Disastrous Weather Events and Analysts' Earnings Forecasts

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July 2020

Working Draft: Please do not quote without permission.

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Abstract

We examine whether disastrous weather events affect the mood of sell-side analysts located near such disasters. Specifically, we examine the impact of seventeen severe weather events (1998 – 2008) on analyst earnings forecasts and stock recommendations in the U.S. market. Our investigation compares forecasts issued by analysts in proximity to disaster zones with forecasts issued by analysts distant from disaster zones (i.e., difference in difference design). We show that conservative analysts who directly experience disastrous weather event are more likely to issue pessimistic earnings forecasts, whereas their less conservative counterparts are less likely to issue significantly more pessimistic earnings forecasts despite direct experience of a disastrous weather event. The impact of disastrous natural events on conservative analysts' pessimism strengthens over time. The effects of natural disaster risks on analysts' forecasting performance can be amplified during *economic downturns*. Our findings are consistent with the conjecture that earnings forecasts made immediately after the event occurrence are more dependent on information and judgements made prior to the events and are therefore less sensitive to the impact of negative experiences. We further find that analysts who are directly affected by disastrous weather events and who issue low-ball forecasts are more likely to issue negative (i.e., less accurate) forecasts in the period following the weather event. Our findings reveal that, despite being professional information agents, analysts are susceptible to the emotional and/or cognitive impacts of severe weather events. Lastly, we find that analysts' forecasts remain unchanged in the nine-month period following a disastrous weather event. However, we find that in the longer period, 12 months, and 24 months after the event, affected analysts are actually less likely to downgrade their recommendation of a firm's stock. These findings are consistent with the view that analysts' personal experiences have less impact on their recommendations over time. This study contributes to the current literature on how information processing and opinions are affected by analysts' personal experiences. This study provides evidence for understanding the impact of disastrous weather events on market participants, namely sell-side analysts, in an era of increasing climate risk.

JEL codes: G14; M41

Keywords: Analysts; Earnings forecasts; Disastrous weather events: Pessimism; Accuracy; Economic downturns

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1. Introduction

Sell-side analysts perform a critical role in capital markets by providing trading recommendations, industry reports, and firm analyses (Bradshaw, 2004; L. D. Brown, Call, Clement, & Sharp, 2015; Gleason & Lee, 2003). A large body of research has identified factors that affect analyst performance, including individual analyst characteristics (M. B. Clement, 1999; Jacobs, Lys, & Neale, 1999; Mikhail, Walther, & Willis, 1997; Stickel, 1992), information environments (Byard, Darrough, Suh, & Tian, 2018; M. B. Clement, 1999; Hope, 2003; Lang & Lundholm, 1996), regulatory actions (Call, Sharp, & Wong, 2019), and peer-analyst performance (Do & Zhang, 2020). However, few studies have addressed the impact of natural disasters on analyst performance. To address this issue, we focus on disastrous weather events that an individual analyst can experience and explore its effect on the professional performance of the analyst.[1]

We compare the performance of analysts in proximity to disaster zones with that of analysts distant from disaster zones. Our choice of focusing on analysts who experience exogenous extreme weather events is based on the need to account for endogeneity and selection bias. Extreme weather events could affect analysts' subsequent professional performance for reasons likely unrelated to characteristics of the firms covered or to their own performance. As such, extreme weather events provide a pseudo-natural experiment that addresses the issue of endogeneity in assessing the impact of external adversities on analyst performance. We focus on a treatment group of analysts who experience an extreme weather event and subsequently issue earnings forecasts and stock recommendations. We then study

[1] In 2015, global investment consultant Mercer (2015) identified risks from extreme weather events: a significant source of portfolio risk for institutional investors to manage over the next 20 years." Regulatory bodies are also concerned that market participants may not attend to this type of risk and urge both voluntary and mandatory disclosures of firms' exposure (e.g.,(SEC, 2010)).

how their tendency to offer either optimistic or pessimistic forecasts changes differently against a control group.[2]

A number of studies found that dangerous events lead to increased risk-aversion (Jackson 1981; Slovic 1987, 2000; Weinstein 1989). Studies in economics and psychology have documented that personal experiences of natural disasters often result in heightened pessimism (Cameron & Shah, 2015; Castillo & Carter, 2011; Jaycox et al., 2010; Kessler et al., 2008; Wang et al., 2007). Specifically, Antoniou, Kumar, and Maligkris (2018) find that analysts in areas where either terrorist attacks or mass shootings occurred issue more pessimistic forecasts.[3] In addition, the affect heuristic documented in the psychology literature (Slovic et al., 2004; Wright and Bower, 1992; Johnson and Tversky, 1983; Zajonc, 1980) predicts that individuals experiencing a recent negative emotion are more likely to perceive higher risks and lower benefits in their judgements of risks.[4] It is expected that analysts carry this affect heuristic from a recent extreme weather event, exhibit a general negative mental frame of mind in how they analyse firms, and therefore make more pessimistic forecasts.

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[2] Earlier studies emphasized the importance of analysts' roles in minimizing information asymmetry (Zhang, 2008; Chen, Cheng and Lo, 2010; Grinblatt, Jostova, and Philipov, 2016). However, the accuracy of the information provided by financial analysts is to a large extent subject to analysts' behavioural biases (Klein, 1990; DeBondt and Thaler, 1990; Zhang, 2006; Williams, 2013, DeHaan, Madsen and Piotroski, 2016). In this study, we extend research on analysts' behavioural biases using salient information from natural disasters near analysts' locations. In particular, we investigate how the incidence of natural disaster events affects analysts' earnings forecasts and recommendations.

[3] Cassar, Healy, and Von Kessler (2011) and Cameron and Shah (2015) find that financial analysts' personal experiences of disastrous weather events lead to temporary risk aversion in terms of making personal financial decisions. Ramirez and Altay (2011) and Dessaint and Matray (2017) document similar effects on professionals' financial decision making. The impact of disastrous weather events is likely to be strongest among analysts located close to the events, though certain extreme events might affect non-local individual analysts as well. In the area of analyst behaviour, Bourveau and Law (2016) find that Louisianan analysts issued more pessimistic forecasts, presumably due to the impact of the deadly Hurricane Katrina in 2005. Lo and Wu (2010) find that that financial analysts tend to issue pessimistic earnings forecasts in autumn and optimistic forecasts in spring, thereby providing evidence of the effect of Seasonal Affective Disorder on financial analysts.

[4] Finucane, Alhakami, Slovic, and Johnson (2000) put forward the theory of heuristic affect that a feeling towards a situation (i.e., positive or negative affect) would lead to a biased perception of risk and benefit, even when this is logically not warranted for that situation. Several experimental studies (Averbeck, Jones, & Robertson, 2011; Slovic & Peters, 2006; Wilson & Arvai, 2006) support this theory and show that the effects from this heuristic can be particularly long lasting.

Due to the size and geographic diversity of the United States, the country experiences a variety of different natural disasters on a frequent basis. Therefore, not all natural disasters generate the same level of economic and psychological impacts (Cavallo, Galiani, Noy, & Pantano, 2013), especially on professionals such as financial analysts. In our study, we capture the impact on analyst forecasts of 17 major and severe natural events from 1998 to 2008 (see table 1), which are defined as disasters that last for less than 30 days and cause damages of at least 1 billion 2013 constant dollars (Barrot & Sauvagnat, 2016; Hsu, Lee, Peng, & Yi, 2018). Our sample consists of earnings forecasts of U.S. firms surrounding the 17 major and severe natural events over the period from 1998 through 2008. We obtain the information on natural disaster events from the Spatial Hazard Events and Losses Database for the United States (SHELDUS) of the University of South Carolina. SHELDUS contains a historical record of the names, dates, and direct losses of the natural hazards at county level, from 1960 to present. 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 manually collect analysts' full names and corresponding brokerage house addresses from Nelson's Directory of Investment Research biographical dataset. Then, we use these analysts' full names to extract and match analysts with their corresponding forecasts and recommendations from Thomson Reuters (Jiang, Kumar, & Law, 2016).

We predict that analysts who experience natural disasters become more pessimistic and/or more accurate in their earnings forecasts.[5] We argue that, as analysts focus on a firm's future performance, their perception of risk is potentially influenced by prior experiences,

[5] Prior research examining potential biases in analyst forecasts shows that analysts have a predilection to issue optimistic forecasts because of the pressure to please investment banking clients (Dugar & Nathan, 1995; H.-w. Lin & McNichols, 1998; Michaely & Womack, 1999) the desire to achieve favourable career outcomes (Hong & Kubik, 2003), the incentive to generate trading commissions (Cowen, Groysberg, and Healy, 2006(Jackson, 2005) (Cowen, Groysberg, & Healy, 2006), and the pressure from institutional clients to support their stock positions (Firth, Lin, Liu, & Xuan, 2013; Gu, Li, & Yang, 2013; Mola & Guidolin, 2009).

including those of extreme weather and natural catastrophe. Therefore, we conjecture that analysts who recently experienced natural disasters (such as extreme weather events) exhibit heightened risk perception. Specifically, our surmise is that analysts who have experienced natural disasters are more likely to be pessimistic in their financial forecasts than are their counterparts who have not experienced natural disasters.[6] In addition, we argue that the systematic optimism in analysts' forecasts documented in prior studies might be mitigated by the rising pessimism in forecasts from analysts experiencing extreme weather events, resulting in more accurate forecasts.[7]

We compare forecasts issued by analysts in proximity to disaster zones with forecasts issued by analysts distant from disaster zones (i.e., difference in difference design). A drawback of our design is that we cannot directly measure analysts' emotional states induced by disastrous weather events. We document that, personal experience of disastrous weather events does forthwith motivate conservative analysts to issue significantly more pessimistic earnings forecasts, while affected analysts who are optimistic do not show any impacts of these events in their forecast behaviours. The impact of catastrophic natural events on conservative analysts' pessimism strengthens over time. The effects of the natural disaster risks on conservative analyst forecasting performance can be increased during *economic downturns*. The findings are consistent with our conjecture that earnings forecasts made immediately after the event occurrence are more dependent on information and judgements

[6] It is also possible that financial analysts are incentivized to avoid emotional and cognitive biases, given that their professional trajectories depend on the accuracy of their firm's value estimation (Dyck, Morse, & Zingales, 2010). If this is the case, we expect no impact from extreme weather events on analysts' performance.

[7] There are limited cases where forecast pessimism has been displayed. Some evidence of this comes from Ke and Yu (2006), Hilary and Hsu (2013) and Horton, Serafeim, and Wu (2017)who find that analysts try to please firm managers by adjusting their forecasts downward before an earnings announcement date so that firms can more easily beat analysts' latest forecasts. Hong and Kacperczyk (2010) document that competition imposes discipline on analysts so that they have less incentive to please managers, thereby lowering optimism bias. Call et al. (2019) Call et al. (2019)document that regulatory oversight in the form of formal brokerage sanctions discipline sell-side research to produce less optimistic recommendations.

made prior to the events, and therefore are less sensitive to the impact of the negative experiences.

Our study contributes to the literature on financial analysts by identifying factors that can explain the presence of biases in analyst forecasts. Previous studies, including Hong and Kubik (2003) and Horton et al. (2017)examine analyst career concerns and work incentives as factors that motivate analysts to issue more optimistic forecasts. We use a different identification strategy, comparing the forecasts issued by analysts who have experienced extreme weather events with those issued by other analysts, for the same firm and time period. Our setting is not susceptible to the typical endogeneity and omitted variable concerns that can be pervasive in cross-agent settings. Similar to studies that have investigated the impact that life events have on managerial and investor behaviour (Bernile, Bhagwat, & Rau, 2017; Hood, Kamesaka, Nofsinger, & Tamura, 2013; Roussanov & Savor, 2014), our study shows that how financial analysts respond to a life event can also be an important line of study, considering analysts' roles as disseminators of financial information to the market.

Second, we show that affected analysts who issue low-ball forecasts issue further negative forecasts (that is, less accurate) in the period following a severe disaster. These findings contradict the notion that analysts are firms' professional information agents, so they would not consciously compromise their career goal under the emotional and/or cognitive impact of a natural disaster.

Finally, as conservative analysts become more pessimistic after experiencing disastrous weather events, we further analyse the impact that these events have on analysts' recommendations. By estimating a logistic regression, we examine whether the likelihood of an analyst degrading a firm's stock recommendation is affected by their negative experience with natural disaster in comparison to a group of control analysts who do not have the same experience. Stock recommendations are the expressions of analysts' beliefs about share values relative to their market prices, which is a product of analysts' forecasts (Francis & Soffer, 1997). The results suggest that analysts do not exhibit a change in their recommendation behaviours in the 9 months after experiencing natural disasters. However, we find that in the longer period, 12 months and 24 months after the event, affected analysts are actually less likely to downgrade their recommendation of a firm's stock. While analysts might be more pessimistic in estimating firms' earnings, their recommendation is the result of a complex process that requires the analysts to use their earnings forecasts along with other information to estimate a stock's value, compare it to the trading price of the stock, and form the basis of the recommendations (Healy & Palepu, 2001). Our findings are consistent with the view that analysts' personal experiences have less impact on their recommendations.

