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Natural disasters and analysts' earnings forecasts[☆]

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ABSTRACT

The effects of natural disasters on capital markets have been investigated by limited evidence even though these calamities bring considerable damages or loss of life. To fill this gap, we investigate the impacts of natural disasters, particularly earthquakes, on security analysts' earnings forecasts for affected firms in China. We obtain three key findings. First, analysts' optimism significantly decreases for firms located in neighborhood areas. Second, earthquakes do not significantly affect firm earnings and stock returns, thereby indicating that post-earthquake analyst pessimism is not based on rational judgment. Third, media attention promotes irrational pessimism among analysts, and post-earthquake pessimism is a result of heuristics bias attributable to psychological shocks. However, analysts correct the bias after initial irrational forecasts. Taken together, our findings contribute to the broader psychology and economics literature on the effects of natural disasters on analyst forecasts.

1. Introduction

In recent decades, approximately 300 natural disasters occur worldwide and cause $100 billion in economic costs each year.[1] Although natural disasters cause widespread destruction, major collateral damage, or loss of life, studies scarcely evaluate the consequences of natural disasters in capital markets.

This research examines whether and how natural disasters affect security analysts' earnings forecasts. Analysts are important market participants because they collect, analyze, and transmit information, especially in times of information shortage (Charitou et al. (2019)). Prior literature has thoroughly investigated the determinants and consequences of analysts' optimism bias stemming from

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[1] https://ourworldindata.org/natural-disasters#empirical-view.

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conflicts of interests,[2] but surprisingly, few studies investigate the effect of natural disasters on analysts' forecasts. In addition, whether this effect is driven by irrational or rational recognition remains unclear. Given the crucial role of analysts in transmitting information, further understanding of their decisions is essential to learn the evolution of information efficiency in financial markets.

Motivated by psychology studies that people often make decisions on the basis of heuristics with only a subset of available information (Tversky and Kahneman (1973)), we investigate whether natural disasters irrationally lead to security analysts' pessimism and eventually affect analysts' forecasts. A salient characteristic of natural disasters is generally causing considerable losses to human society. The huge impact of this salience induces people to overestimate the actual low probability of natural disasters (Bordalo et al. (2012); Bordalo et al. (2013)). Although analysts may irrationally react to natural disasters, an alternatively rational story predicts that natural disasters may bring adverse effects on firm operations or the local economy and thus negatively affect analysts' forecasts.

Therefore, although we expect that natural disasters lead to security analysts' pessimistic forecasts, distinguishing the irrational from the rational story is quite challenging. We overcome this difficulty by using the earthquakes in China to represent natural disasters and identify its relationship and mechanisms with analyst forecasts. Several advantages of earthquake events in China result in its suitability for our empirical tests. First, the occurrence of earthquakes is exogenous to firm characteristics and analysts' judgments. Compared with other natural disasters, such as hurricanes or floods, predicting the occurrence of a specific earthquake is nearly impossible under the current level of scientific development (Geller et al. (1997)). Compared with negative social events, the occurrence of earthquakes is unlikely affected by the local economic and social environment. In other words, analysts would unlikely adjust their forecasts in advance owing to expectations of an earthquake occurring in a specific place. Second, severe earthquakes, which bring huge damage to the affected areas, are salient events. This salience of earthquake events not only directly affects the emotional states of people in disaster areas but also those of people in non-disaster areas via news media. Third, we can easily identify the exact location of earthquakes, thereby enabling us to set up an identification strategy according to the distance from the epicenters, which helps us evaluate the causal influence of earthquakes on analyst forecasts.

In this study, we investigate the impact of earthquakes on analyst forecasts. Based on their geographical distance from the epicenter of earthquakes, we assign firms into three groups, namely, disaster zone, neighborhood area, and control group. Following the literature on the historical geography of earthquake-affected areas, we define the disaster zone as the area located within 150 km from the epicenter and define the neighborhood area as the area located 150 km to 500 km from the epicenter. Given their proximity to epicenters, firms in disaster zones are likely to be affected by earthquakes, whereas those firms in neighborhood areas have a relatively low chance to be affected. After the occurrence of earthquakes, analysts become significantly pessimistic in their earnings forecasts for firms in neighborhood areas. However, such a decline in optimism does not indicate that the earnings forecasts of analysts are without optimism bias. Instead, we contend that such decline reflects analyst pessimism under the prevalence of optimism bias. The dynamic investigation does not reveal any pre-event trends in the pessimistic sentiment of analysts, thereby suggesting that such pessimism is driven by the occurrence of earthquakes rather than analysts' anticipation of earthquakes.

We further explore our baseline results by examining whether post-earthquake analyst pessimism is driven by rational judgments or behavioral biases. First, we examine the impact of earthquakes on corporate earnings and stock returns. If earthquakes negatively affect neighborhood area firms, then the pessimism among analysts is rational. In other words, post-earthquake analyst pessimism is supported by a rational story where firms are expected to demonstrate poor financial performance or have low stock returns after earthquakes. Meanwhile, earthquakes negatively affect the earnings of disaster zone firms, thereby suggesting that these disasters can influence the operations of certain firms. However, the changes in the post-earthquake earnings of neighborhood area firms do not show any significant negative impact. In addition, the stock returns of neighborhood area firms do not significantly change in the short (within 1 month) or long term (within 36 months). Collectively, analysts show over-pessimism for neighborhood area firms even though they are not significantly affected by earthquakes. These findings help us explore the irrational story of post-earthquake analyst pessimism.

An alternative explanation of the post-earthquake analyst pessimism could be behavior biases. If earthquakes have no negative impact on corporate financial performance and stock returns, then, analyst pessimism after earthquakes could be irrational. To test this irrational story, we refer to the discussion of the salience of earthquake events in the existing literature to investigate whether the analyst pessimism is the result of heuristic bias. The salience of any event is affected by the availability of information. A substantial availability of information increases the likelihood that events would lead to availability bias. Using media attention to investigate the availability of earthquake information, post-earthquake analyst pessimism is generated if an earthquake event has considerable availability of information. Media attention strengthens psychological shocks to analysts. Such analyst pessimism thus exhibits the feature of availability bias and may be caused by the analysts' heuristic biases. What's more, we find that post-earthquake analyst pessimism is observed just in the initial few forecasts after earthquakes, suggesting analysts' ability to correct behavioral biases.

We contribute to related literature in the following ways. First, this research contributes to the growing literature on the economic consequence of natural disasters in capital markets. Recently, research has begun to focus on how natural disasters influence capital markets, such as corporate manager behaviors (e.g., Dessaint and Matray (2017)), financial fragility (e.g., Klomp (2014)), the response of banks (e.g., Cortés and Strahan (2017)), and household wealth allocations (e.g., Shi et al., 2020). The current research contributes to these studies by studying analyst responses to earthquakes and presenting causal evidence that natural disasters significantly lead to analyst pessimism in earnings forecasts. Our findings thus shed new insights on previous studies on analysts, which focus on their characteristics. Limited attention is paid to natural disasters or how such events affect decision making and cognitive ability.

[2] Prior studies focus on the characteristics of analysts or emphasize the errors derived from conflicts of interest (e.g., Michaely and Womack (1999), Ljungqvist et al. (2007), Clarke et al. (2007), Mola and Guidolin (2009), Kirk (2011), and Kothari et al. (2016)).

