	0.149	0.116	0.130	0.130
	(13.01)	(11.93)	(11.68)	(10.48)	(7.34)	(12.02)	(11.86)
Exposure - Exposure 1 Yr. Anniv.	0.031	0.031	0.030	0.029	0.035	0.036	0.036
	(0.03)	(0.04)	(0.06)	(0.09)	(0.05)	(0.01)	(0.02)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst FE	No	Yes	No	Yes	Yes	No	No
Time FE	No	No	Yes	Yes	Yes	No	No
Firm FE	No	No	No	No	Yes	No	No
N	21,339	21,054	21,337	21,052	20,543	20,543	20,543
Adj./Pseudo R Sq.	0.020	0.031	0.020	0.031	0.017	0.014	0.014

Table 5
Terrorist Attacks, Anniversaries, and Analyst Pessimism (Continued...)

Panel C: 2 Year Anniversary

	Dependent Variable: Pessimism						
	(1)	(2)	(3)	(4)	(5)	Logit	Probit
Exposure	0.142	0.133	0.136	0.130	0.113	0.136	0.137
	(22.66)	(20.26)	(20.78)	(18.81)	(16.09)	(22.64)	(22.54)
Exposure 1 Yr. Anniversary	0.134	0.120	0.114	0.103	0.085	0.128	0.128
	(22.49)	(18.43)	(18.29)	(14.83)	(11.97)	(22.30)	(22.17)
Exposure 2 Yr. Anniversary	0.146	0.135	0.129	0.120	0.101	0.139	0.140
	(24.16)	(20.35)	(20.23)	(17.03)	(14.12)	(23.89)	(23.76)
Exposure - Exposure 1 Yr. Anniv.	0.008	0.013	0.022	0.027	0.028	0.008	0.008
	(0.31)	(0.12)	(0.02)	(0.00)	(0.00)	(0.29)	(0.29)
Exposure - Exposure 2 Yr. Anniv.	-0.004	-0.002	0.007	0.011	0.012	-0.003	-0.003
	(0.66)	(0.81)	(0.43)	(0.24)	(0.19)	(0.75)	(0.75)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst FE	No	Yes	No	Yes	Yes	No	No
Time FE	No	No	Yes	Yes	Yes	No	No
Firm FE	No	No	No	No	Yes	No	No
N	78,774	78,347	78,774	78,347	78,000	78,000	78,000
Adj./Pseudo R Sq.	0.025	0.045	0.030	0.048	0.062	0.018	0.018

Panel D: 2 Year Anniversary Excluding New York Analysts

	Dependent Variable: Pessimism						
	(1)	(2)	(3)	(4)	(5)	Logit	Probit
Exposure	0.164	0.174	0.163	0.171	0.151	0.158	0.158
	(16.18)	(15.51)	(14.91)	(14.09)	(11.79)	(15.57)	(15.53)
Exposure 1 Yr. Anniversary	0.137	0.148	0.136	0.147	0.121	0.130	0.130
	(12.83)	(12.43)	(11.55)	(11.16)	(8.54)	(12.19)	(12.14)
Exposure 2 Yr. Anniversary	0.134	0.142	0.128	0.132	0.109	0.126	0.126
	(12.63)	(11.84)	(11.56)	(10.47)	(8.05)	(11.85)	(11.81)
Exposure - Exposure 1 Yr. Anniv.	0.027	0.026	0.027	0.024	0.030	0.028	0.028
	(0.32)	(0.34)	(0.35)	(0.69)	(0.32)	(0.05)	(0.05)
Exposure - Exposure 2 Yr. Anniv.	0.030	0.032	0.034	0.038	0.042	0.032	0.033
	(0.03)	(0.02)	(0.56)	(0.26)	(0.08)	(0.02)	(0.02)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst FE	No	Yes	No	Yes	Yes	No	No
Time FE	No	No	Yes	Yes	Yes	No	No
Firm FE	No	No	No	No	Yes	No	No
N	31,825	31,550	31,823	31,548	31,073	31,073	31,073
Adj./Pseudo R Sq.	0.018	0.032	0.019	0.032	0.027	0.013	0.013

Panel E: 3 Year Anniversary

	Dependent Variable: Pessimism						
	(1)	(2)	(3)	(4)	(5)	Logit	Probit
Exposure	0.143	0.136	0.136	0.132	0.115	0.138	0.138
	(22.92)	(20.90)	(20.79)	(19.13)	(16.53)	(22.95)	(22.84)
Exposure 1 Yr. Anniversary	0.134	0.123	0.116	0.107	0.090	0.129	0.129
	(22.59)	(18.99)	(18.68)	(15.51)	(12.77)	(22.44)	(22.31)
Exposure 2 Yr. Anniversary	0.146	0.137	0.128	0.121	0.103	0.140	0.141
	(24.39)	(20.99)	(20.21)	(17.42)	(14.56)	(24.18)	(24.06)
Exposure 3 Yr. Anniversary	0.033	0.022	0.039	0.029	0.022	0.032	0.032
	(3.13)	(1.99)	(3.20)	(2.34)	(1.69)	(3.04)	(3.06)
Exposure - Exposure 1 Yr. Anniv.	0.009	0.013	0.020	0.025	0.026	0.009	0.009
	(0.26)	(011)	(0.02)	(0.00)	(0.00)	(0.24)	(0.24)
Exposure - Exposure 2 Yr. Anniv.	-0.003	-0.002	0.007	0.011	0.012	-0.003	-0.003
	(0.69)	(0.83)	(0.41)	(0.25)	(0.18)	(0.77)	(0.78)
Exposure - Exposure 3 Yr. Anniv.	0.110	0.114	0.097	0.103	0.094	0.106	0.106
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst FE	No	Yes	No	Yes	Yes	No	No
Time FE	No	No	Yes	Yes	Yes	No	No
Firm FE	No	No	No	No	Yes	No	No
N	82,379	81,956	82,379	81,956	81,593	81,593	81,593
Adj./Pseudo R Sq.	0.025	0.044	0.029	0.047	0.059	0.018	0.018

Table 5
Terrorist Attacks, Anniversaries, and Analyst Pessimism (Continued...)