The evidence in this study also contributes to the nascent literature on the effects of personal experience – as opposed to common knowledge – on professional judgements. While traditional economic models often assume that individuals incorporate all available data in forming their preferences, the psychology literature suggests that individuals weigh the knowledge obtained through personal experience heavily (Hertwig, Barron, Weber, & Erev, 2004) and individual preferences are, therefore, not necessarily stagnant. As personal experience differs among financial analysts and also differs across time for the same analyst, their professional judgments can differ significantly, given the same set of knowledge and facts.[8]

This study adds to the current literature on how analysts' extreme personal experiences can affect their information processing and opinions. Second, this thesis extends the strand of research on the impact of climate risks on the financial market. We examine 17

[8] The affect heuristic predicts that negative emotion will increase the perception of risks (Slovic, Finucane, Peters, & MacGregor, 2004; Zajonc, 1980). While the literature on the affect heuristics is mostly based on laboratory experiments (Johnson & Tversky, 1983), we can objectively measure analyst performance by comparing analyst forecasts against actual earnings and/or a consensus forecast. Our findings indicate that the effects of laboratory-induced affect hold up among financial analysts experiencing real-life emotion.

"Billion-dollar events" across 11 years, which provides an extensive study on how major disastrous weather events can affect analysts' behaviours. More research studies suggest an increasing risk of natural disasters worldwide. For example, Bender et al. (2010) predict a doubling of category 4 and 5 storms by the end of the 21st century in moderate scenarios. N. Lin, Kopp, Horton, and Donnelly (2016), by examining hurricane frequency data beginning 1800, predict that in the New York area the return period of Hurricane Sandy's flood height is estimated to decrease 4 to 5 times between 2000 and 2100. A series of recent studies predict a similar increase in natural disaster risk over the course of the 21st century (Elsner & Jagger, 2006; Garner et al., 2017; Grinsted, Moore, & Jevrejeva, 2013; N. Lin et al., 2016; Mann & Emanuel, 2006; Webster, Holland, Curry, & Chang, 2005). This study extends current concerns within accounting and finance to include the impacts of significant life events on professionals. In practice, this research is useful to investors who consider analysts' forecasts in investment decision making. More importantly, the findings that the effects of the natural disaster risks on the analyst forecasting performance can be amplified and heightened during *economic downturn*s are important for understanding the role of analyst behaviour in processing and disseminating financial information after billion-dollar events, and thus in contributing to market efficiency or inefficiency and resources allocation on capital markets. For regulation-making, the SEC has raised concerns about how exposure to climate risk might affect firms' forecasts, and thus have required firms to disclose such exposure. Overall, this study provides evidence for understanding the impact of climate risk on certain groups of market participants as well as uncovering further the extent to which natural disasters can affect society. [9]

The remainder of this study is structured as follows. Section Two provides a literature review of relevant literature and hypothesis development. Section Three outlines our data and

9 Ouazad and Kahn (2019) document the effects of billon-dollar events on banks' securitization activities.

methodology. Section Four presents our empirical results, discusses the main findings, and provides additional robustness checks. Section Five contains our conclusion.

2. Literature review and motivation

Forecast quality is shaped by a number of factors, including analysts' skills, their general experience as well as firm-specific experience, brokerage size, and task complexity[10] (M. B. Clement, 1999; Clement & Tse, 2005; Mikhail et al., 1997). H.-w. Lin and McNichols (1998) and Dechow, Hutton, and Sloan (2000) find that affiliated analysts are inclined to issue more favorable growth forecasts and recommendations and that the effect is stronger when higher fees are paid to the analysts' employers. Forecast accuracy is also affected by gender. Kumar (2010) finds that female analysts issue bolder and, in general, more accurate forecasts with superior performance in market segments with low concentrations of female analysts. Additionally, research shows that analysts' forecasts are affected by exposure to personal, career-related, or macroeconomic events. Clement and Law (2014) find that analysts who began their careers during economic recessions issue earnings forecasts that are more conservative and more pessimistic than their counterparts; furthermore, these analysts are less likely to become leaders in their fields while tending to issue more negative bold revisions. Jiang et al. (2016) find that analysts with conservative personal traits are more likely to issue conservative earnings forecasts and stock recommendations.[11]

Our study is motivated by a growing strand of literature in finance and economics that documents the impacts of personal traits[12] (Hutton et al., 2015; Shu, Sulaeman, & Yeung, 2012) and personal experience on behaviors of capital market participants. While traumatic

[10] Clement and Tse (2005) show that boldness of analysts' forecasts is associated with private information that they can obtain because of larger brokerage size, experience, and prior accuracy, and negatively associated with the number of industries that analysts follow.

[11] Analysts whose personal political preferences strongly align with the U.S. Republican Party are 3% more likely to issue minor revisions in earnings forecasts and 1.5% more likely to issue modest upgrades and downgrades in their stock recommendations (Jiang et al., 2016).

[12] Political values affect the probability that a firm engages in corporate misconduct (Hutton, Jiang, & Kumar, 2015). (Shu, Sulaeman, & Yeung, 2017) show that local religious belief affects the risk-taking behaviours of mutual funds analysts.

early-life experiences have a permanent effect in the decisions of corporate managers[13] (Bernile et al., 2017), the experience of extreme events later in life has an immediate and short-term impact on risk perception of corporate managers[14] (Antoniou et al., 2018) and fund managers[15] (Shu et al., 2012, 2017). Financial analysts also display behavioral biases as a result of personal life experience. Cen, Hilary, and Wei (2013) find that analysts are subject to anchoring bias as they are more optimistic when a firm's forecasted earnings are lower than the industry median, given that they rely on salient but irrelevant information. Analysts who experienced success in the past tend to be overconfident in their ability to forecast future earnings (Hilary & Menzly, 2006). Antoniou et al. (2018) find that analysts located near major terrorist attacks and mass shootings are more pessimistic and more accurate in their forecasts, especially when they are in proximity to the traumatic event, when the forecasts are closer to the event date, and when analysts are located in the areas that have low-crime rates.

Climatic factors also have significant impacts on the mood and behavior of relevant market participants. Lo and Wu (2010) find that stock investors as well as analysts are affected by Seasonal Affective Disorder in that earnings forecasts are more pessimistic in autumn. Dehaan, Madsen, and Piotroski (2017) find that analysts in locations with adverse weather exhibit slower information processing behaviours as measured by the level of analysts' activity in terms of forecasts, recommendations, and target price updates. Natural disasters are extreme climatic events that have both short-term and long-term impacts on individuals (Cameron & Shah, 2015). At the firm level, Truong, Nguyen, and Huynh (2017)

[13] Bernile et al. (2017) document that CEOs who experience fatal disaster without severe personal consequences are more aggressive in managing firms, while CEOs that experience an extreme downside of disaster are more conservative. The authors investigate whether the effect of early-life experiences on a CEO's risk perception varies with the severity of the experience.

[14] Antoniou et al. (2018) show that later extreme event experiences have a short term effect on the decisions of corporate managers. Dessaint and Matray (2017) find that managers of firms that are not affected by but located in the neighborhood areas of a hurricane event temporarily increase corporate cash holdings in response to the hurricane while the actual hurricane risk remains unchanged.

[15] Shu et al. (2017) show that bereavement due to parental loss influences the trades and profitability of mutual fund managers.

find that severe drought conditions lead to poor firm performance, higher profitability uncertainty, and a higher firm risk profile. Moreover, both the intensity and duration of drought experienced by firms in the affected areas is positively and significantly related to the *ex-ante* cost of equity implied in stock prices (Truong et al., 2017). Elnahas, Kim, and Kim (2018) document that firms located in areas with a higher probability of natural disasters have 3.6% lower leverage as well as higher earnings volatility and less favourable credit terms. Furthermore, the aforementioned firms tend to be more financially conservative than their counterparts in areas with a low chance of natural disasters. Bourveau and Law (2016) in their study of analysts working in New Orleans during and after the Hurricane Katrina event, found that analysts' earnings forecasts and recommendations were more pessimistic than those of analysts living outside of the disaster zone, a discrepancy that persisted for 12 to 18 months after the hurricane.

3. Hypotheses Development

Extreme weather events affect both mood and behaviour, as has been documented by researchers in the field of psychology (Denissen, Butalid, Penke, & Van Aken, 2008; Howarth & Hoffman, 1984; Kööts, Realo, & Allik, 2011). Following such events, individuals exhibit a greater level of risk aversion at a personal level (Cameron & Shah, 2015) and at a professional level (Dessaint & Matray, 2017; Ramirez & Altay, 2011). Furthermore, individuals experiencing extreme weather events are more likely to temporarily adopt pessimistic and negative outlooks. Risk perception and beliefs about the frequency and magnitude of future extreme weather-related events heighten after a traumatic event (P. Brown, Daigneault, Tjernström, & Zou, 2018). Consistent with "availability heuristics," individuals irrationally assess probability or risk of an extreme event "by the ease with which instances or associations could be brought to mind" (Tversky & Kahneman, 1973, p. 208).

While Bayes' rule suggests that the probability of occurrence of an extreme weather event and its anticipated magnitude should be based on both prior and current observations, availability heuristics claim that "if more recent and more salient observations are easier to retrieve from memory, then recent exposure to severe disasters will dramatically increase expectations of future risks" (P. Brown et al., 2018, p. 4). Personal experience of extreme weather events thus further exaggerates perceived risk (Finucane et al., 2000; Keller, Siegrist, & Gutscher, 2006).

Financial analysts are not immune to the psychological effect of extreme weather events. As analysts focus on a firm's future performance, their perception of risk is potentially influenced by prior experiences, including those of extreme weather and natural catastrophe. We conjecture that analysts who recently experienced natural disasters (such as extreme weather events) have heightened risk perception. Specifically, our surmise is that analysts who have experienced natural disasters are more likely to be pessimistic in their financial forecasts than are their counterparts who have not experienced natural disasters. Of course, financial analysts are incentivized to avoid emotional and cognitive biases, given that their professional trajectories depend on the accuracy of their firm's value estimation (Dyck et al., 2010). Therefore, analysts strive to assess a firm's prospects objectively and without undue influence from circumstances irrelevant to the stock valuation process. This argument encounters our predictions on the possible effects that natural disastrous weather events have on analysts' performance. Our first hypothesis is stated in null form:

> *H1(null): Forecast bias of sell-side equity analysts located in areas where natural disastrous weather events occur are not different from the prevailing consensus for the same firm at the same time.*

Our second hypothesis compares the accuracy of analysts' forecasts between pre- and post-disastrous events to determine if analysts' forecasts are closer or further away from the firm's actual announced earnings. A substantial body of research documents the excessive optimism associated with analysts' expectations about firms' prospects (La Porta, 1996) because analysts' employment incentives create potential biases in their output and coverage decisions. Due to the fear of jeopardizing potential investment banking business and losing access to management as a source of information, analysts avoid issuing negative earnings news by choosing to drop coverage of which they have unfavourable views (Das, Guo, & Zhang, 2006; Doukas, Kim, & Pantzalis, 2005; McNichols & O'Brien, 1997; Scherbina, 2008). Michaely and Womack (1999) stated that corporate financing, brokerage services, and proprietary trading are the three main sources of income for investment banks. Therefore, analysts are more likely to be optimistic in their recommendations, especially when their employer company receives trading commission fees from large institutional investors who have funds in these brokerage houses (Gu et al., 2013). If the exposure to natural disastrous weather events counterbalances the optimism in analysts' forecasts, we would expect analysts to be more accurate after experiencing unfavourable incidents. On the other hand, if the impact of analysts' pessimism is greater than that of their pre-existing optimism, analysts' forecast accuracy might decline. Our second hypothesis is stated in null form:

> *H2(null): Forecast accuracy of sell-side equity analysts located in areas where natural disastrous weather events occur is not different from the forecast accuracy of analysts located in non-affected areas.*

4. Data and research design

a. Natural Disaster Data

We obtain information on natural disaster events from the Spatial Hazard Events and Losses Database for the United States (SHELDUS) of the University of South Carolina. SHELDUS contains a historical record of the names, dates, and direct losses of the natural hazards at county level from 1960 to present. We restrict the list to major natural disasters that occurred from 1998 to 2008, the period in which we are able to identify analysts' locations. Due to the size and geographic diversity of the United States, the country experiences a variety of different natural disasters on a frequent basis. Therefore, not all natural disasters generate the same level of economic and psychological impacts (Cavallo et al., 2013). We capture the impact on analyst forecasts of 17 major and severe natural events from 1998 to 2008 (see table 1), which are defined as disasters that last for less than 30 days and cause damages of at least 1 billion 2013 constant dollars (Barrot & Sauvagnat, 2016; Hsu et al., 2018).