Second, we contribute to psychology and economics literature by presenting evidence on how heuristic bias irrationally affects analyst judgments after natural disasters. To the best of our knowledge, scant research exists on the heuristic bias in analyst behaviors. Hirshleifer et al. (2019) focus on heuristic analyst forecasts derived from decision fatigue. By comparison, this study focuses on the heuristic bias in analysts' earnings forecasts owing to psychological shocks caused by earthquakes. We also underline the role of salience, thereby extending the application of behavioral science to the discussion of analyst behaviors. The conclusions of this research also show that heuristic bias can further influence the information structure of analyst forecasts. Prior studies believe that analysts typically overreact to positive news of firms but underreact to negative news (e.g., Easterwood and Nutt (1999)). Based on this idea, numerous studies explored the positive sentiment of analysts. The present study finds that when natural disasters occur, heuristic bias leads analysts to focus excessively on the negative impact of the event on firms. This finding indicates that analysts are overreacting to negative news. Thus, the occurrence of natural disasters is suggested to cause an excessive increase in the proportion of negative news on analyst forecasts. This phenomenon confirms the possibility that behavioral bias could incorrectly change the information structure in analyst reports. Consequently, our research enriches the previous discussion on the information content of analyst forecasts.

Third, we believe that our discussion regarding the behavioral biases of capital market participants in emerging markets is important for policymakers. Prior studies tend to conclude that emerging markets are characterized by inefficiencies (e.g., Bhattacharya et al. (2000)) and higher transaction costs and information costs (e.g., Griffin et al. (2010)). As a typical emerging market economy, China provides an ideal research setting to explore the influence of natural disasters on the sentiment of market participants in the early stage of capital market development. China's capital market has a relatively short history and is dominated by retail investors (Li and Wang (2010)). Retail investors are generally viewed as unsophisticated investors who have a short-term speculative investment perspective and tend to be influenced by behavioral biases (Kaniel et al. (2008); Dhar and Zhu (2006); Seasholes and Zhu (2010)). Lower investor sophistication makes Chinese investors, especially retail investors, easier to be affected by analyst sentiments because of investors' inability to recognize the full implications of market information (Bernard and Thomas (1990)). Therefore, in China, investors will be prone to be influenced by the analysts' behavior bias, for which policymakers should consider policy nudge for investor protection.

The rest of this paper proceeds as follows. Section 2 reviews related literature and develops the hypotheses. Section 3 presents the data source and explains the empirical design. Section 4 examines the impact of earthquakes on analyst forecasts and explores the underlying mechanism. Section 5 discusses the robustness tests and additional analyses. Section 6 presents a brief conclusion.

2. Literature and hypotheses

2.1. Related literature

Previous literature has pointed out that analysts often underreact to negative news and overreact to positive news, indicating a systematic over-optimism (Easterwood and Nutt (1999)). Indeed, analysts have been shown to have strong incentives to be overly optimistic in earnings forecasts or stock recommendations. The two main sources of over-optimism are pressure from clients and career concerns.

Analysts benefit from connections with their brokerage firms, thereby enabling pressure from clients to often exert an influence on analysts through their employers. On the one hand, the investment banking relationship can lead analysts affiliated with investment banking to be overly optimistic for their client companies. Related analysts may frequently comment on and recommend the firms they recently issued (Michaely and Womack (1999)) and release optimistic earnings forecasts and investment recommendations for these firms (Dugar and Nathan (1995)) to maintain a good relationship with clients. In addition, optimistic earnings forecasts can also help analysts obtain other private information (Ke and Yu (2006)). Lin and McNichols (1998) show that compared with unrelated analysts, related analysts from lead underwriters and co-underwriters are more optimistic about the growth forecast and stock recommendation and tend to selectively deliver positive information of their related firms. O'Brien et al. (2005) show that related analysts quickly respond to the good news of client firms but are reluctant to release bad news. Moreover, quick and frequent recommendations of buying rates from related analysts are observed after stock issues, but the decline in recommendation rate is slow. Rees et al. (2017) show that analysts strategically time the release of recommendation revisions to maintain favorable relationships with their management. All these studies conclude that investment–banking relationships may induce over-optimism among related analysts.

On the other hand, generating commission income for brokerage firms is also an incentive for the over-optimism among analysts. Irvine (2004) shows that analyst forecasts affect brokerage commission income such that analysts help generate higher trading fees for their employers through optimistic stock recommendations. Commissions from both institutional and individual investors could prompt analysts to issue upbeat ratings. Mola and Guidolin (2009) find that pressure from fund clients could lead to a frequent issuance of positive ratings by related analysts on the stocks invested by clients. A greater shareholding of clients leads to further optimistic ratings from related analysts. Firth et al. (2013) find that a stronger positive rating by related analysts of the stocks held by fund clients can increase the commission income from such fund clients. Malmendier and Shanthikumar (2014) show that analysts may intentionally issue overly optimistic buying rates for individual investors to increase the commission income from them. Thus, analysts also have an incentive to be overly optimistic to boost commission income of their brokerage firms.

Moreover, career concerns lead analysts to be overly optimistic. Discussions on analyst behavior commonly assume that analysts behave independently of each other. However, this case is relatively untrue (Mokoaleli-Mokoteli et al. (2009)). Welch (2000) believes that the stock rating from several analysts would positively influence the subsequent stock recommendations from other analysts, indicating the existence of the herding effect. In this case, career concerns play an important role. Analysts may lose their jobs owing to deviations from consensus forecasts, and thus, inexperienced analysts tend to delay releasing forecasts and to deviate less from consensus forecasts (Hong et al. (2000)). With widespread optimism bias in the market, the herd behavior undoubtedly strengthens the overall optimism bias of the entire analyst group. Hong and Kubik (2003) show that analysts' career advancement depends on the degree of optimism rather than the accuracy of their forecasts. This case is especially true in hot markets, where brokerage firms reward optimistic analysts who drive stock prices high. Ke and Yu (2006) show that analysts who issue optimistic earnings forecasts are less likely to be fired. Thus, career concerns can also induce over-optimism among analysts. In summary, analysts have strong incentives to be over-optimistic because of pressure from clients and career concerns.

Chinese analysts also have similar incentives to be overly optimistic. In China, pressure from clients drives analysts to maintain their optimism. For example, Xu et al. (2013a, 2013b) indicate that in China, affiliations with listed firms, such as investment banking relationships, may promote analysts to conceal negative news for firms. In addition, the generation of commission income is a source of analyst optimism in China. Firth et al. (2013) use a unique dataset from China and provide evidence that the optimism in analyst recommendations increases the commission revenue from fund clients. Career concerns play an important role in the optimism of Chinese analysts. Similar to analysts in the U.S. or European countries, the optimism of analysts is also related to their career advancement. In China, being voted as a star analyst is viewed as a huge career step, which is followed by a significant increase in reputation and compensation. Gu et al. (2019) find that Chinese analysts tend to issue optimistic recommendations for stocks held by fund managers, and in return, they likely acquire favorable votes from these managers in the selection of star analysts. Basically, pressure from clients and career concerns also provides Chinese analysts with optimism motivation like it does for analysts in the U.S. and European countries. Therefore, regarding the tendency of optimism, we argue that Chinese analysts have similar behavior patterns as analysts in the U.S. and Europe.