Panel F: 3 Year Anniversary Excluding New York Analysts							
	Dependent Variable: Pessimism						
	(1)	(2)	(3)	(4)	(5)	Logit	Probit
Exposure	0.165	0.175	0.164	0.172	0.155	0.159	0.160
	(16.28)	(15.65)	(15.02)	(14.32)	(12.23)	(15.71)	(15.67)
Exposure 1 Yr. Anniversary	0.138	0.148	0.136	0.146	0.122	0.131	0.131
	(12.91)	(12.45)	(11.71)	(11.29)	(8.75)	(12.29)	(12.25)
Exposure 2 Yr. Anniversary	0.135	0.144	0.129	0.134	0.111	0.127	0.127
	(12.74)	(12.05)	(11.58)	(10.66)	(8.34)	(12.01)	(11.97)
Exposure 3 Yr. Anniversary	0.021	0.016	0.020	0.018	0.016	0.020	0.020
	(1.10)	(0.79)	(0.98)	(0.82)	(0.67)	(1.05)	(1.05)
Exposure - Exposure 1 Yr. Anniv.	0.027	0.027	0.027	0.026	0.033	0.028	0.028
	(0.06)	(0.07)	(0.08)	(0.11)	(0.05)	(0.05)	(0.05)
Exposure - Exposure 2 Yr. Anniv.	0.030	0.031	0.035	0.038	0.044	0.032	0.033
	(0.04)	(0.04)	(0.02)	(0.02)	(0.01)	(0.03)	(0.02)
Exposure - Exposure 3 Yr. Anniv.	0.144	0.159	0.143	0.154	0.139	0.139	0.139
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst FE	No	Yes	No	Yes	Yes	No	No
Time FE	No	No	Yes	Yes	Yes	No	No
Firm FE	No	No	No	No	Yes	No	No
N	33,483	33,208	33,481	33,206	32,722	32,722	32,722
Adj./Pseudo R Sq.	0.018	0.032	0.018	0.032	0.026	0.013	0.013

Table 6
Terrorist Events and Forecast Accuracy

This table examines whether exposure to terrorist attacks affects the accuracy of analyst forecasts. Columns (1) to (4) present the results for the OLS regressions. Columns (1) and (2) do not include any fixed effects. However, columns (3) and (4) include analyst-level fixed effects. The dependent variable is the proportional median absolute error (PMAFE), as defined in equation (2). An advantage of using this measure is that it accounts for firm $\times$ time fixed effects (Clement, 1999). *Exposure* is a dummy variable equal to one if the distance between the location of an analyst and the location of the attack is less than 100 miles and if the forecast is issued during the 30-day period following the terrorist attack. The set of covariates is constant throughout all the specifications. *Forecast Horizon* is the number of days between an analysts' forecast date for a specific company and the corresponding company's earnings announcement. *Companies* is the number of companies an analyst follows during a specific year. *Firm Experience* is the number of years an analyst has covered a certain firm. *General Experience* is the number of years since an analyst issued a forecast for a company and the first forecast of the analyst available in the I/B/E/S database. *Broker Size* is the number of analysts employed by an analyst's brokerage firm. *Female* is a dummy variable equal to one if analyst i is female. *All Star* is a dummy variable equal to one if an analyst is ranked as first, second, third, or runner-up in the Institutional Investor magazine in the previous year. *Distance* is the natural logarithm of the distance between an analyst and the firm for which she issued a forecast. *Industry* is the number of two-digit SIC codes followed by an analyst. Lagged AFE (LAFE) is an analyst absolute forecast error for a certain company at time $t-1$. Heteroskedasticity robust t-statistics are presented in parentheses and are clustered at the firm-year level.

	Dependent Variable: PMAFE			
Exposure	-0.022	-0.019	-0.027	-0.023
	(-2.73)	(-2.30)	(-2.49)	(-2.00)
Forecast Horizon	0.001	0.001	0.001	0.001
	(6.03)	(6.13)	(6.39)	(6.42)
Companies	0.001	0.001	0.000	0.000
	(1.72)	(1.97)	(0.17)	(0.39)
Firm Experience	0.006	0.005	0.007	0.007
	(1.29)	(1.12)	(1.23)	(1.15)
General Experience	0.000	-0.001	0.008	0.008
	(0.03)	(-0.21)	(1.53)	(1.50)
Broker Size	0.001	0.001	0.000	0.000
	(2.59)	(2.20)	(1.05)	(0.92)
Female	0.001	0.004		
	(0.09)	(0.38)		
All Star	-0.002	-0.001	0.003	0.003
	(-0.22)	(-0.13)	(0.16)	(0.19)
Distance	0.003	0.004	0.003	0.003
	(1.63)	(1.73)	(1.01)	(1.09)
Industry	-0.002	-0.002	0.000	-0.001
	(-0.91)	(-1.08)	(-0.09)	(-0.33)
LAFE		-0.089		-0.090
		(-1.53)		(-1.44)
Analyst FE	No	No	Yes	Yes
Time FE	No	No	No	No
Firm FE	No	No	No	No
N	29,641	27,929	29,043	27,367
Adj. R Sq.	0.003	0.003	0.007	0.007