INSERT TABLE 1 HERE

b. Analyst Data

The study requires analysts' names and locations to match locations of natural disasters and analysts' forecasts. Following Jiang et al. (2016), we use Nelson's Directory of Investment Research biographical dataset to hand-collect analysts' names and their corresponding brokerage house addresses for the period 1998 to 2008. Then, we extract and match individual analysts with their corresponding forecasts and recommendations from Thomson Reuters (Jiang et al., 2016). We select information on analyst forecasts for U.S firms traded on NYSE, AMEX, and NASDAQ from I/B/E/S. Forecasts made by unidentified analysts with missing stock price information from the Centre for Research in Security Prices (CRSP) database are excluded. To be consistent with the analyst literature, we retain only the latest forecast from each analyst for each firm and for each forecast ending period (Antoniou et al., 2018).

Table 2 panel A reports the sample selection process. We first match the analyst location data with SHELDUS to identify 1,812 affected analysts across 54 counties over the 11-year period. We then obtain all forecasts issued by these analysts from I/B/E/S Detail History and Recommendation datasets. The analyst forecast sample period is extended to two years prior to the first natural disaster and two years after the last natural disaster in order to capture the change in analysts' forecast behaviours from the period preceding a disaster event to the period following such event. We are able to identify 1,006 distinct analysts from 46 affected counties who issued 1,182,285 forecasts from 1996 to 2010 for 4,915 distinct firms. Finally, we obtain a group of control analysts, who are non-affected and who issued earnings forecasts for the same firm for the same fiscal period on the same month from I/B/E/S. Observations that do not have a matched control observation for both the pre- and post-disaster periods are excluded. The final dataset contains information about 661 affected analysts from 39 affected counties and 2,545 control analysts who issued 414,849 forecasts for 2,319 firms over the 13-year period. Table 2 panel B reports the sample distribution by year.

INSERT TABLE 2 HERE

c. Research design

To compare the earnings forecasts made by analysts from the affected area with non-affected analysts between the pre- and post-disastrous event period, we employ a difference-in-difference research design. In particular, we compare the properties of analysts' forecasts made by the group of analysts in the natural disastrous weather area to those made for the same set of firms by the group of analysts in non-affected areas. Our main model specification is given below:

$$
\begin{aligned}
&Forecast\ Properties_{ijt} \\
&\qquad = \beta_0 + \beta_1 Affected_i + \beta_2 Post_t + \beta_3 Affected_i \times Post_t + Controls_t \\
&\qquad + Fixed\ Effects + \varepsilon_{ijt}
\end{aligned}
$$

where *i*, *j*, and *t* denote analysts, firms, and years, respectively. The dependent variable is *Forecast Properties*: *Pessimism_level* in model (1) and *Forecast_Accuracy* or *Forecast_Error* in model (2). *Pessimism_level* is the difference between the consensus forecast of analysts who cover the same firm *j* on the same month and an analyst's earnings forecast, scaled by the share price in the month prior to the announcement date. *Forecast accuracy* is the absolute difference between an analyst's earnings forecast and the actual earnings, scaled by the share price in the month prior to the announcement date. It is multiplied by -1 for ease of interpretation. The higher the *Forecast_Accuracy*, the more accurate is the analyst. Furthermore, to observe whether analysts' forecasts are higher or lower than the actual, we run the DiD model, using positive and negative *Forecast_Error*, which is the raw difference between analysts' forecast and actual earnings announced by firms. If *Forecast_Error* is positive, the analyst is optimistic as they issue a forecast that is higher than the actual earnings announced by the firm. Otherwise, the analyst is considered pessimistic, as their expectation of the firm's earnings is lower than the actual figure.

The main independent variables include *Affected, Post,* and the interaction between *Affected* and *Post, Affected*Post. Affected* is an indicator variable coded as 1 if the analyst works for a brokerage house in an affected area on the same year that a disastrous event occurs, and 0 otherwise. *Post* is an indicator variable that takes 1 if a forecast is made after the occurrence of a disastrous event and 0 otherwise. The coefficient of interest is β_3 for *Affected * Post* captures the change in affected analysts' forecasting behaviour before and after a disastrous event relative to a matched control group of analysts who did not experienced the disastrous event. If β_3 is positive and significant in model (1), where *Pessimism_level* is the dependent variable, we infer that affected analysts are more pessimistic than their peers and issue more accurate forecast after experiencing natural disasters. If β_3 is negative and significant where *Forecast_Accuracy* is the dependent variable, affected analysts issue higher and less accurate forecasts than their peers after the disaster hits their brokerage house location.

Our set of control variables include brokerage house and analyst-specific characteristics commonly used in analysing analyst earnings forecast properties. Michael B

Clement (1999) finds that brokerage size is positively associated with level of resources and analysts' forecast accuracy. Clement also found that analysts' general as well as firm-specific experience becomes more accurate as they gain skill and knowledge. Job complexity and the forecast horizon are negatively related to accuracy, given availability of information. Analysts typically begin with optimistic forecasts before moderating their outlook as the earnings announcement date approaches; therefore, the number of lapsed days is positively associated with forecast accuracy (Ke & Yu, 2006; Richardson, Teoh, & Wysocki, 2004). *Log_brokerage_size* is the number of analysts in the same brokerage house in the same year. *General experience* is the number of months since an analyst appeared in the I/B/E/S. *Experience_firm* is the number of months analyst *i* covers firm *j*. *Log_number_of_companies* is the number of companies an analyst covers in a year that captures analysts' task complexity. *Log_forecast_horizon* is the number of days to a firm's fiscal year-end. *Log_day_lapsed* is the number of days between earnings forecast and its earlier earnings forecast.[16] We include year fixed effects and firm fixed effects to capture the influence of aggregate (time-series) trends and absorb any time-invariant differences in unobservable analyst characteristics.

For each forecast made by an affected analyst, we obtain forecasts made by other analysts covering the same firm for the same forecast ending period on the same month. This setting mitigates the concern of any firm heterogeneity correlated with analyst forecast properties because the forecasts are made by both affected and non-affected analysts for the same firm-fiscal year. To examine the duration of disastrous events on analysts, we construct subsamples that include only forecasts made within 3 months, 6 months, 9 months, 12 months, and 24 months of the disastrous event. Significant coefficients of the interaction

[16] We do not include firm-specific control variable because DiD research design allows us to compare affected and non-affected analysts' forecast of the same firm in the same month, which mitigates the impact of firm specific characteristics on our results.

terms between *Affect* and *Post* indicate the lasting duration of these events on analysts' forecast performance.

5. Main Results

5.1 Summary Statistics

Table 3 presents the summary statistics of the main variables used in our study. The mean (median) of variable *Pessimism_level* in our full sample is -0.00033 (0), which suggests that, on average, analysts exhibit a high level of consensus. A negative average *Pessimism_level* is also consistent with findings in prior studies on analyst optimism bias (Doukas et al., 2005). The average (median) *Forecast_Accuracy* is -0.02017 (-0.00193), which is close to 0 and consistent with the expectation that analysts collectively are fairly accurate. The group of affected analysts, on average, consists of 36.3% of the total sample. Our sample is balanced in the number of firms in both the pre-disaster period and the post-disaster period. Hence, variable *Post* has a mean and median of 0.5. On average, the analysts have 7.5 years of general experience, with 2 years of firm-specific experience, and they follow an average of 12 firms at any point in time. The sample of brokerage houses has an average size of 31 analysts. The average forecast horizon is 170 days, with an average of 10 days between earnings forecasts.

INSERT TABLE 3 HERE

5.2 Forecast Pessimism

Next, we discuss the results of our multivariate analysis. Table 4 reports the result of our baseline regression, by which the level of pessimism of affected analysts is compared to the level of pessimism of non-affected analysts. The dependent variable is *Pessimism_level,* which is the difference between the average forecasts of all analysts following a firm and an analyst's forecast in the same month. A positive *Pessimism_level* indicates that the analyst issues a lower forecast than their average peers' forecasts (more conservative analysts) while a negative *Pessimism_level* occurs when the analyst's forecast is higher than that of their peers (more optimistic analysts). Due to the fundamental distinction between positive and negative *Pessimism_level*, we split our sample into two subsamples and run the DiD model on these two subsamples to observe the change in the analyst forecast after the occurrence of natural disastrous events.

INSERT TABLE 4 HERE

The coefficients of *Affected*Post* are positive and significant across different time periods for the subsample of forecasts that are lower than the average consensus forecast. The results suggest that the level of analysts' pessimism increases for affected analysts in the period following a major natural disaster. We then examine the timing of the effects of extreme weather events on forecasts of analysts located in affected areas. Interestingly, the impact of catastrophic natural events on conservative analysts' pessimism strengthens over time as the coefficients of *Affected*Post* increase from 0.014 (t-stat = 3.85) in the 3-month period to 0.023 (t-stat = 10.71) in the 24-month period. A unit increase in *Affected*Post* is equivalent to an increase from 11% to 19% in the level of analysts' pessimism.[17] We posit that earnings forecasts made immediately after the event occurrence are more dependent on information and judgements made prior to the events, and are therefore less sensitive to the impact of the negative experiences. Our results are robust to firm-fixed effects and year-fixed effects, indicating that personal experience of a natural disaster causes conservative analysts to become more pessimistic in their forecasts.

The results for the subsample of forecasts that are higher than the average forecast vary across different periods and are largely inconsistent with our expectation. The negative and significant coefficients of *Affected*Post* for the 3-month and 24-month periods indicate

[17] Calculated based on the mean *Pessimism_level* of 0.00123 for forecasts lower than the consensus forecast.

that analysts who issue more optimistic forecasts become more optimistic after experiencing natural disasters. We attribute this finding to the notion that analyst optimism is more strongly driven by economic incentives such as investment banking business and access to firm management (Lin & McNichols, 1998; McNichols & O'Brien, 1997) than the psychological impacts of the disastrous events. Hence, the results observed for the negative *Pessimism_level* do not support our view about the detrimental impact of natural disaster on analysts' forecasts.

5.3 Forecast Accuracy

This section focuses on whether the experience of a natural disastrous event affects analysts' forecast accuracy. Table 5 presents the estimation output of our second difference-in-difference model with *Forecast_Accuracy* as the dependent variable. Our main conjecture is that the systematic optimism in analysts' forecasts documented in prior studies is mitigated by the negative impact of extreme weather events on analysts, leading to more accurate forecasts.

INSERT TABLE 5 HERE

The effect of natural disaster events on analyst forecast accuracy is reported in Table 5. The negative and significant coefficients of *Affected*Post* across different periods suggest that analysts' forecasts are less accurate after they are affected by an extreme natural disaster event. This finding contradicts the notion that analysts are firms' professional information agents, so they would not consciously compromise their career goal under the emotional and/or cognitive impact of a natural disaster.

To investigate analysts' forecasting behaviour associated with disastrous weather events, we run our difference-in-difference model on *Forecast Error*, which is the directional difference between an analyst's forecast and actual earnings. We obtain the results for two subsamples, including the negative *Forecast Error* subsample (analysts' forecasts are lower than actual earnings) and the positive *Forecast Error* subsample (analysts' forecasts are higher than actual earnings).

Regression results reported in Table 5 Panel B show negative and significant coefficients of the interaction terms in the negative forecast error subsample, while the insignificant coefficients are observed for the positive forecast error subsample. This result aligns with our findings about pessimism level wherein only conservative analysts exhibit more negative forecast behaviour after experiencing natural disasters. Affected analysts who issue low-ball forecasts issue further negative forecasts in the period following a severe disaster. On average, a unit increase in *Affected*Post* is associated with a decrease in accuracy of 1% in the 3-month period to 4% in the 24-month period.

To summarise, only conservative analysts who issue forecasts lower than those of their peers and lower than the actual forecasts are negatively affected by extreme weather events. As a result, these analysts issue more pessimistic, more negative, and less accurate forecasts compared to the control group of analysts.

6. Sensitivity tests

The September 11 attacks in 2001 (also referred to as 9/11) destroyed the World Trade Centre Complex in Lower Manhattan, leading to the closure of Wall Street until September 17 and to a massive number of closings and relocation of brokerage houses. Given this event, we test the robustness of our results on the sample period from 2001 to 2008 after the relocation of a large number of brokerage houses.