Owing to these strong incentives, we argue that over-optimism has become a common phenomenon among analysts. However, this contention does not necessarily mean that analysts show no pessimism. In specific situations, including during natural disasters, such as earthquakes, we believe that analysts may become pessimistic. On the one hand, earthquakes may have negative impacts on firm operations or stock returns, thereby creating a tendency among analysts to show pessimism when making earnings forecasts for nearby firms to express concerns about their future developments. On the other hand, analysts' behavioral biases caused by psychological shocks from the earthquakes may also prompt analysts' pessimism in earnings forecasts.

2.2. Unpredictability of earthquakes

The occurrence of earthquakes is exogenous to analysts' forecasts because it is unpredictable. Earthquakes tend to cluster in certain areas with active geological activities, and we cannot deny that a single fatal earthquake may be followed by a sequence of small earthquakes. In this case, predicting a specific earthquake is nearly impossible. This view has been confirmed in geographical research. Geller et al. (1997) found that we cannot predict earthquakes based on certain anomalous phenomena because "the pattern of alleged precursors tends to vary greatly from one earthquake to the next, and the alleged anomalies are frequently observed at only one point, rather than throughout the epicentral region." In sum, no powerful evidence suggests that earthquakes can be accurately predicted by certain precursors. Unlike other natural disasters such as hurricanes, which can be detected in advance based on changes in weather conditions, the occurrence of an earthquake, including its exact time, location, and intensity, is nearly impossible to predict.

China has a mature warning system for many natural disasters. For example, the Typhoon Warning Signal has five typhoon warning levels that correspond to different wind force levels. Similar warning signals include the Snowstorm Warning Signal, Sandstrom Warning Signal, Rainstorm Warning Signal, and Drought Warning Signal. Therefore, analysts can obtain information on the occurrence of these disasters whenever they want. However, China and other countries have not built a similar warning system for earthquakes given their unpredictable nature. In special cases, the occurrence of an earthquake can be predicted in advance, but only for a few seconds. For example, in 2014, the Berkeley Seismological Laboratory successfully detected an earthquake 10 s prior to its occurrence.[3] However, no Chinese institution has yet claimed to capture signals of a fatal earthquake in advance. Compared with modern technologies that can predict other natural disasters days in advance, the current scientific technologies for predicting earthquakes are unlikely to help analysts issue their forecast reports a few seconds in advance.

2.3. Hypothesis development

Earthquakes may cause analysts' pessimistic forecasts through both rational and irrational channels. In the rational channel, earthquakes are naturally assumed to exert negative effects on firms' operations and the local economy. Prior literature shows that severe natural disasters have a significant negative impact on local economic development. Compared with developed countries, developing countries with the inadequate accumulation of capital and knowledge may cause greater severity of the negative impact of natural disasters (Loayza et al. (2012); Klomp (2016)). After earthquakes, the operating uncertainty for local firms may rationally induce pessimism among analysts. Worse, for listed firms, performance in the capital market may decline owing to negative events, such as earthquakes. Empirical research has proven the shock to stock returns caused by negative events, such as terrorist attacks (e.g., Carter and Simkins (2004)). Thus, owing to concerns on corporate operations and stock returns after earthquakes, rational analysts tend to release pessimistic earnings forecasts for nearby firms.

[3] https://www.cbsnews.com/news/experimental-warning-system-gave-10-second-alert-before-quake-hit.

Alternatively, a behavioral story may predict the analyst's pessimism after earthquakes. The salience of earthquakes may lead analysts to overestimate the negative impact of earthquakes on nearby firms. Prior research has shown that people pay excessive attention to events that cause serious loss, despite its low probability of occurrence. The salience of the negative impact leads people to overestimate the risk and present risk aversion (Slovic et al. (1977) and Bordalo et al. (2012)). The probability of severe earthquakes occurring is extremely low, but they cause considerable casualties and property losses. This feature renders the earthquake a salient event. People reflect uncertainty and threats of such an event in their feelings of fear, dread, and anxiety, and overestimate the event influence in their decision-making process (Loewenstein et al. (2001)). Thus, analysts also tend to focus on earthquake events when forecasting earnings. Even if earthquakes may not affect a firm, analysts possibly allocate a heavy decision-making weight to earthquake events in their earnings forecasts as an expression of heuristic bias. A typical anecdote is from Sinolink Securities, a Chinese listed brokerage firm. In 2008, this brokerage firm issued an analyst report for Sichuan Chuantou Energy Co. LTD. (600674.SH) after Wenchuan earthquake, entitled "The Impact of Earthquake Is Limited and We Maintain the Buying Rate". In this report, the analyst didn't only maintain the buying rate for the listed firms but also stated his view that the impact of the earthquake is "limited" for many times. However, the analyst still issued a decreased forecasted EPS for the firm in this report. As a comparison, instead of worse performance, Sichuan Chuantou Energy Co. LTD. finally achieved the growth in EPS in 2008. In this example, although the analyst tried to keep optimistic in the statements and recommendations for some reasons, too much attention was still paid to the possible negative impact of the earthquake, leading to the pessimism when forecasting EPS. Thus, the use of heuristics is likely to prompt pessimism among analysts in their earnings forecasts.

Therefore, we propose that earthquakes could lead to analysts' pessimism as the first hypothesis:

H1. Analysts will significantly exhibit pessimism for earnings forecasts of firms possibly affected by earthquakes.

Regarding the rational channel, previous literature has shown that natural disasters physically destroy the factors of production, at least in the short term (e.g., Kahn (2005); Mel et al. (2012)). Similarly, natural disasters could indirectly hurt firm operations, such as by local credit conditions. Garmaise and Moskowitz (2009) and Klomp (2014) find that after natural disasters, local credit conditions also deteriorate. These factors may lead to the deterioration of corporate profitability. For firms near epicenters, natural disasters also affect stock performance. Literature shows that negative events exert a negative impact on stock returns. For example, Carter and Simkins (2004) find that the stock price of air-transport firms declined after the terrorist attack of September 11, 2001. If earthquakes could result in a long-term effect on the firm operation and local economy, analysts would rationally update their forecasts with a pessimistic judgment. Investigating the corporate financial status and stock returns after earthquakes is necessary to examine the underlying mechanism of analysts' rational forecast revisions. If the rational story is true, then, we can expect that nearby firms exhibit the worse financial status and lower stock returns than other firms after earthquakes. We propose the second hypothesis:

H2. Firms affected by earthquakes will exhibit worse financial performance and lower stock returns than unaffected firms.

As previously discussed, another underlying mechanism could simply stem from behavioral bias. If earthquakes have no negative impacts on nearby firms, post-earthquake analyst pessimism could be considered the result of irrationality. However, directly investigating the use of heuristics in analysts' judgments is difficult. Instead, we try to examine whether post-earthquake analyst pessimism shows the features of the heuristic bias that have been discussed in the existing literature.