Table 7
Market Reaction to Forecast Revisions

This table analyzes the market's reaction to treated analysts' forecast revisions. The dependent variable as a firm's three-day market adjusted excess return centered on the forecast revision date. The dependent variable *Forecast Revision*, is a measure of the difference between analyst i's current forecast for firm j at time t and the forecast issued immediately before the current forecast, scaled by the standard deviation of forecasts of all analysts who follow firm j in time t. The set of covariates is constant throughout all the specifications and suppressed for brevity. *Forecast Horizon* is the number of days between an analysts' forecast date for a specific company and the corresponding company's earnings announcement. *Companies* is the number of companies an analyst follows during a specific year. *Firm Experience* is the number of years an analyst has covered a certain firm. *General Experience* is the number of years since an analyst issued a forecast for a company and the first forecast of the analyst available in the I/B/E/S database. *Broker Size* is the number of analysts employed by an analyst's brokerage firm. *Female* is a dummy variable equal to one if analyst i is female. *All Star* is a dummy variable equal to one if an analyst is ranked as first, second, third, or runner-up in the Institutional Investor magazine in the previous year. *Distance* is the natural logarithm of the distance between an analyst and the firm for which she issued a forecast. *Industry* is the number of two-digit SIC codes followed by an analyst. Lagged AFE (LAFE) is an analyst absolute forecast error for a certain company at time $t-1$. *Friday Dummy* is a dummy variable equal to one on Fridays, and zero otherwise. *Q4 Dummy* is a dummy variable equal to one during the fourth quarter of the year, and zero otherwise. Heteroskedasticity robust t-statistics are presented in parentheses and are clustered at the analyst-level.

	Dependent Variable: 3-day Market-Adjusted Return					
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	0.150	0.230	0.080	0.070	0.060	0.090
	(1.24)	(1.62)	(0.84)	(0.56)	(0.48)	(0.67)
Forecast Revision	0.040	0.050	0.030	0.030	0.040	0.040
	(4.96)	(4.92)	(3.57)	(3.60)	(2.93)	(1.00)
Exposure x Forecast Revision	-0.040	-0.040	-0.020	-0.020	-0.020	-0.020
	(-3.43)	(-3.28)	(-1.67)	(-1.84)	(-1.42)	(-1.11)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes	No	No
Analyst FE	No	Yes	No	Yes	No	No
Firm*Analyst FE	No	No	No	No	Yes	Yes
Controls*Forecast Revision	No	No	No	No	No	Yes
N	21,545	20,976	21,393	20,790	18,139	18,139
Adj. Rsq.	0.010	0.078	0.317	0.332	0.251	0.257

Table 8
Robustness Tests: Different Sample Specifications

This table presents robustness tests for a variety of sample specifications. Panel A tests whether our results are robust to using an alternative dependent variable, *Relative Rank*. Panel B examines whether our findings are robust to excluding the 9/11 attacks while Panel C investigates whether our findings are robust to excluding analysts located in the state of New York. Panel D studies whether our results are robust to Sunny and Cloudy months. Panel E performs a sensitivity analysis on our 30-day window. Panel F is placebo test that shows that our results are statistically insignificant when we randomize attack locations. Columns (1) to (5) present the results for the OLS regressions. Column (1) does not include any fixed effects. However, column (2) only includes analyst-level fixed effects and column (3) only includes time fixed effects. Column (4) incorporates analyst and time fixed effects, while column (5) also incorporates firm fixed effects. *Exposure* is a dummy variable equal to one if the distance between the location of an analyst and the location of the attack is less than 100 miles and if the forecast is issued during the 30-day period following the terrorist attack. The set of control variables is constant throughout all the specifications but suppressed for brevity. *Forecast Horizon* is the number of days between an analysts' forecast date for a specific company and the corresponding company's earnings announcement. *Companies* is the number of companies an analyst follows during a specific year. *Firm Experience* is the number of years an analyst has covered a certain firm. *General Experience* is the number of years since an analyst issued a forecast for a company and the first forecast of the analyst available in the I/B/E/S database. *Broker Size* is the number of analysts employed by an analyst's brokerage firm. *Female* is a dummy variable equal to one if analyst i is female. *All Star* is a dummy variable equal to one if an analyst is ranked as first, second, third, or runner-up in the Institutional Investor magazine in the previous year. *Distance* is the natural logarithm of the distance between an analyst and the firm for which she issued a forecast. *Industry* is the number of two-digit SIC codes followed by an analyst. Lagged AFE (LAFE) is an analyst absolute forecast error for a certain company at time $t-1$. Heteroskedasticity robust t-statistics are presented in parentheses and are clustered at the firm-year level.

Panel A: Alternative Dependent Variable

	Dependent Variable: Relative Rank				
	(1)	(2)	(3)	(4)	(5)
Exposure	-0.732	-0.756	-0.509	-0.566	-0.378
	(-14.69)	(-13.02)	(-10.34)	(-9.54)	(-6.56)
Controls	Yes	Yes	Yes	Yes	Yes
Analyst FE	No	Yes	No	Yes	Yes
Time FE	No	No	Yes	Yes	Yes
Firm FE	No	No	No	No	Yes
N	24,703	24,153	24,703	24,153	23,795
Adj. R Sq.	0.027	0.056	0.034	0.060	0.085

Panel B: Excluding 9/11 Attacks

	Dependent Variable: Pessimism				
	(1)	(2)	(3)	(4)	(5)
Exposure	0.167	0.147	0.144	0.125	0.093
	(22.83)	(15.86)	(19.18)	(12.94)	(8.80)
Controls	Yes	Yes	Yes	Yes	Yes
Analyst FE	No	Yes	No	Yes	Yes
Time FE	No	No	Yes	Yes	Yes
Firm FE	No	No	No	No	Yes
N	22,183	21,568	22,183	21,568	21,168
Adj. R Sq.	0.034	0.060	0.039	0.064	0.082

Table 8
Robustness Tests: Different Sample Specifications (Continued...)