Tables 6 and 7 present the estimation of the two difference-in-difference models with *Pessimism_level and Forecast_Accuracy* as dependent variables. The coefficient estimates are similar to our previously reported finding, thereby indicating that our results are robust even after brokerage houses relocated due to the 9/11 event.

INSERT TABLES 6 AND 7 HERE

In addition, because longer-window forecasts require greater judgment and are likely more susceptible to analyst biases (H.-w. Lin & McNichols, 1998; Tversky & Kahneman, 1974) we estimate our models using subsamples consisting of annual earnings forecasts for year t+1 and quarterly earnings forecasts for the 4 quarters ahead. There are no significant results documented for the one-year-ahead forecasts in terms of analysts' pessimism and forecast accuracy. However, regression results reported in Table 9 Panel B indicate that analysts who previously issued more optimistic forecasts (positive forecast errors) issue lower and more accurate one-year-ahead forecasts after they experienced severe natural disasters.

INSERT TABLES 8 AND 9 HERE

The results reported in Tables 10 and 11 for the quarterly forecasts are mostly consistent with our main results presented in Tables 4 and 5, suggesting that conservative analysts issue more pessimistic quarterly earnings forecasts as they suffer from large and damaging weather events.

INSERT TABLES 10 AND 11 HERE

7. Additional tests

a. Effects of natural disasters on analysts' recommendations

Stock recommendations are the expressions of analysts' beliefs about share values relative to their market prices, which is a product of analysts' forecasts (Francis & Soffer, 1997). As analysts become more pessimistic after experiencing disastrous weather events, we further analyse the impact that these events have on analysts' recommendations.

We run the difference-in-difference model as a logistic regression with *Downward_Recommendation* as the dependent variable to observe whether the likelihood of an analyst downgrading a firm's stock recommendation is affected by negative experience with natural disaster in comparison to stock recommendations by control analysts who do not have the same experience.

INSERT TABLE 12 HERE

The results suggest that analysts do not exhibit a change in their recommendation behaviours in the 9 months after experiencing natural disasters. However, we find that in the longer period, 12 months and 24 months after the event, affected analysts are actually less likely to downgrade their recommendations of a firm's stock (-0.279, t-stat = -4.2). While analysts might be more pessimistic in estimating firms' earnings, their recommendations result from a complex process requiring that analysts use earnings forecasts as well as other information to estimate a stock's value, compare it to the trading price of the stock, and form the basis of the recommendations (Healy & Palepu, 2001). Our findings are consistent with the view that analysts' personal experiences have less impact on their recommendations.

In summary, personal experience of natural disastrous weather events causes analysts to be significantly more pessimistic after the event. Over time, conservative analysts located in areas in which disastrous weather events occur issue even lower forecasts, while affected optimistic analysts seem less affected in their forecast behaviours.

b. Effects of natural disaster on analyst pessimism during economic downturns

The effects of natural disaster risks on analyst forecasting performance can be amplified and heightened during economic downturns. We conjecture that the effects of billion-dollar events during economic downturns on forecast pessimism are more pronounced. There are two recessions in our sample period (March 2001 - Nov 2001 and Dec. 2007 - June 2009), so we estimate the forecast pessimism tests for the four major disasters (one in 2001 and three in 2008) during these recessions. The effect is indeed stronger on analysts' pessimism (approximately three times). Specifically, for the subsample with lower earnings forecasts than those of consensus analysts, during the recession period the estimated coefficient on *Affected*Post* ranges from 0.033 to 0.042, whereas during the entire sample period the estimated coefficient on the interaction term ranges from 0.014 to 0.023. These results are consistent with our conjecture that analysts process information differently across economic states after billion-dollar events.

INSERT TABLE 13 HERE

8. Conclusion

How extreme weather events affect the performance of analysts is an important issue because this will eventually determine the quality of information that analysts provide to the public. In this study, we examined whether disastrous weather events affect earnings forecasts of sell-side analysts located near such disasters. We tested our hypotheses by comparing earnings forecasts issued by analysts in proximity to disaster zones with earnings forecasts issued by analysts distant from such zones.

Using analyst forecasts in the U.S. market surrounding 17 major and severe natural weather events from 1998 to 2008, we documented that personal experience of disastrous weather events motivates conservative analysts to issue significantly more pessimistic earnings forecasts. The impact of catastrophic natural events on conservative analysts' pessimism strengthens over time. The findings are consistent with our conjecture that earnings forecasts made immediately after the event are dependent on information and judgements made prior to the events and are therefore less sensitive to the impact of the negative experiences. Moreover, we found that affected analysts who issue low-ball forecasts issue further negative forecasts (that is, less accurate) in the period following a severe disaster. These findings contradict the notion that analysts are firms' professional information agents, so they would not consciously compromise their career goals under the emotional and/or cognitive impact of a natural disaster. Finally, analysts appear not to exhibit a change in their recommendation behaviours in the 9 months after experiencing natural disasters. However, we found that affected analysts are less likely to downgrade their recommendations of a firm's stock 12 months and 24 months after a catastrophic event. These findings are consistent with the view that analysts' personal experiences have less impact on their recommendations.

This study contributes to ongoing investigation into financial analysts' behaviour in three ways. First, this study clarified how analysts' extreme personal experiences affect information processing and opinions. Second, this study extended the strand of research on the impact of climate risks on the financial market. We examined disastrous weather events across 11 years, thereby providing an extensive study on how disastrous weather events can affect analysts' behaviours. Further, this study extended current concerns within the field of accounting and finance to include the impacts of significant life events on professionals. In practice, this research is useful to investors who consider analysts' forecasts in investment decision-making. For regulation-making, the SEC has raised concerns about how exposure to climate risk might affect firms' forecasts, and thus might require firms to disclose such exposure. Finally, this research facilitates understanding the impact of climate risk on market participants and uncovers the extent to which natural disasters might impact society. This study provided evidence for understanding the impact of disastrous weather events on market participants, namely sell-side analysts, in an era of increasing climate risk. Future research may explore the effects of disastrous weather events on other types of financial intermediaries, for example, credit rating agencies and auditors.

Our study suggests that experiencing negative events of a personal nature affects the behaviour of such sophisticated information intermediaries as financial analysts, thereby influencing information dissemination in financial markets.[18] While most recent work has focused on traumatic early-life experiences and the permanent effects in the decisions of corporate managers and sell-side analysts (Bernile et al., 2016; Clement and Law, 2014), our study shows that extreme personal events experienced later in adulthood also exert lasting effects on the performance of financial analysts. Our study, therefore, suggests an avenue for future research that focuses other important personal life events that may also affect financial analysts' forecasting performance.[19] More importantly, regardless of the state of the economy, natural disasters are always potentially present; however, the effects of the natural disaster risks on analysts' forecasting performance can be amplified and heightened during economic downturns.

[18] Antoniou et al. (2018) document that sell-side equity analysts located near major terrorist attacks and mass shootings issue more pessimistic earnings forecasts. Bourveau and Law (2016) show that Louisiana-based analysts became more pessimistic around the period of Hurricane Katrina.

[19] While several studies (Bernile et al., 2017; Shi et al., 2017; Roussanov and Savor, 2014; Hood et al., 2013; Malmendier et al., 2011) have investigated the impact of life events on the behaviour of firm management and investors, studies on how financial analysts respond to such events can be equally meaningful given the important role of analysts in facilitating the efficient dissemination of market-relevant information.

TABLE 1
List of Major Disasters

This table presents the 17 natural disasters included in the sample from 1998 to 2008. Following Hsu et al. (2018) and Barrot and Sauvagnat (2016), we restrict the list to the events that are classified as Major Disaster in the SHELDUS database at the University of South Carolina. These are events that have total direct estimated damages above one billion 2013 constant dollars and less than 30-day length. Abbreviations for U.S. states used in the table: AL (Alabama), AK (Alaska), AZ (Arizona), AR (Arkansas), CA (California), CO (Colorado), CT Connecticut), DE (Delaware), FL (Florida), GA (Georgia), HI (Hawaii), ID (Idaho), IL (Illinois), IN (Indiana), IA (Iowa), KS (Kansas), KY (Kentucky), LA (Louisiana), ME (Maine), MD (Maryland), MA (Massachusetts), MI (Michigan), MN (Minnesota), MS (Mississippi), MO (Missouri), MT (Montana), NE (Nebraska), NV (Nevada), NH (New Hampshire), NJ (New Jersey), NM (New Mexico), NY (New York), NC (North Carolina), ND (North Dakota), OH (Ohio), OK (Oklahoma), OR (Oregon), PA (Pennsylvania), RI (Rhode Island), SC (South Carolina), SD (South Dakota), TN (Tennessee), TX (Texas), UT (Utah), VT (Vermont), VA (Virginia), WA (Washington), WV (West Virginia), WI (Wisconsin), and WY (Wyoming). The Names, dates, types and affected states are obtained Hsu et al. (2018) and Barrot and Sauvagnat (2016).

Disaster	**Year**	**Month**	**Type**	**Affected States**
Bonnie	1998	8	Hurricane	NC, VA
Georges	1998	9	Hurricane	AL, FL, LA, MS
Floyd	1999	9	Hurricane	CT, DC, DE, FL, MD, ME, NC, NH, NJ, NY, PA, SC, VA, VT
Alison	2001	6	Hurricane	AL, FL, GA, LA, MS, PA, TX
Isabel	2003	9	Hurricane	DE, MD, NC, NJ, NY, PA, RI, VA, VT, WV
Southern California Wildfires	2003	10	Hurricane	CA
Charley	2004	8	Hurricane	FL, GA, NC, SC
Jeanne	2004	9	Hurricane	AL, FL, GA, KY, MD, NC, NY, OH, PA, SC, VA, WV
Ivan	2004	9	Hurricane	AL, FL, GA, KY, MD, NC, NY, OH, PA, SC, VA, WV
Frances	2004	9	Hurricane	AL, FL, GA, KY, LA, MA, MD, MS, NC, NH, NJ, NY, PA, SC, TN, WV
Dennis	2005	7	Hurricane	AL, FL, GA, MS, NC
Katrina	2005	8	Hurricane	AL, AR, FL, GA, IN, KY, LA, MI, MS, OH, TN
Rita	2005	9	Hurricane	AL, AR, FL, LA, M
Wilma	2005	10	Hurricane	FL
Midwest Floods	2008	6	Floods	IA, IL, IN, MN, MO, NE, W
Gustav	2008	9	Hurricane	AL, AR, LA, MS
Ike	2008	9	Hurricane	AR, IL, IN, KY, LA, MI, MO, MS, OH, PA, TN, TX

TABLE 2

Panel A: Sample Selection

	Number of affected analysts	Number of counties	Number of forecasts	Number of firms	Number of control analysts
Dataset with information about analyst location and natural hazards from 1998 to 2008	**1,812**	**54**			
Loss of observations due to missing analyst forecast information in I/B/E/S	(806)	(8)			
Dataset with information about forecasts made by analysts affected by natural hazards from 1996 to 2010	**1,006**	**46**	**1,182,285**	**4,915**	
Loss of observations due to missing control analyst forecast information in I/B/E/S	(345)			(2596)	
Dataset with information about forecasts made by affected and control analysts from 1996 to 2010	**661**	**39**	**414,849**	**2,319**	**2,545**

Panel B: Sample Distribution by Year

Year	Number of affected analysts	Number of control analysts	Number of firms	Number of counties	Number of forecasts
1996	15	18	33	4	64
1997	96	162	290	14	1,391
1998	177	788	734	18	21,164
1999	218	1,094	908	19	40,658
2000	184	531	597	19	9,729
2001	152	439	441	18	6,682
2002	165	451	477	19	4,167
2003	240	883	824	25	20,905
2004	252	1,233	1,011	25	66,288
2005	226	1,260	959	22	82,667
2006	243	1,124	890	25	61,648
2007	236	1,141	878	22	60,846
2008	178	919	848	18	29,294
2009	147	459	551	18	9,019
2010	43	67	76	11	327

TABLE 3
Descriptive statistics

This table reports the descriptive statistics for the main variables. Pessimism_level is the difference between the consensus forecast of analysts who cover the same firm j at the same time and an analyst's earnings forecast, scaled by the share price in the month prior to the announcement date. It is multiplied by 100 for ease of interpretation. Forecast accuracy is the absolute difference between an analyst's earnings forecast and the actual earnings, scaled by the share price in the month prior to the announcement date. It is multiplied by -1 for ease of interpretation. Log_brokerage_size is the number of analysts in the same brokerage in the same year. General experience is the number of months since an analyst had appeared in the I/B/E/S. Experience_firm is the number of months analyst i covers firm j. Log_number_of_companies is the number of companies an analyst covers in a year that captures analysts' task complexity. Log_forecast_horizon is the number of days to a firm's fiscal year-end. Log_day_lapsed is the number of days between an earnings forecast and its earlier earnings forecast.