We test the existence of heuristics biases from the perspective of salience. The salience of events is affected by the availability of information. The greater availability of information increases the likelihood that events would lead to availability bias (Tversky and Kahneman (1973); Tversky and Kahneman (1974)). Media plays an important role in grabbing attention. Extensive media coverage of quake-hit regions increases the availability of earthquake information. Even if analysts are not located in the quake-hit regions, news, pictures, and videos from disaster areas could also evoke memories of terrible experiences, thus increasing their risk aversion and pessimism about the future (Hilary and Menzly (2006); Greenwood and Nagel (2009); Malmendier and Nagel (2011); Bernile et al. (2017)). Thus, after controlling for the impacts of earthquake magnitudes on media coverage, we expect that high media coverage increases the likelihood of analysts to exhibit heuristic biases by issuing pessimistic forecasts after earthquakes. We propose the hypothesis:

H3a. Post-earthquake analyst pessimism will be more pronounced when media coverage of earthquakes is high than when it is low.

Under the story of behavioral bias, we further discuss the horizon of post-earthquake analyst pessimism. If earthquakes substantially influence firms in disaster areas, the post-earthquake analyst pessimism should be persistent because earthquakes have objectively changed the future profitability of firms shocked by earthquakes. However, if the post-earthquake analyst pessimism is driven by heuristic biases, we expect that the pessimism has a short horizon. That is because individuals may have the ability to adjust from behavioral biases (Epley and Gilovich (2006)). Previous studies also provide empirical evidence. For example, Dessaint and Matray (2017) find that corporate managers' behavioral biases caused by heuristic methods are temporary. Analysts are generally viewed as sophisticated market participants. Even if some analysts place excessive weight on the information of earthquakes in the first few forecasts after earthquakes, they can gradually correct their biases in the following forecasts. Therefore, we propose the hypothesis:

H3b. Post-earthquake analyst pessimism is temporary and analysts can correct their behavioral biases.

Previous studies find that the information environment of listed firms influences analyst behaviors (e.g., Lang, Lundholm, and Lang et al. (1996)), and analysts typically use corporate information when making forecasts. Therefore, corporate disclosure will influence the quality of analyst forecasts. Related studies offer evidence that high-quality and unified corporate disclosure will reduce analysts' uncertainty about future earnings, thereby improving analysts' information environment (Byard and Shaw (2003); Hope (2003)).

Based on these studies, we expect that when focusing on firms with low information transparency, analysts may be prone to show pessimism given the difficulties in assessing the earthquake-related losses of firms. We propose the hypothesis:

H3c. Post-earthquake analyst pessimism will be intensified when the information environment of listed firms is less transparent.

3. Data and methodology

3.1. Earthquake data

We obtain earthquake data from the Emergency Events Database (EM-DAT) created by the Centre for Research on the Epidemiology of Disasters (CRED) with the initial support of the World Health Organization (WHO) and the Belgian Government. We can obtain the time, magnitude, location of earthquakes, and the data of casualty from this database.

China is a country with frequent earthquakes. A total of 52 major earthquakes occurred in China from 2007 to 2016 with total casualties of over 90,000, according to data from EM-DAT. During the sample period of this study, a total of 457,060 earthquakes of magnitude 2.0 or above on Richter scale occurred in China.[4] However, the majority of these earthquakes were unknown and did not cause any damage. We remove the earthquake that did not cause death and identify 25 earthquake events during our sample period from EM-DAT to ensure that the earthquakes are adequately salient. We merely retain the first earthquake event that caused casualties in successive earthquakes occurring in the same province and in the same year to minimize induced relations between earthquakes. Table 1 reports the 19 earthquake events in our sample after the screening procedure. Among these 19 earthquake events, the average magnitude was 5.9 on the Richter scale, with a minimum magnitude of 4.4. All were severe earthquakes of magnitude over 4.0 on the Richter scale.

3.2. Analyst data

We obtain analyst data from China Stock Market & Accounting Research Database (CSMAR). The analyst group in China develops rapidly despite their short history than mature capital markets, such as the U.S. The earliest analyst report was released in 2002 according to our raw data. The number of analyst reports released was merely 362, and numerous firms were not covered by analysts in that year. However, the number of analyst reports reached 45,310 in 2016 and shows rapid development. Fig. 1 illustrates a dramatic increase in the number of analyst reports since 2007. We set the sample period starting from 2007 considering the low development level of Chinese analyst group and the small number of analyst reports issued before 2007.

In our dataset of earnings forecasts, all the analyst forecasts focus on annual reports. We dismiss forecasts with information missing in two aspects: 1) Observations missing the analysts' characteristics (e.g., name, gender, educational level, and employer), and 2) observations missing the forecast information of covered firms (e.g., released date of forecasts and the forecasted earnings per share). Since a single analyst report can contain multiple earnings forecasts for the next few years, to alleviate the concern that our empirical results are driven by reports with multiple forecasts, for each analyst report, we just keep the earnings forecast for the current year. During the sample period, a total of 176,769 analyst forecasts were obtained, involving 2353 A-share firms.

3.3. Empirical design

As mentioned above, earthquakes provide an ideal natural experimental framework for testing the causal relationship between earthquakes and analyst sentiments. Following Dessaint and Matray (2017), we examine whether the changes in analyst sentiments and corporate earnings differ across firms that are located different distances away from epicenters after the occurrence of earthquakes.

We classify firms into disaster zone, neighborhood area, and control group firms based on their distance from epicenters. The deadliest earthquake in the history of China and the world took place in Hua County, Shaanxi Province on January 23, 1556, where more than 830,000 people were killed. An investigative report published by the earthquake team of Shaanxi Province in 1976 reveals that the distance between the epicenter and the farthest county to report any damage was approximately 450 km (Yuan and Feng, 2010). Therefore, we defined those areas located within 500 km from epicenters as areas that are possibly affected by earthquakes. However, an earthquake that caused such a large extent of damage was not recorded during our sample period. To identify those areas with a relatively high probability to be directly affected by earthquakes, we used a small scope to define our disaster zone. For example, the earthquake that occurred in Wenchuan County, Sichuan Province on May 12, 2008, was taken as the deadliest earthquake in our sample. According to the China Earthquake Administration (CEA), those areas suffering severe damage from the Wenchuan earthquake had a long axis of approximately 300 km or are located approximately 150 km away from the epicenter. In this case, disaster zone firms include those firms that are located within 150 km from epicenters, a scope that is likely to be severely affected by earthquakes.

[4] These data are from the China Seismic Information Network (CSI). This database provides information about Chinese earthquakes of magnitude 2.0 or above on the Richter scale although the majority of these earthquakes are unknown. However, we cannot obtain the data of casualty from this source. We manually compared other information of earthquakes, except for casualty information, from EM-DAT with information from CSI. Data from these two sources have good consistency. Therefore, we use earthquake data from EM-DAT to examine our results in the following parts of this study.

Table 1
Sample of earthquake events.