Panel C: Excluding New York Analysts					
	Dependent Variable: Pessimism				
	(1)	(2)	(3)	(4)	(5)
Exposure	0.177	0.187	0.162	0.172	0.128
	(16.50)	(13.28)	(13.43)	(10.44)	(6.47)
Controls	Yes	Yes	Yes	Yes	Yes
Analyst FE	No	Yes	No	Yes	Yes
Time FE	No	No	Yes	Yes	Yes
Firm FE	No	No	No	No	Yes
N	10,177	9,867	10,176	9,866	9,341
Adj. R Sq.	0.024	0.039	0.025	0.039	0.009

Panel D: Forecasts on Sunny and Cloudy Months					
	Dependent Variable: Pessimism				
	Sunny			Cloudy	
Exposure	0.161	0.096		0.155	0.089
	(6.67)	(3.34)		(4.71)	(2.09)
Controls	Yes	Yes		Yes	Yes
Analyst FE	Yes	Yes		Yes	Yes
Time FE	Yes	Yes		Yes	Yes
Firm FE	No	Yes		No	Yes
N	7,254	6,921		4,597	4,167
Adj. R Sq.	0.077	0.145		0.086	0.129

Panel E: 5-day Window					
	Dependent Variable: Pessimism				
	(1)	(2)	(3)	(4)	(5)
Exposure	0.263	0.224	0.211	0.172	0.103
	(17.85)	(9.09)	(13.24)	(6.33)	(2.74)
Controls	Yes	Yes	Yes	Yes	Yes
Analyst FE	No	Yes	No	Yes	Yes
Time FE	No	No	Yes	Yes	Yes
Firm FE	No	No	No	No	Yes
N	4,203	3,640	4,202	3,639	3,090
Adj. R Sq.	0.079	0.134	0.103	0.146	0.154

Panel F: Placebo Test - Attack Locations					
	Dependent Variable: Pessimism				
	(1)	(2)	(3)	(4)	(5)
Exposure	0.105	-0.026	0.088	-0.039	-0.032
	(4.03)	(-0.33)	(3.27)	(-0.48)	(-0.34)
Controls	Yes	Yes	Yes	Yes	Yes
Analyst FE	No	Yes	No	Yes	Yes
Time FE	No	No	Yes	Yes	Yes
Firm FE	No	No	No	No	Yes
N	2,771	2,517	2,771	2,517	2,428
Adj. R Sq.	0.009	0.033	0.007	0.030	0.022

Table 9
Pre-Existing Trends and Macroeconomic Conditions

We perform various robustness tests to examine whether alternative hypotheses could justify our main results. In Panel A, we study whether there are any potential pre-existing shocks that could affect our estimations. We include $Exposure_{\text{-90 to -1 days}}$, which is a dummy variable equal to one if the distance between the location of an analyst and the location of the attack is less than 100 miles and if the forecast is issued during the 90-day period prior to a terrorist attack. In Panel B, we examine whether our results are robust to controlling for a state's economic activity. We augment our baseline specification to include *GSP* and *Unemployment*. Columns (1) to (5) present the results for the OLS regressions while the logit and probit specifications can be found in the following columns, respectively. Column (1) does not include any fixed effects. However, column (2) only includes analyst-level fixed effects and column (3) only includes time fixed effects. Column (4) incorporates analyst and time fixed effects, while column (5) also incorporates firm fixed effects. The logit and probit regressions do not include any fixed effects. *Exposure* is a dummy variable equal to one if the distance between the location of an analyst and the location of the attack is less than 100 miles and if the forecast is issued during the 30-day period following the terrorist attack. The set of control variables is constant throughout all the specifications but suppressed for brevity. *Forecast Horizon* is the number of days between an analysts' forecast date for a specific company and the corresponding company's earnings announcement. *Companies* is the number of companies an analyst follows during a specific year. *Firm Experience* is the number of years an analyst has covered a certain firm. *General Experience* is the number of years since an analyst issued a forecast for a company and the first forecast of the analyst available in the I/B/E/S database. *Broker Size* is the number of analysts employed by an analyst's brokerage firm. *Female* is a dummy variable equal to one if analyst i is female. *All Star* is a dummy variable equal to one if an analyst is ranked as first, second, third, or runner-up in the Institutional Investor magazine in the previous year. *Distance* is the natural logarithm of the distance between an analyst and the firm for which she issued a forecast. *Industry* is the number of two-digit SIC codes followed by an analyst. Lagged AFE (LAFE) is an analyst absolute forecast error for a certain company at time $t-1$. Heteroskedasticity robust t-statistics are presented in parentheses and are clustered at the firm-year level.

Panel A: Pre-Existing Effects

	Dependent Variable: Pessimism						
	(1)	(2)	(3)	(4)	(5)	Logit	Probit
$\text{Exposure}_{\text{0 to 30 days}}$	0.050	0.052	0.045	0.046	0.039	0.045	0.045
	(7.95)	(6.81)	(6.86)	(5.85)	(4.73)	(7.00)	(6.99)
$\text{Exposure}_{\text{-90 to -1 days}}$	-0.006	0.008	-0.005	0.009	0.011	-0.008	-0.008
	(-0.84)	(0.89)	(-0.70)	(1.01)	(1.14)	(-1.04)	(-1.04)
$\text{Exposure}_{\text{0 to 30 days}}$ - $\text{Exposure}_{\text{-90 to -1 days}}$	0.057	0.044	0.050	0.037	0.028	0.053	0.053
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst FE	No	Yes	No	Yes	Yes	No	No
Time FE	No	No	Yes	Yes	Yes	No	No
Firm FE	No	No	No	No	Yes	No	No
N	35,219	34,750	35,218	34,749	34,549	34,549	34,549
Adj./Pseudo R Sq.	0.006	0.049	0.009	0.052	0.073	0.005	0.005

Panel B: Controlling for State-level Macroeconomic Conditions

	Dependent Variable: Pessimism						
	(1)	(2)	(3)	(4)	(5)	Logit	Probit
Exposure	0.146	0.136	0.124	0.116	0.082	0.138	0.137
	(8.05)	(8.56)	(10.57)	(10.58)	(6.75)	(7.38)	(7.40)
GSP	0.001	0.002	0.001	0.004	0.005	0.001	0.001
	(1.51)	(0.90)	(2.70)	(2.79)	(2.41)	(1.49)	(1.50)
Unemployment	1.218	1.237	0.231	0.698	0.578	1.214	1.212
	(2.24)	(2.56)	(0.36)	(0.64)	(0.52)	(2.15)	(2.14)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst FE	No	Yes	No	Yes	Yes	No	No
Time FE	No	No	Yes	Yes	Yes	No	No
Firm FE	No	No	No	No	Yes	No	No
N	24,703	24,153	24,703	24,153	23,795	23,795	23,795
Adj./Pseudo R Sq.	0.029	0.056	0.034	0.060	0.086	0.020	0.020