Variable	N	Mean	Std Dev	Lower Quartile	Median	Upper Quartile
Pessimism_level	414,849	-0.00033	0.00489	-0.00035	0.00000	0.00030
Forecast Accuracy	414,849	-0.02017	0.07442	-0.00661	-0.00193	-0.00059
Affected	414,849	0.36353	0.48102	0.00000	0.00000	1.00000
Post	414,849	0.5000	0.49999	0.00000	1.00000	1.00000
Log_brokerage_size	414,849	3.44563	0.85518	2.94444	3.43399	4.07754
General_experience	414,849	4.50167	0.97835	3.95124	4.74493	5.28320
Log_number_of_companies	414,849	2.50642	0.44458	2.19722	2.56495	2.77259
Log_forecast_horizon	414,849	5.14127	0.96248	4.33073	5.37064	5.85220
log_day_lapsed	414,849	2.43842	2.12293	0.00000	3.29584	4.49981
Experience_firm	414,849	3.21255	1.21631	2.56495	3.40120	4.04305

TABLE 4

Effect of disastrous weather events on analyst pessimism

This table reports the estimated coefficients of the difference-in-difference model. The sample period is 1996 to 2010. The dependent variable is *Pessimism_level* which is the difference between the consensus forecast of analysts who cover the same firm j at the same time an analyst's earnings forecast, scaled by the share price in the month prior to the announcement date. *Affected* is an indicator variable coded as 1 if the analyst works for a brokerage house that locates in an affected area on the same year that a disastrous event occurs, and 0 otherwise. *Post* is an indicator variable that takes 1 if a forecast is made after the occurrence of the disastrous event and 0 otherwise. *, ** and *** represent significance at the 10%, 5%, and 1% level, respectively.

	3 months		**6 months**		**9 months**		**12 months**		**24 months**	
	Lower than consensus	**Higher than consensus**	**Lower than consensus**	**Higher than consensus**	**Lower than consensus**	**Higher than consensus**	**Lower than consensus**	**Higher than consensus**	**Lower than consensus**	**Higher than consensus**
Parameter	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**
Affected	-0.064***	0.018***	-0.065***	0.019***	-0.065***	0.02***	-0.066***	0.021***	-0.07***	0.024***
	(-34.07)	(7.56)	(-35.47)	(7.76)	(-36.24)	(7.88)	(-37.24)	(7.96)	(-40.17)	(8.09)
Post	0.004	0.006**	0.000	0.019***	-0.004**	0.028***	-0.007***	0.032***	-0.023***	0.038***
	(1.36)	(2.13)	(0.01)	(7.88)	(-2.06)	(12.37)	(-3.99)	(15.15)	(-16)	(18.71)
Affected*Post	**0.014*** **	**-0.01** **	**0.015*** **	**-0.006**	**0.015*** **	**-0.004**	**0.017*** **	**-0.007* **	**0.023*** **	**-0.02*** **
	(3.85)	**(-2.02)**	**(5.09)**	**(-1.31)**	**(5.89)**	**(-0.97)**	**(6.78)**	**(-1.8)**	**(10.71)**	**(-5.23)**
Log_brokerage_size	0.002	0.007***	0.001	0.006***	0.001	0.005***	0.001	0.005***	0.00	0.005***
	(1.59)	(5.83)	(1.05)	(4.93)	(1.38)	(4.79)	(0.63)	(4.7)	(1.15)	(4.44)
General_experience	0.001	0.003***	0.002*	0.003**	0.001	0.002*	0.001	0.002**	0.002**	0.000
	(1.41)	(2.74)	(1.75)	(2.31)	(1.57)	(1.94)	(1.62)	(2.2)	(2.22)	(0.44)
Log_number_of_companies	-0.009***	-0.004	-0.006***	-0.003	-0.007***	-0.002	-0.006***	-0.002	-0.005***	-0.002
	(-3.97)	(-1.62)	(-2.98)	(-1.27)	(-3.43)	(-0.8)	(-3.34)	(-0.96)	(-2.84)	(-0.97)
Log_forecast_horizon	0.024***	-0.04***	0.024***	-0.037***	0.023***	-0.035***	0.023***	-0.035***	0.023***	-0.037***
	(30.84)	(-40.07)	(33)	(-37.77)	(34.36)	(-36.95)	(35.46)	(-37.2)	(38.4)	(-38.3)
Log_day_lapsed	0.003***	-0.004***	0.004***	-0.004***	0.003***	-0.004***	0.003***	-0.004***	0.003***	-0.004***
	(10.52)	(-10.45)	(11.39)	(-10.16)	(11.22)	(-9.61)	(11.02)	(-8.84)	(12.38)	(-9.23)
Experience_firm	0.004***	-0.004***	0.004***	-0.002**	0.004***	-0.002*	0.003***	-0.002**	0.003***	0.001
	(4.53)	(-3.58)	(4.73)	(-2.35)	(5.07)	(-1.76)	(4.98)	(-2.11)	(5.16)	(0.61)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No of obs.	145,042	102,672	165,402	117,195	182,066	129,214	196,084	139,462	240,031	174,818
R-squared	0.5796	0.7964	0.5727	0.7670	0.5711	0.7419	0.5658	0.7316	0.5349	0.6751

TABLE 5

Panel A: Effect of disastrous weather events on analyst forecast accuracy

This table reports the estimated coefficients of the difference-in-difference model. The sample period is 1996 to 2010. The dependent variable is *Forecast_accuracy* which is the absolute difference between an analyst's earnings forecast and the actual earnings, scaled by the share price in the month prior to the announcement date. It is multiplied by -1 for ease of interpretation. *Affected* is an indicator variable coded as 1 if the analyst works for a brokerage house that locates in an affected area on the same year that a disastrous event occurs, and 0 otherwise. *Post* is an indicator variable that takes 1 if a forecast is made after the occurrence of the disastrous event and 0 otherwise. *, ** and *** represent significance at the 10%, 5%, and 1% level, respectively.

	3 months	**6 months**	**9 months**	**12 months**	**24 months**
Parameter	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**
Affected	-0.014	0.023	0.046**	0.078***	0.204***
	(-0.67)	(1.1)	(2.12)	(3.49)	(7.89)
Post	0.162***	0.356***	0.461***	0.495***	0.507***
	(5.82)	(15.5)	(21.55)	(24.06)	(25.11)
Affected*Post	**-0.019**	**-0.064***	**-0.082****	**-0.147*****	**-0.334*****
	(-0.47)	**(-1.85)**	**(-2.51)**	**(-4.63)**	**(-10.09)**
Log_brokerage_size	0.011	0.012	0.008	0.007	0.007
	(1.07)	(1.12)	(0.75)	(0.74)	(0.68)
General_experience	-0.015	-0.017	-0.02**	-0.022**	-0.022**
	(-1.46)	(-1.64)	(-2)	(-2.22)	(-2.02)
Log_number_of_companies	0.006	-0.007	0.022	0.013	0.010
	(0.24)	(-0.29)	(0.95)	(0.55)	(0.41)
Log_forecast_horizon	-0.672***	-0.624***	-0.593***	-0.582***	-0.59***
	(-77.14)	(-73.52)	(-70.58)	(-70.06)	(-67.02)
Log_day_lapsed	-0.027***	-0.023***	-0.024***	-0.025***	-0.023***
	(-7.27)	(-6.32)	(-6.52)	(-7.08)	(-6.11)
Experience_firm	0.003	0.019**	0.027***	0.02**	0.037***
	(0.35)	(2.2)	(3.17)	(2.4)	(4.09)
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes
No of obs.	247,714	282,597	311,280	335,546	414,849
R-squared	0.7802	0.7394	0.7067	0.6848	0.5879

TABLE 5

Panel B: Effect of disastrous weather events on analyst forecast errors

This table reports the estimated coefficients of the difference-in-difference model. The sample period is 1996 to 2010. The dependent variable is *Forecast error* which is the difference between an analyst's earnings forecast and the actual earnings, scaled by the share price in the month prior to the announcement date. *Affected* is an indicator variable coded as 1 if the analyst works for a brokerage house that locates in an affected area on the same year that a disastrous event occurs, and 0 otherwise. *Post* is an indicator variable that takes 1 if a forecast is made after the occurrence of the disastrous event and 0 otherwise. *, ** and *** represent significance at the 10%, 5%, and 1% level, respectively.

	3 months		**6 months**		**9 months**		**12 months**		**24 months**	
	Negative Forecast Error	**Positive Forecast Error**	**Negative Forecast Error**	**Positive Forecast Error**	**Negative Forecast Error**	**Positive Forecast Error**	**Negative Forecast Error**	**Positive Forecast Error**	**Negative Forecast Error**	**Positive Forecast Error**
Parameter	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**
Affected	-0.009*	0.047*	-0.004	0.042*	0.005	0.043*	0.014**	0.05**	0.041***	0.044*
	(-1.76)	(1.95)	(-0.71)	(1.78)	(0.85)	(1.85)	(2.55)	(2.21)	(6.58)	(1.95)
Post	-0.024***	0.063*	-0.041***	-0.129***	-0.027***	-0.228***	-0.018***	-0.272***	-0.039***	-0.632***
	(-3.75)	(1.82)	(-7.61)	(-4.79)	(-5.39)	(-9.5)	(-3.83)	(-12.22)	(-8.35)	(-33.77)
Affected*Post	**-0.019***	**-0.060**	**-0.027*****	**-0.015**	**-0.036*****	**-0.001**	**-0.055*****	**-0.010**	**-0.077*****	**0.002**
	(-1.9)	**(-1.22)**	**(-3.26)**	**(-0.38)**	**(-4.52)**	**(-0.03)**	**(-7.14)**	**(-0.3)**	**(-9.65)**	**(0.06)**
Log_brokerage_size	0.003	-0.018	0.004	-0.015	0.003	-0.013	0.004*	-0.012	0.006**	-0.013
	(1.44)	(-1.41)	(1.62)	(-1.3)	(1.44)	(-1.19)	(1.68)	(-1.1)	(2.35)	(-1.32)
General_experience	-0.005**	0.008	-0.005*	0.008	-0.005**	0.006	-0.004*	0.005	-0.008***	-0.003
	(-2.05)	(0.67)	(-1.91)	(0.65)	(-2.12)	(0.51)	(-1.82)	(0.47)	(-3.12)	(-0.26)
Log_number_of_companies	0.005	-0.039	0.003	-0.05*	0.005	-0.056**	0.005	-0.053**	0.00	-0.038*
	(0.84)	(-1.33)	(0.58)	(-1.85)	(0.96)	(-2.19)	(0.88)	(-2.15)	(0.72)	(-1.71)
Log_forecast_horizon	-0.152***	0.951***	-0.156***	0.901***	-0.158***	0.879***	-0.161***	0.848***	-0.174***	0.797***
	(-71.2)	(81.38)	(-74.59)	(84.4)	(-76.05)	(87.07)	(-78)	(88.41)	(-80.43)	(90.82)
Log_day_lapsed	-0.013***	0.035***	-0.011***	0.037***	-0.011***	0.037***	-0.011***	0.038***	-0.012***	0.038***
	(-14.74)	(7.77)	(-12.52)	(8.95)	(-12.04)	(9.54)	(-12.27)	(10.07)	(-12.72)	(11.11)
Experience_firm	0.003	-0.006	0.006***	-0.002	0.008***	0.002	0.007***	0.000	0.011***	0.009
	(1.25)	(-0.61)	(2.82)	(-0.24)	(3.91)	(0.17)	(3.73)	(0.02)	(5.27)	(1.05)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No of obs.	119,128	128,586	136,821	145,776	151,624	159,656	164,335	171,211	203,450	211,399
R-squared	0.8220	0.7692	0.7927	0.7778	0.7683	0.7604	0.7562	0.7562	0.6982	0.7173

TABLE 6
Sensitivity test
Effect of disastrous weather events on analyst forecast pessimism for the sub sample: 2001 - 2010

This table reports the estimated coefficients of the difference-in-difference model. The dependent variable is *Pessimism_level* which is the difference between the consensus forecast of analysts who cover the same firm j at the same time and an analyst's earnings forecast, scaled by the share price in the month prior to the announcement date. *Affected* is an indicator variable coded as 1 if the analyst works for a brokerage house that locates in an affected area on the same year that a disastrous event occurs, and 0 otherwise. *Post* is an indicator variable that takes 1 if a forecast is made after the occurrence of the disastrous event and 0 otherwise. *, ** and *** represent significance at the 10%, 5%, and 1% level, respectively.