Earthquake ID	Date	Latitude	Longitude	Magnitude	Casualty	Province
1	6/2/2007	23.028	101.052	6.1	3	Yunnan Province
2	8/21/2008	25.039	97.697	5	6	Yunnan Province
3	7/9/2009	25.632	101.09	5.7	1	Yunnan Province
4	3/10/2011	24.719	97.969	5.5	25	Yunnan Province
5	9/7/2012	27.541	103.97	5.7	81	Yunnan Province
6	8/3/2014	27.189	103.41	6.5	731	Yunnan Province
7	5/18/2016	26.077	99.539	4.8	2	Yunnan Province
8	5/12/2008	31.002	103.322	7.9	87,476	Sichuan Province
9	1/30/2010	30.268	105.668	5.1	1	Sichuan Province
10	6/24/2012	27.776	100.78	5.5	4	Sichuan Province
11	4/20/2013	30.308	102.888	7	198	Sichuan Province
12	11/22/2014	30.34	101.74	5.9	5	Sichuan Province
13	7/3/2015	37.459	78.15	6.4	3	Xinjiang Uygur Autonomous Region
14	11/25/2016	39.238	74.047	6.6	1	Xinjiang Uygur Autonomous Region
15	7/20/2012	32.974	119.6	4.9	1	Jiangsu Province
16	7/22/2013	34.512	104.262	5.9	95	Gansu Province
17	10/6/2008	29.807	90.35	6.3	30	Xizang Autonomous Region
18	1/17/2010	25.558	105.804	4.4	8	Guizhou Province
19	4/14/2010	33.165	96.548	6.9	2968	Qinghai Province

This table shows our earthquake sample over the 2007–2016 period. Firstly, we keep earthquakes occurring in China, resulting in at least one human casualties. Then, we only keep the first earthquake in a series of earthquakes successively occurring in the same province and in the same year. The magnitude of earthquakes is measured by the Ritch scale. The information about earthquakes is available in EM-DAT.

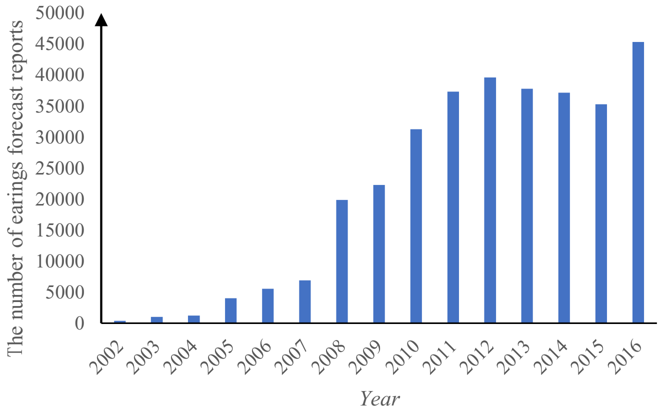

Fig. 1. The number of analyst earnings forecast reports over the years.
This graph presents the total annual number of earnings forecast reports since 2002. The source of this information is China Stock Market & Accounting Research Database (CSMAR).

Meanwhile, neighborhood area firms include those firms that are located 150 km to 500 km from epicenters. These firms may be affected by earthquakes but only at a relatively low probability. In addition, control group firms include those firms that are located 500 km to 1000 km from epicenters.

To examine the effect of earthquakes on analyst forecasts based on the changes in their degree of optimism, we apply a quasi-difference-in-differences (Quasi-DID) design as our baseline regression following the model setting in Dessaint and Matray (2017)[5]:

$$Pessimism_{ijt}=\alpha+\beta_1 Disaster_{ijt}+\beta_2 Neighborhood_{ijt}+\gamma ControlVar_{ijt}+BrokerageFE_{it}++FirmFE_i+YearFE_t+QuarterFE_t+ProvinceFE_{jt}+\varepsilon_{ijt} \tag{1}$$

where i indexes the analyst, j indexes the firm covered by the analyst, and t indexes the day when the analyst forecast is issued. We measure analyst sentiment by using the difference between the forecasted and actual EPS divided by the absolute value of the actual

[5] While our specification could make the statistical inferences on the effects of earthquakes on analyst sentiments, the model specification is not a traditional difference-in-differences design. Specifically, the inclusion of both pre-earthquake and post-earthquake forecasts for firms outside of the earthquake zone in the comparison group prohibits us from determining the change in forecast pessimism for these control group forecasts. We thank one anonymous referee for pointing this out.

EPS. We define *Pessimism* as:

$$Pessimism_{ijt} = \frac{FEPS_{ijt} - EPS_{ijt}}{|EPS_{ijt}|} \tag{2}$$

where *FEPS* is the forecasted EPS in the earnings forecast, and *EPS* is the actual EPS. A small *Pessimism* value strengthens the negative bias of the forecasted EPS relative to the actual EPS, thereby increasing analyst pessimism. Given that *Pessimism* measures the relative change between the forecasted and actual EPS, only when the decline in forecasted EPS is greater than that in actual EPS can we observe a significant analyst pessimism. Such pessimism suggests that analysts irrationally overreact to the impact of earthquakes.

In Eq. (1), *Disaster* is a dummy variable. If an analyst forecast focuses on a disaster zone firm and is issued within a year after the earthquake, *Disaster* takes a value of 1 and a value of 0 otherwise. *Neighborhood* is also a dummy variable that takes a value of 1 if the forecast focuses on a neighborhood area firm and is issued within one year after the earthquake and takes a value of 0 otherwise. *ControlVar* is a vector of control variables. We add three groups of control variables in the analysis.

First, we control for those firm characteristics that have been paid attention to by analysts. Lee and So (2017) argue that analysts' attention is limited and find that a firms' size, liquidity, and past performance profile account for more than 60% of analyst coverage, whereas other firm features only have minimal incremental power. Therefore, we control for company size (*SIZE*), trading volume (*TO*), and annual stock return in the previous year (*MOM*). We also control for institutional holdings (*Inshold*) and external financial needs (*Exfin*) given the potential effects of the holding structure and financial pressure of firms.

Second, we control for the features of analysts who release earnings forecasts.[6] Previous studies show that the individual characteristics of analysts, such as their gender and experience, can affect their forecast behavior (e.g., Kumar (2010); Kim et al. (2011)). Some controls are also issued for certain analyst features. *Groupsize* controls for the size of an analyst team if the forecasts are not issued by a single analyst. *Experience* controls for the experience of analysts. *Comnum* controls for the number of firms examined by an analyst. *Female* and *Master* control for the gender and educational level of analysts, respectively. In addition, to control for the possible influence of salience decrease by time and analyst information acquisition, we include *Interval* representing the number of days between the earthquake and forecast issue date. Prior literature also suggests that analysts herd and issue similar forecasts (Trueman (1994); Hong et al. (2000)). To control for the potential effects of analyst herding, we include analyst consensus (*ConFeps*) and analyst coverage (*AnalystCoverage*).

Third, we control for the severity of earthquakes. We use *Death* to control for the number of earthquake casualties. If an analyst forecast covers a disaster zone or neighborhood area firm, then *Death* is equal to the natural logarithm of one plus the number of earthquake casualties. Otherwise, *Death* is equal to 0. We collect data on earthquake casualty from EM-DAT, and other control variables are obtained from CSMAR.

We use forecast- and firm-level variables at different stages of our empirical examinations. Detailed definitions of variables are presented in Appendix A, where panels A and B report the definitions of the forecast- and firm-level variables, respectively. Table 2 presents the summary statistics for the forecast- (Panel A) and firm-level (Panel B) variables. In this table, *Pessimism* has a mean value of 0.59, which suggests that the optimistic bias of analysts in the whole sample is approximately 60% of the actual corporate earnings. The mean values of *Disaster* and *Neighborhood* are 0.01 and 0.09, respectively, which suggest that the earnings forecasts issued for firms located within 500 km from epicenters no more than a year after the occurrence of earthquakes account for approximately 10% of our sample. The values of the other variables are within a reasonable range.