Table 10
Terrorist Events and Cash Flow Sensitivity of Industries

This table examines whether affected analysts issue more pessimistic forecasts only for firms that belong to industries with a high cash flow sensitivity to terrorist attacks. To identify whether an industry has a high- or a low- cash flow sensitivity to terrorist attacks, we use the following time series regression of excess industry returns, for each of the 48 Fama-French industry portfolios: $r_{i,t} - r_{f,t} = c + \beta_i\ (r_{mkt,t} - r_{f,t}) + \gamma_i\ attack_t + \epsilon_{i,t}$, where $attack_t$ is a dummy variable equal to one for the dates when the attacks took place and $r_{mkt,t} - r_{f,t}$ is the excess market return. If an attack occurred at a date when an industry return is not available, we allow $attack_t$ to be equal to one the next day with available return. From each regression, we collect the coefficient estimates of γ_i and rank them from smaller to larger values. We classify as cash-flow high-sensitive (low-sensitive) industries, $Industry_{\text{High}}$ ($Industry_{\text{Low}}$), the 24 industries for which we obtained the higher (lower) γ_i coefficients. Columns (1) to (5) present the results for the OLS regressions while the logit and probit specifications can be found in the following columns, respectively. Column (1) does not include any fixed effects. However, column (2) only includes analyst-level fixed effects and column (3) only includes time fixed effects. Column (4) incorporates analyst and time fixed effects, while column (5) also incorporates firm fixed effects. The logit and probit regressions do not include any fixed effects. *Exposure* is a dummy variable equal to one if the distance between an analyst and an attack is less than 100 miles and if the forecast is issued during the 30-day period following the terrorist attack. The set of covariates is constant throughout all the specifications. *Forecast Horizon* is the number of days between an analysts' forecast date for a specific company and the corresponding company's earnings announcement. *Companies* is the number of companies an analyst follows during a specific year. *Firm Experience* is the number of years an analyst has covered a certain firm. *General Experience* is the number of years since an analyst issued a forecast for a company and the first forecast of the analyst available in the I/B/E/S database. *Broker Size* is the number of analysts employed by an analyst's brokerage firm. *Female* is a dummy variable equal to one if analyst i is female. *All Star* is a dummy variable equal to one if an analyst is ranked as first, second, third, or runner-up in the Institutional Investor magazine in the previous year. *Distance* is the natural logarithm of the distance between an analyst and the firm for which she issued a forecast. *Industry* is the number of two-digit SIC codes followed by an analyst. Lagged AFE (LAFE) is an analyst absolute forecast error for a certain company at time $t-1$. The differences between the two interaction coefficients can be found below the table along with their respective *p-values*. Heteroskedasticity robust t-statistics are presented in parentheses and are clustered at the firm-year level.

Dependent Variable: Pessimism							
	(1)	(2)	(3)	(4)	(5)	Logit	Probit
Exposure x $\text{Industry}_{\text{High}}$	0.135	0.116	0.116	0.096	0.065	0.123	0.123
	(14.75)	(10.27)	(12.40)	(8.27)	(5.18)	(13.60)	(13.54)
Exposure x $\text{Industry}_{\text{Low}}$	0.167	0.159	0.148	0.140	0.104	0.155	0.156
	(18.05)	(14.77)	(15.97)	(12.70)	(8.81)	(17.00)	(16.97)
Forecast Horizon	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(-5.19)	(-5.04)	(-5.14)	(-5.24)	(-5.45)	(-5.34)	(-5.33)
Companies	0.000	0.000	0.000	0.000	0.000	0.001	0.001
	(0.91)	(-0.38)	(-0.07)	(-0.46)	(-0.33)	(1.21)	(1.21)
Firm Experience	-0.008	-0.013	-0.010	-0.014	0.008	-0.006	-0.006
	(-2.15)	(-2.90)	(-2.60)	(-3.02)	(1.40)	(-1.46)	(-1.47)
General Experience	0.006	-0.004	-0.007	-0.013	-0.021	0.006	0.006
	(1.52)	(-0.78)	(-1.56)	(-0.97)	(-1.43)	(1.40)	(1.40)
Broker Size	-0.002	-0.002	0.000	0.000	0.001	-0.002	-0.002
	(-5.80)	(-4.89)	(-0.09)	(0.42)	(1.25)	(-5.30)	(-5.33)
Female	0.006		0.010			0.010	0.010
	(0.64)		(1.05)			(0.98)	(0.98)
All Star	0.022	0.013	0.009	0.005	-0.002	0.022	0.022
	(2.13)	(0.82)	(0.83)	(0.28)	(-0.11)	(2.12)	(2.13)
Distance	-0.001	0.000	-0.001	0.000	0.003	-0.001	-0.001
	(-0.35)	(0.04)	(-0.64)	(0.02)	(1.02)	(-0.23)	(-0.24)
Industry	0.004	0.002	0.002	0.002	0.001	0.004	0.004
	(2.19)	(0.81)	(1.19)	(0.47)	(0.42)	(2.11)	(2.12)
LAFE	-0.065	-0.117	-0.003	-0.087	-0.141	-0.058	-0.058
	(-0.82)	(-1.39)	(-0.04)	(-0.99)	(-0.96)	(-0.70)	(-0.70)
Exposure x $\text{Industry}_{\text{Low}}$ - Exposure x $\text{Industry}_{\text{High}}$	0.032	0.042	0.033	0.044	0.038	0.033	0.033
	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
Analyst FE	No	Yes	No	Yes	Yes	No	No
Time FE	No	No	Yes	Yes	Yes	No	No
Firm FE	No	No	No	No	Yes	No	No
N	24,561	24,015	24,561	24,015	23,659	23,659	23,659
Adj./Pseudo R Sq.	0.028	0.057	0.035	0.061	0.087	0.019	0.019