	3 months		**6 months**		**9 months**		**12 months**		**24 months**	
	Lower than consensus	**Higher than consensus**	**Lower than consensus**	**Higher than consensus**	**Lower than consensus**	**Higher than consensus**	**Lower than consensus**	**Higher than consensus**	**Lower than consensus**	**Higher than consensus**
Parameter	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**
Affected	-0.06***	0.018***	-0.062***	0.02***	-0.062***	0.021***	-0.063***	0.021***	-0.07***	0.024***
	(-27.99)	(6.8)	(-29.36)	(7.51)	(-30)	(7.44)	(-30.96)	(7.42)	(-40.17)	(8.09)
Post	0.007**	-0.002	0.001	0.013***	-0.002	0.024***	-0.006***	0.033***	-0.023***	0.038***
	(2.41)	(-0.64)	(0.57)	(4.99)	(-1.06)	(9.79)	(-3.09)	(14.17)	(-16)	(18.71)
Affected*Post	**0.016*** **	**-0.018*** **	**0.018*** **	**-0.011** **	**0.019*** **	**-0.007**	**0.019*** **	**-0.009** **	**0.023*** **	**-0.02*** **
	(3.75)	**(-3.33)**	**(5.28)**	**(-2.29)**	**(5.96)**	**(-1.48)**	**(6.63)**	**(-2.19)**	**(10.71)**	**(-5.23)**
Log_brokerage_size	0.002*	0.007***	0.001	0.006***	0.002*	0.006***	0.001	0.005***	0.00	0.005***
	(1.8)	(5.94)	(1.35)	(5.23)	(1.7)	(4.83)	(1.23)	(4.68)	(1.15)	(4.44)
General_experience	0.002*	0.003**	0.002**	0.002*	0.002*	0.002	0.002**	0.002	0.002**	0.000
	(1.73)	(2.45)	(2.02)	(1.69)	(1.93)	(1.31)	(2.12)	(1.45)	(2.22)	(0.44)
Log_number_of_companies	-0.011***	-0.003	-0.008***	-0.002	-0.009***	-0.001	-0.009***	-0.001	-0.005***	-0.002
	(-4.26)	(-1.07)	(-3.51)	(-0.67)	(-3.82)	(-0.32)	(-3.86)	(-0.42)	(-2.84)	(-0.97)
Log_forecast_horizon	0.026***	-0.042***	0.026***	-0.038***	0.025***	-0.036***	0.025***	-0.035***	0.023***	-0.037***
	(29.02)	(-39.23)	(30.44)	(-35.78)	(31.59)	(-34.14)	(32.39)	(-33.82)	(38.4)	(-38.3)
Log_day_lapsed	0.004***	-0.004***	0.004***	-0.004***	0.003***	-0.004***	0.003***	-0.003***	0.003***	-0.004***
	(9.67)	(-9.19)	(10.11)	(-8.73)	(9.92)	(-8.36)	(9.81)	(-7.66)	(12.38)	(-9.23)
Experience_firm	0.004***	-0.003***	0.004***	-0.002*	0.004***	-0.001	0.004***	-0.002*	0.003***	0.001
	(4.55)	(-2.7)	(4.68)	(-1.67)	(4.87)	(-1.39)	(4.79)	(-1.77)	(5.16)	(0.61)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No of obs.	114,620	86,387	129,311	97,727	141,137	106,938	151,399	114,848	240,031	174,818
R-squared	0.5812	0.7973	0.5722	0.7677	0.5718	0.7412	0.5671	0.7285	0.5349	0.6751

TABLE 7
Sensitivity test
Panel A: Effect of disastrous weather events on analyst forecast accuracy for the sub sample: 2001 - 2010

This table reports the estimated coefficients of the difference-in-difference model. The dependent variable is *Forecast accuracy* which is the absolute difference between an analyst's earnings forecast and the actual earnings, scaled by the share price in the month prior to the announcement date. It is multiplied by -1 for ease of interpretation. *Affected* is an indicator variable coded as 1 if the analyst works for a brokerage house that locates in an affected area on the same year that a disastrous event occurs, and 0 otherwise. *Post* is an indicator variable that takes 1 if a forecast is made after the occurrence of the disastrous event and 0 otherwise. *, ** and *** represent significance at the 10%, 5%, and 1% level, respectively.

	3 months	**6 months**	**9 months**	**12 months**	**24 months**
Parameter	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**
Affected	-0.029	0.027	0.051**	0.079***	0.204***
	(-1.34)	(1.22)	(2.16)	(3.28)	(7.12)
Post	-0.019	0.239***	0.394***	0.495***	0.502***
	(-0.66)	(9.75)	(17.09)	(22.37)	(23.05)
Affected*Post	**-0.067**	**-0.139*** **	**-0.127*** **	**-0.189*** **	**-0.365*** **
	(-1.51)	**(-3.63)**	**(-3.47)**	**(-5.32)**	**(-9.76)**
Log_brokerage_size	0.014	0.016	0.010	0.009	0.008
	(1.3)	(1.47)	(0.92)	(0.84)	(0.73)
General_experience	-0.017	-0.02*	-0.026**	-0.028***	-0.028**
	(-1.63)	(-1.86)	(-2.46)	(-2.61)	(-2.44)
Log_number_of_companies	0.003	-0.005	0.033	0.024	0.020
	(0.11)	(-0.21)	(1.3)	(0.94)	(0.76)
Log_forecast_horizon	-0.662***	-0.601***	-0.562***	-0.544***	-0.566***
	(-72.01)	(-65.78)	(-61.3)	(-59.76)	(-57.52)
Log_day_lapsed	-0.019***	-0.017***	-0.018***	-0.02***	-0.018***
	(-5.06)	(-4.3)	(-4.68)	(-5.11)	(-4.35)
Experience_firm	0.010	0.027***	0.033***	0.025***	0.045***
	(1.18)	(3.31)	(3.59)	(2.78)	(4.61)
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes
No of obs.	201,007	227,038	248,075	266,247	335,161
R-squared	0.7956	0.7536	0.7179	0.6934	0.5754

TABLE 7
Sensitivity test
Panel B: Effect of disastrous weather events on analyst forecast errors for the sub sample 2001 - 2010

This table reports the estimated coefficients of the difference-in-difference model. The dependent variable is *Forecast Error, which* is the difference between an analyst's earnings forecast and the actual earnings, scaled by the share price in the month prior to the announcement date. *Affected* is an indicator variable coded as 1 if the analyst works for a brokerage house that locates in an affected area on the same year that a disastrous event occurs, and 0 otherwise. *Post* is an indicator variable that takes 1 if a forecast is made after the occurrence of the disastrous event and 0 otherwise. *, ** and *** represent significance at the 10%, 5%, and 1% level, respectively.

	3 months		**6 months**		**9 months**		**12 months**		**24 months**	
	Negative Forecast Error	**Positive Forecast Error**	**Negative Forecast Error**	**Positive Forecast Error**	**Negative Forecast Error**	**Positive Forecast Error**	**Negative Forecast Error**	**Positive Forecast Error**	**Negative Forecast Error**	**Positive Forecast Error**
Parameter	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**
Affected	-0.015***	0.071***	-0.005	0.058**	0.003	0.054**	0.011*	0.06**	-0.006**	0.05***
	(-2.86)	(2.68)	(-0.96)	(2.26)	(0.48)	(2.13)	(1.87)	(2.41)	(-2.09)	(3.17)
Post	-0.041***	0.139***	-0.05***	-0.059**	-0.027***	-0.148***	-0.008	-0.212***	0.181***	0.184
	(-5.99)	(3.68)	(-8.76)	(-2)	(-5.16)	(-5.59)	(-1.55)	(-8.65)	(4.94)	(1.01)
Affected*Post	**-0.017**	**-0.016**	**-0.042*** **	**0.031**	**-0.044*** **	**0.032**	**-0.059*** **	**0.027**	**-0.007* **	**-0.013**
	(-1.6)	**(-0.29)**	**(-4.54)**	**(0.7)**	**(-4.98)**	**(0.8)**	**(-6.95)**	**(0.72)**	**(-1.71)**	**(-0.57)**
Log_brokerage_size	0.001	-0.028**	0.002	-0.028**	0.002	-0.024**	0.002	-0.021*	-0.001	-0.019***
	(0.48)	(-2.11)	(0.85)	(-2.23)	(0.71)	(-2.03)	(0.96)	(-1.86)	(-1.16)	(-3.08)
General_experience	-0.005**	0.012	-0.005**	0.011	-0.006**	0.009	-0.005*	0.006	-0.002	0.011*
	(-1.98)	(0.91)	(-2.1)	(0.85)	(-2.36)	(0.75)	(-1.96)	(0.55)	(-1.6)	(1.82)
Log_number_of_companies	0.015**	-0.034	0.014**	-0.051*	0.017***	-0.058**	0.014**	-0.058**	-0.004*	-0.014
	(2.56)	(-1.04)	(2.5)	(-1.68)	(2.88)	(-2.03)	(2.51)	(-2.08)	(-1.71)	(-0.97)
Log_forecast_horizon	-0.151***	0.922***	-0.152***	0.866***	-0.153***	0.846***	-0.153***	0.812***	-0.215***	1.207***
	(-65.38)	(71.28)	(-67.94)	(72.78)	(-68.13)	(74.69)	(-68.61)	(75.5)	(-155.81)	(152.3)
Log_day_lapsed	-0.014***	0.024***	-0.012***	0.027***	-0.011***	0.028***	-0.011***	0.029***	-0.01***	0.023***
	(-14.33)	(4.91)	(-12.34)	(5.92)	(-11.7)	(6.46)	(-11.95)	(7.03)	(-22.7)	(9.41)
Experience_firm	0.003	-0.012	0.006***	-0.005	0.008***	-0.001	0.008***	-0.002	0.007***	-0.015***
	(1.35)	(-1.07)	(2.76)	(-0.48)	(3.63)	(-0.13)	(3.63)	(-0.15)	(7.47)	(-2.79)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No of obs.	97,559	103,448	110,768	116,270	121,727	126,348	131,224	135,023	448,129	491,308
R-squared	0.8286	0.7715	0.8060	0.7678	0.7811	0.7636	0.7669	0.7595	0.8193	0.8407

TABLE 8

Sensitivity Test

Effect of disastrous weather events on analyst pessimism (one year ahead earnings forecasts)

This table reports the estimated coefficients of the difference-in-difference model. The sample period is 1996 to 2010. The dependent variable is *Pessimism_level* which is the difference between the consensus forecast of analysts who cover the same firm j at the same time and an analyst's earnings forecast, scaled by the share price in the month prior to the announcement date. *Affected* is an indicator variable coded as 1 if the analyst works for a brokerage house that locates in an affected area on the same year that a disastrous event occurs, and 0 otherwise. *Post* is an indicator variable that takes 1 if a forecast is made after the occurrence of the disastrous event and 0 otherwise. *, ** and *** represent significance at the 10%, 5%, and 1% level, respectively.

	3 months		**6 months**		**9 months**		**12 months**		**24 months**	
	Lower than consensus	**Higher than consensus**	**Lower than consensus**	**Higher than consensus**	**Lower than consensus**	**Higher than consensus**	**Lower than consensus**	**Higher than consensus**	**Lower than consensus**	**Higher than consensus**
Parameter	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**
Affected	-0.019***	0.007	-0.019***	0.005	-0.019***	0.005	-0.018***	0.010	-0.022***	0.021
	(-2.99)	(0.67)	(-2.95)	(0.52)	(-3)	(0.48)	(-2.92)	(0.93)	(-3.58)	(1.6)
Post	0.006	0.039***	0.009*	0.042***	0.008*	0.038***	0.006	0.047***	-0.011***	0.081***
	(1.13)	(5.15)	(1.76)	(5.98)	(1.74)	(5.72)	(1.31)	(7.21)	(-2.93)	(11.92)
Affected*Post	**0.002**	**0.009**	**-0.005**	**0.008**	**-0.005**	**0.010**	**-0.004**	**0.011**	**0.01**	**0.002**
	(0.27)	**(0.59)**	**(-0.57)**	**(0.6)**	**(-0.74)**	**(0.78)**	**(-0.54)**	**(0.82)**	**(1.56)**	**(0.11)**
Log_brokerage_size	-0.009***	0.001	-0.007***	0.000	-0.007***	0.002	-0.009***	0.003	-0.006***	0.002
	(-3.42)	(0.2)	(-2.59)	(0.06)	(-2.75)	(0.47)	(-3.71)	(0.93)	(-2.66)	(0.51)
General_experience	0.012***	-0.004	0.011***	-0.007*	0.011***	-0.007*	0.011***	-0.008**	0.012***	-0.009**
	(4.34)	(-1.17)	(4.14)	(-1.81)	(4.03)	(-1.93)	(4.32)	(-2.09)	(4.75)	(-2.12)
Log_number_of_companies	0.002	-0.001	0.007	0.001	0.004	0.001	0.001	0.003	0.00	-0.003
	(0.3)	(-0.09)	(1.11)	(0.08)	(0.65)	(0.12)	(0.17)	(0.34)	(0.47)	(-0.28)
Log_forecast_horizon	-0.013**	-0.002	-0.005	0.007	-0.007	-0.007	-0.004	-0.014	0.00	-0.012
	(-2.07)	(-0.14)	(-0.84)	(0.69)	(-1.37)	(-0.71)	(-0.88)	(-1.41)	(-0.45)	(-1.06)
Log_day_lapsed	0.001	-0.007**	0.001	-0.008***	0.002	-0.007***	0.001	-0.006**	0.003*	-0.006*
	(0.39)	(-2.39)	(0.55)	(-2.86)	(0.99)	(-2.58)	(0.69)	(-2.03)	(1.76)	(-1.67)
Experience_firm	-0.006**	0.003	-0.004	0.002	-0.003	0.002	-0.004*	0.002	-0.004*	0.006
	(-2.33)	(0.83)	(-1.64)	(0.76)	(-1.38)	(0.64)	(-1.74)	(0.69)	(-1.88)	(1.64)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No of obs.	10,630	8,820	12,020	9,846	12,880	10,472	13,991	11,231	17,951	14,589
R-squared	0.8878	0.9188	0.8834	0.9122	0.8813	0.9074	0.8761	0.8912	0.8461	0.7953