In Eq. (1), we include a set of fixed effects. *Brokerage FE* is the fixed effect of brokerage firms to capture the possible influence of non-observed heterogeneity of analysts' brokerages on analyst sentiment. *Firm FE* presents firm fixed effects to control for the influence of non-observed firms' features on analyst sentiment. *Year FE* presents time fixed effect to capture the influence of macro-economic factors on analysts' sentiment and the potential trend of improvement in analyst skills. *Quarter FE* is the fixed effect of quarters, which is used to control for the possible improvement of analyst forecast accuracy with the time closest to the annual report release date.[7] *Province FE* is the fixed effect for the observed cluster of earthquakes in certain provinces and the potential effects of local economic conditions.

We use different samples to capture the impacts of earthquakes on analyst sentiments. The first sample contains all analyst forecasts for listed firms within 1000 km away from epicenters of earthquakes between 2007 and 2016. The sample, which we mark as Sample #1, enables us to examine the overall effects of earthquakes on analyst forecasts. To capture the effects of earthquakes more precisely, we construct the second sample and mark it as Sample #2. In Sample #2, we only keep forecasts issued by analysts who simultaneously focus on firms within 500 km away from epicenters and firms in the control group. Besides, we require analysts to issue forecasts for a firm within 500 km within one year before the earthquake and for the same firm within one year after earthquakes. Sample #2

6 Some earnings forecasts in our sample have been issued by analyst teams. For this part of our sample, the control variables for analyst characteristics are used to control the features of analyst teams. However, the majority of the forecasts in our sample are issued by a single analyst. Specifically, the analyst reports issued by analyst teams account for less than 30% of all reports issued in each year of our sample period. Therefore, we do not distinguish analyst teams from analysts and collectively label them as "analysts" in the following sections.

7 We thank the anonymous reviewer for pointing out that analyst's optimism may change throughout the forecast horizon. Several studies have shown that the accuracy of analysts' forecasts increases as analysts successfully obtain further information over time (e.g., Crichfield et al. (1978); and Richardson et al. (1999)). Therefore, we control for the quarterly fixed effects in all specifications to capture the impact of the forecast horizon. Since only annual analyst earnings forecast data are provided in China, the quarter of the forecast release date represents the time proximity to the release date of annual earnings reports.

Table 2
Summary statistics.

Variable	Obs.	Mean	SD	Min	Median	Max
Panel A. Summary statistics for forecast-level variables						
Pessimism	176,796	0.59	1.53	0.13	−0.53	11.10
Disaster	176,796	0.01	0.11	0.00	0.00	1.00
Neighborhood	176,796	0.09	0.28	0.00	0.00	1.00
Size	176,796	23.31	1.15	23.14	21.19	26.73
To	176,796	4.58	3.45	3.65	0.30	16.88
Mom	176,796	0.27	0.64	0.11	−0.65	2.60
Inshold	176,796	0.19	0.16	0.14	0.00	0.68
Exfin	176,796	0.14	0.44	0.03	−0.39	2.88
Groupsize	176,796	0.16	0.31	0.00	0.00	1.10
Experience	176,796	1.00	0.67	1.10	0.00	2.30
Comnum	176,796	2.80	0.85	2.83	0.00	4.96
Gender	176,796	0.28	0.42	0.00	0.00	1.00
Master	176,796	0.91	0.27	1.00	0.00	1.00
Interval	176,796	9.96	47.38	0.00	0.00	365
AnalystCoverage	176,796	2.51	0.71	2.64	0.00	3.61
ConFeps	176,796	0.90	0.67	0.73	0.05	3.80
Death	176,796	0.19	0.91	0.00	0.00	11.38
Panel B. Summary statistics for firm-level variables						
EPS	19,251	0.34	0.45	−0.70	0.26	1.78
Disaster_Firm	19,251	0.01	0.12	0.00	0.00	1.00
Neighborhood_Firm	19,251	0.08	0.27	0.00	0.00	1.00
Size	19,251	21.79	1.29	19.44	21.62	25.35
Leverage	19,251	0.46	0.22	0.06	0.46	0.94
Ppe	19,251	0.23	0.17	0.00	0.20	0.68
Inshold	19,251	0.08	0.11	0.00	0.03	0.49
Indratio	19,251	0.37	0.05	0.33	0.33	0.50
Boardsize	19,251	2.16	0.20	1.61	2.20	2.71
Cashratio	19,251	0.20	0.15	0.01	0.15	0.67
NWC	19,251	0.18	0.16	−0.08	0.16	0.64
IntervalToEnd	19,251	15.70	51.48	0.00	0.00	227

This table reports the summary statistics for the main variables over the 2007–2016 period. The variables are defined in Appendix A. Panel A of this table reports summary statistics for forecast-level variables. In Panel A, the data used for calculating the variables of firm features and analyst characteristics are from CSMAR. The data used for defining *Disaster*, *Neighborhood*, and *Death* is from EM-DAT. Panel B reports summary statistics for firm-level variables. In Panel B, all the data for variables on firm features are acquired from CSMAR.

constitutes a clean DID design that allows us to compare analysts' forecasts between earthquake-affected firms and control firms before and after the earthquake. Finally, we construct Sample #3 to ensure that the pre- and post-earthquake earnings forecast is issued for the same fiscal period. If the pre-earthquake forecast estimates earnings for the current fiscal year while the post-earthquake forecast estimates earnings for the next fiscal year, we cannot identify the impact of earthquakes on forecast pessimism by comparing earnings forecasts issued pre- and post-earthquake. Therefore, based on Sample #2, we further require that the earthquake year, the forecast issue year, and the forecast target year be the same in Sample #3.

4. Empirical analysis

4.1. Baseline results: do earthquakes induce analyst pessimism?

We examine the effect of earthquake events on analyst sentiment by testing the changes in the degree of analyst optimism in earnings forecasts after earthquakes.

Table 3 presents the estimation results of Eq. (1), column (1) to (3) report the estimation result based on Sample #1, Sample #2, and Sample #3, respectively. All coefficients of *Neighborhood* are significantly negative although the significance level decreases with the strictness of sample restriction, whereas those of *Disaster* are insignificant. Table 3 shows that within a year after an earthquake, analysts hold a significantly lower degree of optimism for firms in neighborhood areas and that the average decline in the forecasted EPS is ranging from 9.7% to 13.9% of the actual EPS.

Coefficients of *Disaster* are all insignificant in Table 3, showing that analysts do not show a significant over-pessimism for disaster zone firms. In this case, analysts overreact to earthquakes and show irrational pessimism for neighborhood area firms. They may also rationally evaluate the effects of earthquakes on disaster zone firms and reduce their forecasted earnings to match the post-earthquake losses of these firms. These findings are consistent with H1, which posits that earthquakes lead to post-earthquake analyst pessimism for neighborhood area firms. Given that neighborhood areas have a relatively low probability to be directly affected by earthquakes, post-earthquake analyst pessimism may be a result of the behavioral biases of analysts. We will discuss the underlying mechanism in the following sections.