Table 11
Robustness Test: Terrorist Events and Forecast Revisions

This table examines whether affected analysts are more likely to issue bold forecasts. *Bold Revision* is a dummy variable equal to one if the analyst issues a forecast that is above or below, both the prior consensus and her previous forecast, and zero otherwise. *Downward Bold Revision* is a dummy variable equal to one if the analyst issues a forecast below the prior consensus and her previous forecast, and zero otherwise. *Upward Bold Revision* is a dummy variable equal to one if the analyst issues a forecast above the prior consensus and her previous forecast, and zero otherwise. Columns (1), (3), and (5) include analyst and time fixed effects. Columns (2), (4), and (6) include firms fixed effects as well. *Exposure* is a dummy variable equal to one if the distance between an analyst and an attack is less than 100 miles and if the forecast is issued during the 30-day period following the terrorist attack. The set of covariates is constant throughout all the specifications. *Forecast Horizon* is the number of days between an analysts' forecast date for a specific company and the corresponding company's earnings announcement. *Companies* is the number of companies an analyst follows during a specific year. *Firm Experience* is the number of years an analyst has covered a certain firm. *General Experience* is the number of years since an analyst issued a forecast for a company and the first forecast of the analyst available in the I/B/E/S database. *Broker Size* is the number of analysts employed by an analyst's brokerage firm. *Female* is a dummy variable equal to one if analyst i is female. *All Star* is a dummy variable equal to one if an analyst is ranked as first, second, third, or runner-up in the Institutional Investor magazine in the previous year. *Distance* is the natural logarithm of the distance between an analyst and the firm for which she issued a forecast. *Industry* is the number of two-digit SIC codes followed by an analyst. Lagged AFE (LAFE) is an analyst absolute forecast error for a certain company at time $t-1$. The differences between the two interaction coefficients can be found below the table along with their respective *p-values*. Heteroskedasticity robust t-statistics are presented in parentheses and are clustered at the firm-year level.

	Bold Revision		*Downward Bold Revision*		*Upward Bold Revision*	
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	-0.448	-0.447	0.030	0.040	-0.477	-0.488
	(-32.44)	(-26.75)	(1.59)	(1.99)	(-30.60)	(-27.56)
Forecast Horizon	-0.002	-0.002	-0.003	-0.003	0.001	0.001
	(-6.23)	(-5.30)	(-7.50)	(-6.06)	(5.36)	(4.09)
Companies	-0.001	0.000	0.001	0.003	-0.002	-0.003
	(-0.55)	(0.26)	(0.63)	(1.45)	(-1.45)	(-1.79)
Firm Experience	-0.002	0.000	-0.004	-0.005	0.003	0.005
	(-0.23)	(0.00)	(-0.48)	(-0.50)	(0.49)	(0.75)
General Experience	0.017	0.016	-0.003	-0.029	0.020	0.045
	(0.98)	(0.76)	(-0.11)	(-1.05)	(1.17)	(2.26)
Broker Size	-0.001	-0.002	-0.001	-0.001	0.000	-0.001
	(-1.48)	(-1.73)	(-1.08)	(-0.98)	(-0.13)	(-0.66)
All Star	-0.009	-0.034	-0.001	-0.033	-0.007	-0.001
	(-0.40)	(-1.34)	(-0.05)	(-0.97)	(-0.34)	(-0.05)
Distance	0.003	0.000	0.004	0.005	-0.001	-0.004
	(0.82)	(0.09)	(0.82)	(0.80)	(-0.23)	(-0.76)
Industry	-0.006	-0.011	-0.006	-0.013	0.000	0.003
	(-1.41)	(-2.20)	(-0.95)	(-2.00)	(-0.00)	(0.50)
LAFE	0.262	0.308	0.319	0.285	-0.057	0.023
	(2.51)	(1.63)	(2.34)	(0.93)	(-0.63)	(0.10)
Analyst FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes	No	Yes
N	7,852	7,287	7,852	7,287	7,852	7,287
Adj. R Sq.	0.311	0.362	0.083	0.197	0.358	0.394

Figure A1
Terrorist Attacks and Locations

This figure shows the states, in grey, where terrorist attacks and mass shootings ocurred. The data for terrorist attacks and mass shootings are collected from the Global Terrorism Database (GTD) and Mother Jones, respectively. The time period is from January 1994 to December 2016.

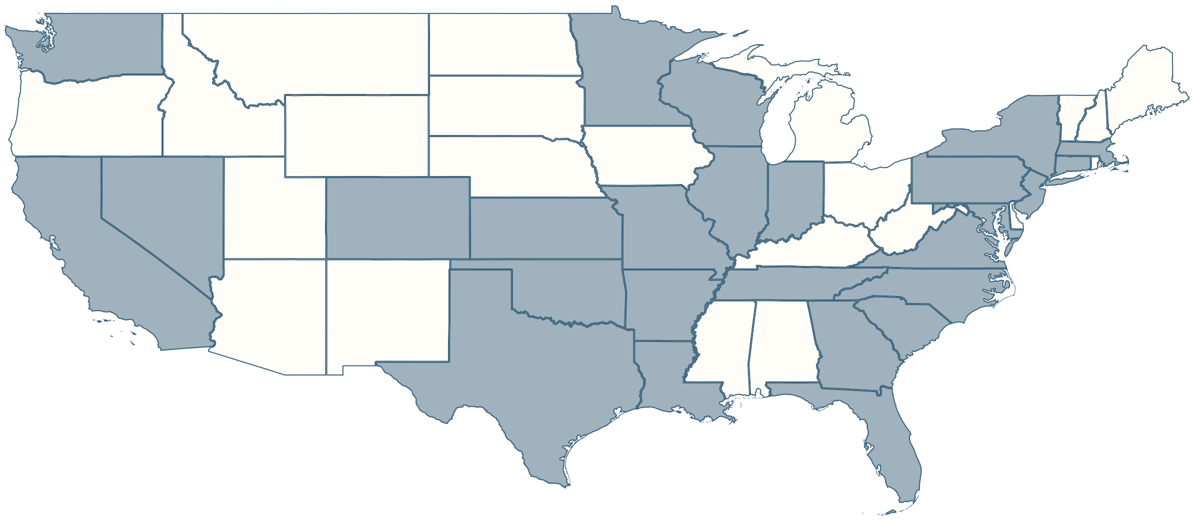


Figure A2
Forecasts and Locations

This figure shows the distribution of forecasts across different states. States with no forecasts are highlighted in off-white.