TABLE 9
Sensitivity Test
Panel A: Effect of disastrous weather events on analyst forecast accuracy (one year ahead earnings forecasts)

This table reports the estimated coefficients of the difference-in-difference model. The sample period is 1996 to 2010. The dependent variable is *Forecast accuracy* which is the absolute difference between an analyst's earnings forecast and the actual earnings, scaled by the share price in the month prior to the announcement date. It is multiplied by -1 for ease of interpretation. *Affected* is an indicator variable coded as 1 if the analyst works for a brokerage house that locates in an affected area on the same year that a disastrous event occurs, and 0 otherwise. *Post* is an indicator variable that takes 1 if a forecast is made after the occurrence of the disastrous event and 0 otherwise. *, ** and *** represent significance at the 10%, 5%, and 1% level, respectively.

	3 months	**6 months**	**9 months**	**12 months**	**24 months**
Parameter	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**
Affected	0.010	0.010	0.007	0.005	-0.004
	(0.44)	(0.44)	(0.27)	(0.21)	(-0.16)
Post	0.058	0.084	-0.036	-0.061	-0.017
	(0.15)	(0.23)	(-0.09)	(-0.15)	(-0.04)
Affected*Post	**0.031**	**0.038**	**0.052**	**0.037**	**0.032**
	(0.43)	**(0.8)**	**(1.24)**	**(0.94)**	**(0.94)**
Log_brokerage_size	0.068***	0.069***	0.06***	0.054***	0.027***
	(5.06)	(5.7)	(5.07)	(4.81)	(2.69)
General_experience	0.007	0.003	-0.005	-0.002	-0.002
	(0.54)	(0.27)	(-0.46)	(-0.14)	(-0.22)
Log_number_of_companies	-0.018	-0.010	-0.003	-0.008	-0.005
	(-0.63)	(-0.38)	(-0.12)	(-0.32)	(-0.25)
Log_forecast_horizon	-0.656***	-0.617***	-0.605***	-0.564***	-0.609***
	(-9.95)	(-10.18)	(-9.97)	(-9.96)	(-11.41)
Log_day_lapsed	-0.032***	-0.034***	-0.03***	-0.028***	-0.022***
	(-3.39)	(-4.03)	(-3.59)	(-3.49)	(-3.18)
Experience_firm	0.008	0.014	0.014	0.012	0.014
	(0.65)	(1.34)	(1.36)	(1.25)	(1.58)
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Analyst fixed effect	Yes	Yes	Yes	Yes	Yes
No of obs.	37,259	43,754	50,367	54,014	68,952
R-squared	0.9781	0.9771	0.9744	0.9744	0.9729

TABLE 9
Sensitivity Test
Panel B: Effect of disastrous weather events on analyst forecast errors
(one year ahead earnings forecasts)

This table reports the estimated coefficients of the difference-in-difference model. The sample period is 1996 to 2010. The dependent variable is *Forecast Error* which is the difference between an analyst's earnings forecast and the actual earnings, scaled by the share price in the month prior to the announcement date. *Affected* is an indicator variable coded as 1 if the analyst works for a brokerage house that locates in an affected area on the same year that a disastrous event occurs, and 0 otherwise. *Post* is an indicator variable that takes 1 if a forecast is made after the occurrence of the disastrous event and 0 otherwise. *, ** and *** represent significance at the 10%, 5%, and 1% level, respectively.

	3 months		**6 months**		**9 months**		**12 months**		**24 months**	
	Negative Forecast Error	**Positive Forecast Error**	**Negative Forecast Error**	**Positive Forecast Error**	**Negative Forecast Error**	**Positive Forecast Error**	**Negative Forecast Error**	**Positive Forecast Error**	**Negative Forecast Error**	**Positive Forecast Error**
Parameter	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**
Affected	-0.039**	-0.071	-0.037**	0.005	-0.034**	0.061	-0.026	0.065	-0.001	0.187***
	(-2.24)	(-1.3)	(-2.08)	(0.08)	(-1.98)	(1.02)	(-1.46)	(1.07)	(-0.05)	(3)
Post	0.055***	-0.12**	0.05***	-0.121**	0.048***	-0.158***	0.067***	-0.165***	0.124***	-0.256***
	(3.66)	(-2.43)	(3.51)	(-2.48)	(3.64)	(-3.28)	(5.09)	(-3.62)	(9.15)	(-6.28)
Affected*Post	**0.029**	**-0.096**	**0.029**	**-0.222*** **	**0.034**	**-0.348*** **	**0.011**	**-0.314*** **	**-0.040**	**-0.397*** **
	(1.16)	**(-1.25)**	**(1.24)**	**(-2.94)**	**(1.51)**	**(-4.64)**	**(0.47)**	**(-4.36)**	**(-1.57)**	**(-5.74)**
Log_brokerage_size	0.001	-0.031	0.002	-0.006	0.003	-0.007	0.006	-0.004	0.006	-0.007
	(0.12)	(-1.4)	(0.25)	(-0.27)	(0.47)	(-0.29)	(0.85)	(-0.18)	(0.84)	(-0.3)
General_experience	-0.013*	0.011	-0.015**	-0.001	-0.015**	-0.011	-0.017**	-0.022	-0.021***	-0.025
	(-1.83)	(0.46)	(-2.17)	(-0.06)	(-2.22)	(-0.44)	(-2.46)	(-0.87)	(-2.74)	(-1.04)
Log_number_of_companies	-0.012	0.046	-0.004	0.046	0.000	0.048	0.004	0.041	0.015	0.000
	(-0.81)	(0.93)	(-0.24)	(0.91)	(0.03)	(0.92)	(0.28)	(0.8)	(0.91)	(-0.01)
Log_forecast_horizon	-0.059***	0.438***	-0.059***	0.421***	-0.081***	0.408***	-0.092***	0.436***	-0.106***	0.433***
	(-3.12)	(6.84)	(-3.42)	(6.81)	(-4.86)	(6.55)	(-5.51)	(7.14)	(-5.51)	(7.6)
Log_day_lapsed	-0.005	0.034*	-0.007	0.033*	-0.008	0.038*	-0.007	0.038*	-0.006	0.043**
	(-0.93)	(1.78)	(-1.24)	(1.68)	(-1.56)	(1.88)	(-1.17)	(1.93)	(-0.95)	(2.25)
Experience_firm	0.010	-0.023	0.010	-0.021	0.009	-0.019	0.009	-0.017	0.004	-0.016
	(1.64)	(-1.11)	(1.54)	(-0.98)	(1.42)	(-0.86)	(1.44)	(-0.76)	(0.56)	(-0.74)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No of obs.	12,002	7,448	13,384	8,482	14,211	9,141	15,334	9,888	19,973	12,567
R-squared	0.9040	0.9680	0.8955	0.9635	0.8941	0.9577	0.8771	0.9544	0.7828	0.9371

TABLE 10
Sensitivity Test
Effect of disastrous weather events on analyst forecast pessimism
(four-quarter-ahead earnings forecasts)

This table reports the estimated coefficients of the difference-in-difference model. The sample period is 1996 to 2010. The dependent variable is *Pessimism_level* which is the difference between the consensus forecast of analysts who cover the same firm j at the same time and an analyst's earnings forecast, scaled by the share price in the month prior to the announcement date. *Affected* is an indicator variable coded as 1 if the analyst works for a brokerage house that locates in an affected area on the same year that a disastrous event occurs, and 0 otherwise. *Post* is an indicator variable that takes 1 if a forecast is made after the occurrence of the disastrous event and 0 otherwise. *, ** and *** represent significance at the 10%, 5%, and 1% level, respectively.

	3 months		**6 months**		**9 months**		**12 months**		**24 months**	
	Lower than concensus	**Higher than concensus**	**Lower than concensus**	**Higher than concensus**	**Lower than concensus**	**Higher than concensus**	**Lower than concensus**	**Higher than concensus**	**Lower than concensus**	**Higher than concensus**
Parameter	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**
Affected	-0.078*	0.001	-0.063	-0.009	-0.08**	-0.045	-0.081**	-0.026	-0.022***	0.021
	(-1.65)	(0.01)	(-1.46)	(-0.12)	(-2.03)	(-0.68)	(-2.13)	(-0.41)	(-3.58)	(1.6)
Post	-0.006**	0.003	-0.004*	0.005*	-0.003	0.006***	-0.006***	0.008***	-0.011***	0.081***
	(-2.4)	(0.8)	(-1.93)	(1.9)	(-1.53)	(3.01)	(-3.75)	(4.02)	(-2.93)	(11.92)
Affected*Post	**0.007***	**0.000**	**0.004**	**0.000**	**0.001**	**-0.003**	**0.003**	**-0.004**	**0.01**	**0.002**
	(1.82)	**(-0.04)**	**(1.24)**	**(-0.05)**	**(0.28)**	**(-0.64)**	**(1.01)**	**(-0.92)**	**(1.56)**	**(0.11)**
Log_brokerage_size	-0.04**	0.048	-0.036**	0.059*	-0.037***	0.052*	-0.036***	0.056**	-0.006***	0.002
	(-2.26)	(1.39)	(-2.28)	(1.94)	(-2.76)	(1.88)	(-2.73)	(2.06)	(-2.66)	(0.51)
General_experience	-0.025***	-0.031***	-0.024***	-0.057***	-0.023***	-0.071***	-0.021***	-0.062***	0.012***	-0.009**
	(-3.31)	(-3.35)	(-3.49)	(-6.44)	(-3.47)	(-8.23)	(-3.39)	(-7.4)	(4.75)	(-2.12)
Log_number_of_companies	-0.006	0.040	-0.026	0.066**	-0.006	0.074**	0.017	0.081**	0.00	-0.003
	(-0.26)	(1.16)	(-1.25)	(2.04)	(-0.32)	(2.29)	(0.93)	(2.54)	(0.47)	(-0.28)
Log_forecast_horizon	0.015***	-0.015***	0.016***	-0.014***	0.016***	-0.014***	0.015***	-0.015***	0.00	-0.012
	(15.43)	(-11.42)	(17.54)	(-11.15)	(18.4)	(-11.57)	(18.75)	(-12.29)	(-0.45)	(-1.06)
Log_day_lapsed	-0.003***	0.003***	-0.003***	0.003***	-0.003***	0.003***	-0.003***	0.003***	0.003*	-0.006*
	(-8.46)	(5.11)	(-7.93)	(5.3)	(-8.53)	(5.57)	(-9.15)	(5.71)	(1.76)	(-1.67)
Experience_firm	0.017***	-0.009**	0.015***	0.012***	0.017***	0.026***	0.018***	0.016***	-0.004*	0.006
	(5.73)	(-1.99)	(5.75)	(2.97)	(6.8)	(6.32)	(7.47)	(4)	(-1.88)	(1.64)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No of obs.	89,847	67,815	104,093	78,481	116,423	87,813	126,411	95,337	17,951	14,589
R-squared	0.8182	0.9244	0.8125	0.9120	0.8075	0.9017	0.7992	0.8950	0.8461	0.7953

TABLE 11
Sensitivity Test
Panel A: Effect of disastrous weather events on analyst forecast accuracy
(four-quarter-ahead earnings forecasts)

This table reports the estimated coefficients of the difference-in-difference model. The sample period is 1996 to 2010. The dependent variable is *Forecast accuracy* which is the absolute difference between an analyst's earnings forecast and the actual earnings, scaled by the share price in the month prior to the announcement date. It is multiplied by -1 for ease of interpretation. *Affected* is an indicator variable coded as 1 if the analyst works for a brokerage house that locates in an affected area on the same year that a disastrous event occurs, and 0 otherwise. *Post* is an indicator variable that takes 1 if a forecast is made after the occurrence of the disastrous event and 0 otherwise. *, ** and *** represent significance at the 10%, 5%, and 1% level, respectively.