If analysts can predict earthquakes, then a pre-event pessimism will be observed. To ensure that analysts are unable to predict

Table 3
The impact of earthquakes on analyst pessimism.

	Dependent variable: *Pessimism*		
	Sample #1	Sample #2	Sample #3
	(1)	(2)	(3)
Disaster	−0.028	−0.155	−0.165
	(−0.48)	(−1.13)	(−1.52)
Neighborhood	−0.097***	−0.141**	−0.139*
	(−3.20)	(−2.30)	(−1.91)
Size	−0.336***	−0.379***	−0.330***
	(−12.89)	(−7.70)	(−7.14)
To	0.041***	0.065***	0.059***
	(13.15)	(10.58)	(10.03)
Mom	−0.165***	−0.293***	−0.285***
	(−10.74)	(−9.72)	(−10.08)
Inshold	0.089	0.006	−0.143
	(1.47)	(0.04)	(−1.11)
Exfin	−0.062***	−0.131***	−0.118***
	(−4.27)	(−4.23)	(−3.93)
Groupsize	−0.019	0.008	0.012
	(−0.86)	(0.19)	(0.33)
Experience	−0.003	0.005	0.002
	(−0.29)	(0.28)	(0.16)
Commun	−0.003	−0.002	−0.006
	(−0.39)	(−0.12)	(−0.42)
Female	0.006	0.006	0.009
	(0.47)	(0.27)	(0.42)
Master	−0.033	−0.020	−0.020
	(−1.64)	(−0.53)	(−0.54)
Interval	−0.000	−0.000	−0.002***
	(−0.03)	(−0.34)	(−2.91)
AnalystCoverage	−0.168***	−0.195***	−0.189***
	(−8.20)	(−5.33)	(−5.16)
ConFeps	0.448***	0.215***	0.211***
	(19.93)	(8.42)	(8.33)
Death	0.012	0.026	0.043*
	(1.44)	(1.50)	(1.76)
Broker FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Observations	176,796	154,251	147,212
R-squared	0.298	0.289	0.304

This table presents the difference-in-differences estimates of the effects of the proximity of firms to the epicenter on the sentiment of analysts covering these firms. Analyst sentiment, *Pessimism*, is measured by the deviation of analyst predicted earnings per share (*EPS*) relative to actual EPS. *Disaster* is a dummy variable equal to 1 if an analyst forecast focuses on a firm in the disaster zone and is issued within one year after the earthquake, otherwise 0. *Neighborhood* is also a dummy variable that equals 1 if the forecast focusing on a firm in the neighborhood area and is issued within one year after the earthquake and 0 if not. Column (1) to (3) report estimation results based on basis of Sample #1, Sample #2, and Sample #3, respectively. Detailed definitions of variables are presented in Panel A of Appendix A. We control for brokerage, firm, year, quarter, and province fixed effects and cluster the standard errors by analysts. T-stats are reported in parentheses. *, ** and *** measure significance at the 10%, 5%, and 1% levels, respectively.

earthquakes in advance, we investigate the dynamic changes in analyst sentiments. Specifically, we replace *Neighborhood* in Eq. (1) with four dummy variables, namely, *Neighborhood_Before2*, *Neighborhood_Before1*, *Neighborhood_After1*, and *Neighborhood_After2+*, to capture dynamic changes in analyst sentiment for neighborhood area firms. Among these variables, *Neighborhood_Before2* denotes the analyst forecasts for neighborhood area firms that have been issued in the second quarter before an earthquake, *Neighborhood_Before1* denotes the analyst forecasts issued in one quarter before an earthquake, *Neighborhood_After1* indicates the analyst forecasts for neighbor firms that have been issued no later than a quarter after an earthquake, and *Neighborhood_After2+* denotes the analyst forecasts issued between the second to fourth quarters after an earthquake. Similar replacements are also applied in *Disaster*. We dismiss those forecast observations that are affected by more than one earthquake over quarters [−2, 4] because these observations cannot identify the points in time relative to the date of an earthquake. Therefore, our number of overall observations decreases from 176,796 to 172,937.

Table 4 presents the estimation results. The coefficients of independent variables related to *Disaster* are insignificant across all three columns, consistent with our baseline finding that analysts have a relatively appropriate evaluation of disaster zone firms. For those forecasts that focus on neighbor firms, no statistically significant change in analyst sentiments is observed before the occurrence of

Table 4
The dynamic effects of earthquakes on analyst pessimism.

	Dependent variable: *Pessimism*		
	Sample #1	Sample #2	Sample #3
	(1)	(2)	(3)
Disaster_Before2	−0.145	−0.458	−0.452
	(−0.63)	(−0.98)	(−0.97)
Disaster_Before1	0.095	−0.013	0.007
	(0.39)	(−0.03)	(0.01)
Disaster_After1	−0.306	−0.487	−0.489
	(−1.56)	(−1.65)	(−1.63)
Disaster_After2+	−0.213	−0.179	−0.385
	(−0.97)	(−0.27)	(−1.38)
Neighborhood_Before2	−0.081	−0.233	−0.229
	(−1.41)	(−1.44)	(−1.42)
Neighborhood_Before1	−0.138	−0.193	−0.216
	(−1.35)	(−0.97)	(−1.16)
Neighborhood_After1	−0.217***	−0.305**	−0.352*
	(−3.33)	(−2.04)	(−1.84)
Neighborhood_After2+	−0.003	−0.001	−0.255*
	(−0.02)	(−0.01)	(−1.74)
Size	−0.393***	−0.382***	−0.327***
	(−8.76)	(−3.25)	(−3.08)
To	0.062***	0.062***	0.059***
	(11.24)	(3.33)	(3.32)
Mom	−0.238***	−0.279***	−0.283***
	(−9.43)	(−4.19)	(−4.77)
Inshold	0.193	−0.032	−0.137
	(1.63)	(−0.08)	(−0.37)
Exfin	−0.111***	−0.136*	−0.120
	(−3.98)	(−1.77)	(−1.60)
Groupsize	−0.035	0.006	0.016
	(−1.02)	(0.19)	(0.53)
Experience	−0.007	0.002	−0.009
	(−0.46)	(0.13)	(−0.60)
Comnum	−0.002	−0.005	0.007
	(−0.13)	(−0.38)	(0.29)
Female	0.009	0.003	−0.024
	(0.47)	(0.11)	(−0.83)
Master	−0.043	−0.025	−0.002
	(−1.32)	(−0.85)	(−0.59)
Interval	−0.001	−0.001	−0.202***
	(−1.63)	(−1.02)	(−3.13)
AnalystCoverage	−0.183***	−0.208***	0.218**
	(−5.29)	(−3.04)	(2.56)
ConFeps	0.320***	0.244**	0.058
	(11.11)	(2.51)	(0.81)
Death	0.018	0.018	−0.452
	(0.90)	(0.35)	(−0.97)
Broker FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Observations	172,937	150,938	144,949
R-squared	0.263	0.301	0.314