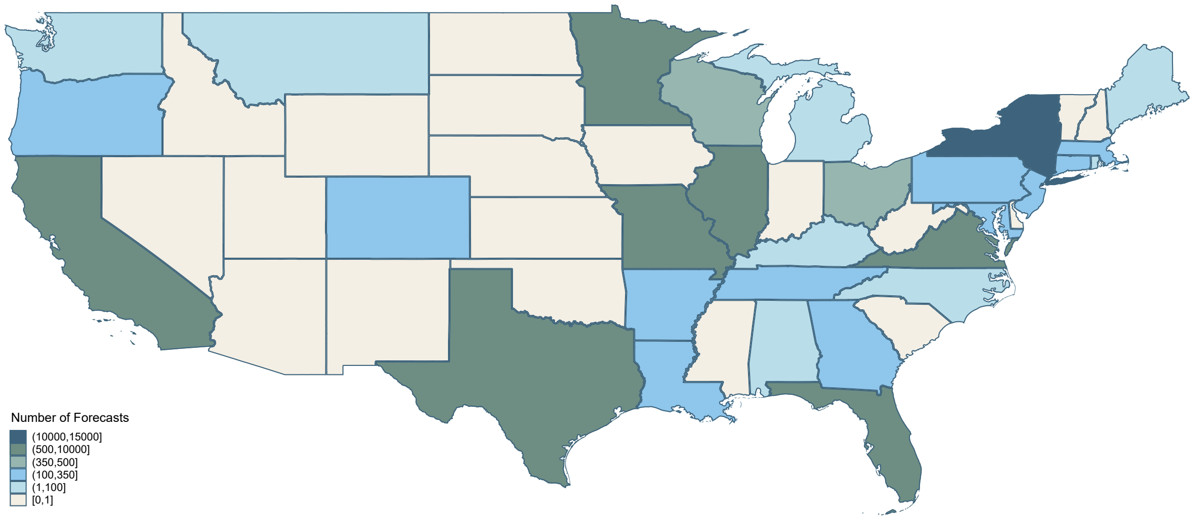


Table A1
Sample of Terrorist Events

This table presents the terrorist attacks and mass shootings in our sample. We consider only events that took place in the U.S. from 1994 to 2016, resulted in at least one human casualty, and have analysts located within a 100 mile radius.

Date	*Attack Type*	*State*	*City*	*Date*	*Attack Type*	*State*	*City*
March 1, 1994	Terrorist	NY	New York City	February 21, 2012	Shooting	GA	Norcross
May 29, 1994	Terrorist	NY	New York City	April 2, 2012	Shooting	CA	Oakland
June 20, 1994	Shooting	WA	Fairchild Air Force Base	May 20, 2012	Shooting	WA	Seattle
December 10, 1994	Terrorist	NJ	Caldwell	July 20, 2012	Shooting	CO	Aurora
April 3, 1995	Shooting	TX	Corpus Christi	August 5, 2012	Terrorist	WI	Oak Creek
April 19, 1995	Terrorist	OK	Oklahoma City	September 27, 2012	Shooting	MN	Minneapolis
April 24, 1995	Terrorist	CA	Sacramento	December 14, 2012	Shooting	CT	Newtown
December 8, 1995	Terrorist	NY	New York City	March 13, 2013	Shooting	NY	Herkimer County
January 23, 1996	Terrorist	FL	Miami	April 15, 2013	Terrorist	MA	Boston
July 27, 1996	Terrorist	GA	Atlanta	April 18, 2013	Terrorist	MA	Cambridge
February 23, 1997	Terrorist	NY	New York City	April 19, 2013	Terrorist	MA	Watertown
March 6, 1998	Shooting	CT	Newington	April 21, 2013	Shooting	WA	Federal Way
March 24, 1998	Shooting	AR	Jonesboro	June 7, 2013	Shooting	CA	Santa Monica
April 20, 1999	Shooting	CO	Littleton	July 26, 2013	Shooting	FL	Hialeah
July 1, 1999	Terrorist	CA	Redding	November 1, 2013	Terrorist	CA	Los Angeles
July 2, 1999	Terrorist	IL	Skokie	April 3, 2014	Shooting	TX	Fort Hood
July 4, 1999	Terrorist	IN	Bloomington	April 13, 2014	Terrorist	KS	Overland Park
July 29, 1999	Shooting	GA	Atlanta	April 27, 2014	Terrorist	WA	Seattle
September 15, 1999	Shooting	TX	Fort Worth	May 23, 2014	Terrorist	CA	Isla Vista
December 26, 2000	Shooting	MA	Wakefield	June 1, 2014	Terrorist	WA	Seattle
February 5, 2001	Shooting	IL	Melrose Park	June 6, 2014	Terrorist	GA	Cumming
September 11, 2001	Terrorist	VA	Arlington	June 8, 2014	Terrorist	NV	Las Vegas
September 11, 2001	Terrorist	NY	New York City	June 25, 2014	Terrorist	NJ	West Orange
September 11, 2001	Terrorist	PA	Shanksville	September 12, 2014	Terrorist	PA	Blooming Grove
October 2, 2001	Terrorist	FL	Boca Raton	October 23, 2014	Terrorist	NY	New York City
October 29, 2001	Terrorist	NY	New York City	October 24, 2014	Shooting	WA	Marysville
November 14, 2001	Terrorist	CT	Oxford	November 28, 2014	Terrorist	TX	Austin
January 5, 2002	Terrorist	FL	Tampa	December 18, 2014	Terrorist	NC	Morganton
July 4, 2002	Terrorist	CA	Los Angeles	December 20, 2014	Terrorist	NY	New York City
March 12, 2005	Shooting	WI	Brookfield	March 20, 2015	Terrorist	LA	New Orleans
March 21, 2005	Shooting	MN	Red Lake	May 3, 2015	Terrorist	TX	Garland
January 30, 2006	Shooting	CA	Goleta	June 11, 2015	Shooting	WI	Menasha
March 25, 2006	Shooting	WA	Seattle	June 17, 2015	Terrorist	SC	Charleston
July 28, 2006	Terrorist	WA	Seattle	July 16, 2015	Shooting	TN	Chattanooga
October 2, 2006	Shooting	PA	Lancaster County	July 23, 2015	Terrorist	LA	Lafayette
February 7, 2008	Shooting	MO	Kirkwood	October 31, 2015	Shooting	CO	Colorado Springs
February 14, 2008	Shooting	IL	DeKalb	November 4, 2015	Terrorist	CA	Merced
June 1, 2009	Terrorist	AR	Little Rock	November 27, 2015	Shooting	CO	Colorado Springs
November 5, 2009	Shooting	TX	Fort Hood	December 2, 2015	Shooting	CA	San Bernardino
November 29, 2009	Shooting	WA	Parkland	June 12, 2016	Terrorist	FL	Orlando
February 18, 2010	Terrorist	TX	Austin	July 7, 2016	Terrorist	TX	Dallas
March 4, 2010	Terrorist	VA	Arlington	July 7, 2016	Terrorist	TN	Bristol
August 3, 2010	Shooting	CT	Manchester	July 17, 2016	Terrorist	LA	Baton Rouge
September 1, 2010	Terrorist	MD	Silver Spring	September 17, 2016	Terrorist	MN	St. Cloud
September 6, 2011	Shooting	NV	Carson City	September 23, 2016	Shooting	WA	Burlington
October 12, 2011	Shooting	CA	Seal Beach				