	3 months	**6 months**	**9 months**	**12 months**	**24 months**
Parameter	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**
Affected	-0.006**	-0.004	-0.002	0.000	0.007**
	(-2)	(-1.33)	(-0.85)	(-0.04)	(2.46)
Post	0.015***	0.02***	0.023***	0.023***	0.014***
	(3.82)	(6.73)	(8.76)	(9.51)	(6.76)
Affected*Post	**-0.002**	**-0.002**	**-0.004**	**-0.007***	**-0.015*****
	(-0.43)	**(-0.49)**	**(-0.88)**	**(-1.73)**	**(-4.13)**
Log_brokerage_size	0.007***	0.007***	0.006***	0.006***	0.006***
	(4.99)	(5.04)	(5.11)	(5.26)	(5.47)
General_experience	0.009***	0.008***	0.007***	0.006***	0.006***
	(6.25)	(6.19)	(5.39)	(5.31)	(5.4)
Log_number_of_companies	0.002	0.005	0.006**	0.007***	0.007***
	(0.75)	(1.52)	(2.01)	(2.66)	(2.9)
Log_forecast_horizon	0.002	0.002	0.003**	0.003***	0.001
	(1.21)	(1.58)	(2.55)	(2.58)	(0.5)
Log_day_lapsed	0.000	0.000	0.000	0.000	0.000
	(-0.34)	(0.28)	(0.36)	(0.33)	(0.23)
Experience_firm	-0.003***	-0.003***	-0.002*	-0.003**	-0.001
	(-2.9)	(-2.76)	(-1.84)	(-2.43)	(-1.3)
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes
No of obs.	157,662	182,574	204,236	221,748	276,196
R-squared	0.3393	0.2989	0.2691	0.2564	0.2270

TABLE 11
Sensitivity Test
Panel B: Effect of disastrous weather events on analyst forecast errors (four-quarter-ahead earnings forecasts)

This table reports the estimated coefficients of the difference-in-difference model. The sample period is 1996 to 2010. The dependent variable is *Forecast Error* which is the difference between an analyst's earnings forecast and the actual earnings, scaled by the share price in the month prior to the announcement date. *Affected* is an indicator variable coded as 1 if the analyst works for a brokerage house that locates in an affected area on the same year that a disastrous event occurs, and 0 otherwise. *Post* is an indicator variable that takes 1 if a forecast is made after the occurrence of the disastrous event and 0 otherwise. *, ** and *** represent significance at the 10%, 5%, and 1% level, respectively.

	3 months		**6 months**		**9 months**		**12 months**		**24 months**	
	Negative Forecast Error	**Positive Forecast Error**	**Negative Forecast Error**	**Positive Forecast Error**	**Negative Forecast Error**	**Positive Forecast Error**	**Negative Forecast Error**	**Positive Forecast Error**	**Negative Forecast Error**	**Positive Forecast Error**
Parameter	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**
Affected	-0.002	0.005	-0.001	0.004	0.008	0.008	0.016***	0.012	0.04***	0.011
	(-0.32)	(0.21)	(-0.16)	(0.16)	(1.3)	(0.33)	(2.71)	(0.52)	(5.51)	(0.48)
Post	0.013**	-0.024	-0.003	-0.164***	0.001	-0.205***	0.005	-0.224***	-0.009*	-0.545***
	(1.98)	(-0.7)	(-0.51)	(-6.38)	(0.18)	(-9.03)	(0.98)	(-10.75)	(-1.74)	(-30.48)
Affected*Post	**-0.013**	**0.026**	**-0.016***	**0.027**	**-0.02****	**0.030**	**-0.039*****	**0.026**	**-0.061*****	**0.016**
	(-1.24)	**(0.53)**	**(-1.86)**	**(0.68)**	**(-2.4)**	**(0.87)**	**(-4.79)**	**(0.8)**	**(-6.71)**	**(0.55)**
Log_brokerage_size	0.001	-0.016	0.002	-0.012	0.002	-0.010	0.001	-0.008	0.003	-0.009
	(0.61)	(-1.26)	(0.64)	(-1.06)	(0.69)	(-0.96)	(0.59)	(-0.8)	(0.98)	(-0.99)
General_experience	-0.002	0.012	-0.002	0.011	-0.004*	0.009	-0.003	0.009	-0.006**	0.003
	(-0.86)	(0.97)	(-1)	(0.99)	(-1.66)	(0.86)	(-1.09)	(0.85)	(-2.35)	(0.36)
Log_number_of_companies	0.008	-0.061**	0.003	-0.067**	0.008	-0.073***	0.005	-0.066***	0.005	-0.056**
	(1.43)	(-2.11)	(0.61)	(-2.54)	(1.44)	(-2.93)	(0.94)	(-2.78)	(0.77)	(-2.55)
Log_forecast_horizon	-0.073***	0.533***	-0.076***	0.492***	-0.08***	0.48***	-0.083***	0.462***	-0.099***	0.419***
	(-30.81)	(41.74)	(-32.32)	(42.75)	(-33.48)	(44.57)	(-35.11)	(45.71)	(-37.77)	(44.51)
Log_day_lapsed	0.002**	-0.054***	0.003***	-0.05***	0.004***	-0.048***	0.004***	-0.045***	0.003***	-0.04***
	(2.02)	(-11.77)	(3.78)	(-11.95)	(4.11)	(-12.25)	(4.77)	(-11.98)	(2.97)	(-11.48)
Experience_firm	-0.001	0.009	0.002	0.011	0.004**	0.014	0.004*	0.013	0.007***	0.021**
	(-0.5)	(0.88)	(0.89)	(1.13)	(1.99)	(1.5)	(1.75)	(1.51)	(3.07)	(2.5)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No of obs.	78,640	79,022	91,662	90,912	103,243	100,993	112,646	109,102	140,235	135,961
R-squared	0.8762	0.8084	0.8468	0.8043	0.8156	0.8003	0.8003	0.7968	0.7237	0.7479

TABLE 12

Effect of natural disaster on analyst recommendation

This table reports the estimated coefficients of the difference-in-difference model. The sample period is 1996 to 2010. The dependent variable is *Downward_Recommendation, which* is a dummy variable that takes the value of 1 if an analyst degrades a firm's stock recommendation. *Affected* is an indicator variable coded as 1 if the analyst works for a brokerage house that locates in an affected area on the same year that a disastrous event occurs, and 0 otherwise. *Post* is an indicator variable that takes 1 if a forecast is made after the occurrence of the disastrous event and 0 otherwise. *, ** and *** represent significance at the 10%, 5%, and 1% level, respectively.

	3 months	**6 months**	**9 months**	**12 months**	**24 months**
Parameter	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**
Affected	0.978***	0.984***	0.987***	0.995***	0.985***
	(16.95)	(17.12)	(17.25)	(17.42)	(17.64)
Post	0.844***	0.939***	1.059***	1.089***	1.347***
	(5.46)	(8.39)	(11.3)	(12.73)	(23.43)
Affected*Post	**-0.090**	**-0.089**	**-0.201**	**-0.209****	**-0.279*****
	(-0.5)	**(-0.69)**	**(-1.85)**	**(-2.11)**	**(-4.2)**
Log_brokerage_size	0.05*	0.058**	0.065***	0.071***	0.063***
	(1.82)	(2.24)	(2.61)	(3.01)	(4.1)
General_experience	-0.289***	-0.294***	-0.3***	-0.314***	-0.252***
	(-10.88)	(-11.58)	(-12.31)	(-13.4)	(-14.19)
Log_number_of_companies	-0.247***	-0.239***	-0.244***	-0.234***	-0.222***
	(-6.12)	(-6.22)	(-6.56)	(-6.52)	(-9.31)
Experience_firm	0.341***	0.335***	0.336***	0.329***	0.271***
	(18.94)	(19.44)	(20.08)	(20.32)	(23.46)
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes
No of downward recommendations	2,087	2,334	2,562	2,778	6,157
No of obs.	43,680	45,686	47,462	49,149	71,765
R-squared	0.0608	0.0699	0.0763	0.0808	0.1050

TABLE 13
Sensitivity Test
Effect of disastrous weather events on analyst forecast pessimism in economic downturns

This table reports the estimated coefficients of the difference-in-difference model. The test is conducted for observations affected by the two economic downturns in 2001 and 2008. The dependent variable is *Pessimism_level* which is the difference between the consensus forecast of analysts who cover the same firm j at the same time, scaled by the share price in the month prior to the announcement date. *Affected* is an indicator variable coded as 1 if the analyst works for a brokerage house that locates in an affected area on the same year that a disastrous event occurs, and 0 otherwise. *Post* is an indicator variable that takes 1 if a forecast is made after the occurrence of the disastrous event and 0 otherwise. *, ** and *** represent significance at the 10%, 5%, and 1% level, respectively.

	3 months		**6 months**		**9 months**		**12 months**		**24 months**	
	Lower than consensus	**Higher than consensus**	**Lower than consensus**	**Higher than consensus**	**Lower than consensus**	**Higher than consensus**	**Lower than consensus**	**Higher than consensus**	**Lower than consensus**	**Higher than consensus**
Parameter	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**	**Coefficient (t)**
Affected	-0.083***	0.023***	-0.083***	0.023***	-0.083***	0.023***	-0.084***	0.022***	-0.084***	0.022***
	(-13.33)	(3.21)	(-13.5)	(3.19)	(-13.54)	(3.18)	(-13.58)	(3.11)	(-13.76)	(3.16)
Post	0.017	-0.026**	0.013	-0.03***	0.016	-0.029***	0.021**	-0.025**	0.02**	-0.025**
	(1.52)	(-2.29)	(1.22)	(-2.81)	(1.61)	(-2.79)	(2.14)	(-2.47)	(2.1)	(-2.46)
Affected*Post	**0.042*** **	**-0.03***	**0.047*** **	**-0.014**	**0.04*** **	**-0.013**	**0.031*** **	**-0.021**	**0.033*** **	**-0.024***
	(2.94)	**(-1.77)**	**(3.83)**	**(-0.94)**	**(3.43)**	**(-0.94)**	**(2.77)**	**(-1.6)**	**(3.1)**	**(-1.91)**
Log_brokerage_size	0.013***	0.009***	0.012***	0.009***	0.013***	0.009***	0.013***	0.01***	0.013***	0.01***
	(4.2)	(2.76)	(3.86)	(2.8)	(4.24)	(2.94)	(4.45)	(3.09)	(4.6)	(3.28)
General_experience	-0.009***	0.000	-0.009***	0.001	-0.009***	0.000	-0.009***	0.001	-0.008***	0.001
	(-2.61)	(0.1)	(-2.69)	(0.35)	(-2.82)	(0.13)	(-2.75)	(0.32)	(-2.61)	(0.25)
Log_number_of_companies	-0.021***	-0.003	-0.022***	-0.004	-0.02***	-0.003	-0.018**	-0.004	-0.015**	-0.004
	(-2.72)	(-0.41)	(-2.96)	(-0.57)	(-2.82)	(-0.45)	(-2.46)	(-0.58)	(-2.2)	(-0.51)
Log_forecast_horizon	0.025***	-0.044***	0.027***	-0.044***	0.026***	-0.043***	0.026***	-0.042***	0.026***	-0.043***
	(9.79)	(-14.47)	(10.8)	(-15.36)	(10.75)	(-15.17)	(10.75)	(-15.12)	(11.24)	(-15.96)
Log_day_lapsed	0.006***	-0.003**	0.006***	-0.003***	0.006***	-0.003***	0.006***	-0.003**	0.006***	-0.003***
	(5.14)	(-2.27)	(5.5)	(-2.66)	(5.68)	(-2.58)	(5.61)	(-2.38)	(5.86)	(-2.61)
Experience_firm	0.008***	-0.003	0.008***	-0.004	0.008***	-0.004	0.008***	-0.003	0.007***	-0.003
	(2.92)	(-1.1)	(3.04)	(-1.38)	(3.04)	(-1.33)	(2.99)	(-1.22)	(2.87)	(-1.08)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No of obs.	21,004	15,783	22,705	17,032	23,558	17,617	24,179	18,048	25,569	19,149
R-squared	0.5813	0.8315	0.5873	0.8309	0.5908	0.8295	0.5882	0.8278	0.5894	0.8259

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