Table A2
Robustness Test: Stock Characteristics of Firms Followed by Treated Analysts

This table analyzes whether there are any systematic differences between the firms for which treated analysts issue pessimistic forecasts versus the firms for which they issue non-pessimistic forecasts. $Market\ Capital$ is a firm's number of shares multiplied by the stock price. *Size* is the natural logarithm of $Market\ Capital$. *Illiquidity* is the sum of daily absolute value returns divided by the dollar daily volume over a the last 12 months, divided by the number of days in the estimation period (Amihud, 2002). *Lottery %* is the percentage of lottery stocks, defined as firms in the lowest 50^{th} stock price percentile, the highest 50^{th} idiosyncratic volatility percentile, and the highest 50^{th} skewness percentile of the CRSP/Compustat sample (Kumar, 2009). All three sorts are carried out independently. 1 $mo.\ Unc.\ Beta$, 3 $mo.\ Unc.\ Beta$, and 12 $mo.\ Unc.\ Beta$ are the one, three and 12 month uncertainty betas following the methodology of Bali et al. (2017). $Idio.\ Vol.$ is a firm's idiosyncratic volatility measured as the standard deviation of residuals from a time-series regression of daily stock returns over the previous month on the market, SMB, and HML factors. *Idio. Skewness* is the third moment of the residual obtained by regressing the market factor and the market factor squared on a firm's excess return (Kumar, 2009). $Stock\ Price$ is a firm's stock price. $Firm\ Age$ measures the number of available fiscal years for a specific firm. % $in\ S\&P$ 500 $Index$ measures the percentage of firms included in the S&P 500 Index. $CAPM\ Beta$ and $VIX\ Beta$ are the betas associated with regressing a firm's excess return on the market factor or on VIX returns. $Ln(Turnover)$ is a firm's natural logarithm of the volume of shares traded divided by the total number of shares (Chae, 2005). $Profitability$ (ROA) is a firm's capital expenditure scaled by total assets. *Capex* is a firm's capital expenditure scaled by sales. *R&D* is a firm's R&D expenditure scaled by PPE. *BM* is the natural logarithm of a firm's book-to-market ratio. The differences between these stock characteristics can be found under the *Diff* column along with their *p-values*.

	Pessimistic Forecast		*Non-pessimistic Forecast*			
	Mean	*Stdv.*	*Mean*	*Stdv.*	*Diff.*	*p-value*
Market Capital	9,498,115	8,159,643	8,988,293	6,779,406	509,822	(0.40)
Size	14.629	0.878	14.752	0.784	-0.123	(0.85)
Illiquidity	0.007	0.008	0.006	0.008	0.001	(0.68)
Lottery %	5.242%	8.543%	7.282%	15.217%	-2.040%	(0.32)
1 mo. Unc. Beta	0.101	0.293	0.067	0.223	0.034	(0.31)
3 mo. Unc. Beta	0.086	0.264	0.060	0.223	0.027	(0.58)
12 mo. Unc. Beta	0.134	0.382	0.093	0.379	0.042	(0.83)
Idio. Vol.	41.299	15.687	40.987	16.279	0.312	(0.90)
Idio. Skewness	-0.050	0.284	-0.010	0.263	-0.039	(0.12)
Stock Price	31.265	10.634	33.451	10.372	-2.186	(0.89)
Firm Age	21.295	10.241	20.280	7.556	1.015	(0.17)
% in S&P 500 Index	4.245%	12.297%	6.482%	15.028%	-2.238%	(0.57)
Capm Beta	1.218	0.372	1.248	0.400	-0.030	(0.82)
VIX Beta	-0.170	0.101	-0.181	0.113	0.011	(0.77)
Ln(Turnover)	0.516	0.514	0.694	0.403	-0.179	(0.61)
Profitability (ROA)	0.012	0.103	-0.010	0.193	0.021	(0.61)
Capex	0.071	0.031	0.081	0.062	-0.010	(0.25)
R&D	0.739	0.850	0.691	0.733	0.049	(0.99)
BM	0.524	0.432	0.513	0.271	0.011	(0.17)