This table presents the results from regressions examining the dynamic effects of earthquakes on the sentiment of analysts covering firms possibly affected by earthquakes. We replace *Neighborhood* in Eq. (1) with 4 dummy variables, *Neighborhood_Before2*, *Neighborhood_Before1*, *Neighborhood_After1*, and *Neighborhood_After2+* to capture the dynamic changes in analyst optimism degree for neighbor firms. Similarly, we replace *Disaster* in Eq. (1) with *Disaster_Before2*, *Disaster_Before1*, *Disaster_After1*, and *Disaster_After2+*. Column (1) to (3) report estimation results based on basis of Sample #1, Sample #2, and Sample #3, respectively. Detailed definitions of variables are presented in Panel A of Appendix A. We control for brokerage, firm, year, quarter, and province fixed effects and cluster the standard errors by analysts. T-stats are reported in parentheses. *, ** and *** measure significance at the 10%, 5%, and 1% levels, respectively.

earthquakes. However, the optimism degree for these firms significantly decreases after the occurrence of earthquakes, thereby suggesting that post-earthquake analyst pessimism does not show any pre-trends before the occurrence of earthquakes. Therefore, the decline in optimism degree for neighborhood area firms is indeed caused by earthquakes, and analysts are unable to predict the occurrence of earthquakes. The following sections discuss how the post-earthquake analyst pessimism for neighborhood area firms arises.

4.2. Underlying mechanism: rational judgment

This section considers the possibility that analyst pessimism is caused by rational or non-behavioral factors, that is, is analyst pessimism based on rational judgment? To answer this question, we examine the impacts of earthquakes on firm profitability and stock returns. If post-earthquake analyst pessimism is driven by rational judgment, we expect to observe negative movement in firm profitability and stock returns after earthquakes.

4.2.1. Firm profitability

We investigate the reduced degree of optimism in earnings forecasts that may be ascribed to concerns related to firm profitability. Given that the analyst forecasts in our sample focus on the annual EPS of listed firms, we empirically examine the impact of earthquakes on annual EPS. As mentioned above, we can only observe a significant analyst pessimism when the decline in forecasted EPS is greater than the decline in actual EPS. The results in Table 3, which show that the coefficients of *Disaster* are insignificant whereas those of *Neighborhood* are significantly negative, suggest that analysts reduce their forecasted earnings for disaster zone firms to relatively match their losses. Meanwhile, the analyst pessimism for neighborhood area firms can be ascribed to these analysts' behavioral biases. To prove this inference, we run the following regression by using firm-level data:

$$EPS_{jt} = \alpha + \beta_1 Disaster\_Firm_{jt} + \beta_2 Neighborhood\_Firm_{jt} + \gamma ControlVariables_{j,t-1} + Firm\ FE_j + Year\ FE_t + Province\ FE_{jt} + \varepsilon_{jt} \tag{3}$$

where *EPS* denotes the earnings per share of firm *j* in year *t*, *Disaster_Firm* is a dummy variable that equals to 1 if the firm is located in the disaster zone during the year of an earthquake, *Neigborhood_Firm* is a dummy variable that denotes neighbor firms in the earthquake-occurring year, and *ControlVariable* is a vector of lagged control variables. We control for certain firm features, including

Table 5
The impact of earthquakes on corporate earnings.

	Dependent variable: *EPS*	
	(1)	(2)
Disaster_Firm	−0.035**	−0.064*
	(−2.02)	(−1.84)
Neighborhood_Firm	−0.007	−0.039
	(−0.63)	(−1.00)
Size		−0.002
		(−0.18)
Leverage		0.119***
		(3.08)
Ppe		−0.605***
		(−11.31)
Inshold		0.837***
		(16.60)
Indratio		0.102
		(0.77)
Boardsize		0.047
		(1.06)
Cashratio		0.207***
		(5.63)
NWC		−0.135***
		(−2.66)
IntervalToEnd		0.000
		(0.81)
Firm FE	Yes	Yes
Year FE	Yes	Yes
Province FE	Yes	Yes
Observations	19,251	19,251
R-squared	0.587	0.605

This table presents results from regressions examining whether corporate earnings are affected by earthquakes. We estimate Eq. (3) using firm-year data and report the results in this table. *EPS* is earnings per share of a firm at the end of the year. *Disaster_Firm* is a dummy variable equaling 1 if the firm is in the disaster zone in the year when the earthquake occurs. Similarly, *Neigborhood_Firm* is a dummy variable indicating neighbor firms in the earthquake-occurring year. We control for some firms' features and fixed effects including *Firm, Year*, and *Province* representing firm, year, and province fixed effects. Detailed definitions of variables are in Panel B of Appendix A. The standard errors are clustered by firms. T-stats are reported in parentheses. *, ** and *** measure significance at the 10%, 5%, and 1% levels, respectively.

firm size (*Size*), debt burden (*Leverage*), the ratio of fixed assets (*Ppe*), institutional holdings (*Inshold*), the ratio of independent directors in the board (*Indratio*), size of board members (*Boardsize*), the ratio of cash to total assets (*Cashratio*), and the ratio of net working capital to total assets (*NWC*). In addition, we include *IntervalToEnd* to control for the proximity of the earthquake date to the end of the fiscal year, because the magnitude of an earthquake's impact on a firm's earnings is likely to associate with this time interval. In Eq. (3), *Firm FE* represents firm fixed effects, *Year FE* represents year fixed effects, and *Province FE* represents province fixed effects. The detailed definitions of these variables are reported in Panel B of Appendix A. We dismiss those observations with missing values and obtain 19,251 firm-year observations. All financial variables are winsorized at the 1st and 99th percentiles to eliminate the influence of outliers.

The estimation results of Eq. (3) are reported in Table 5. The coefficients of *Disaster_Firm* are significantly negative, thereby suggesting that earthquakes can reduce the earnings of firms located close to epicenters. Given that analysts do not demonstrate over-pessimism for disaster zone firms (Table 3), we believe that these analysts rationally reduce their degree of optimism to match the actual earnings losses of firms after the occurrence of earthquakes. Meanwhile, the coefficients of *Neighborhood_Firm* are insignificant, and this result is robust to control variables. Earthquakes do not have any significant influence on the earnings of neighborhood area firms, which have a low probability to be affected by such disasters. However, Table 3 shows that analysts demonstrate pessimism for neighborhood area firms after earthquakes, and this result is inconsistent with the actual effects of earthquakes on the earnings of these firms. Therefore, post-earthquake analyst pessimism for neighbor firms is a result of analysts' irrational overreaction to earthquakes.

4.2.2. Stock returns

Previous studies show that the change in stock prices after disasters may be driven by market sentiment (e.g., Kaplanski and Levy (2010); Berkman et al. (2011)). Although earthquakes do not significantly influence the corporate earnings of neighborhood area firms, investors may overreact to news of earthquakes. Such responses may lead to negative changes in post-earthquake stock returns. If analyst pessimism is related to concerns regarding the firms' future stock returns, then can such pessimism be justified? We examine the changes in stock returns after earthquakes to answer this question.

We study the impact of earthquakes on the short-term returns of disaster zone and neighborhood area firms. Using the market model, we focus on the cumulative abnormal return (*CAR*) of these firms after the occurrence of earthquakes to measure their market reactions to such disasters. The parameters of the market model are estimated by an estimation window of 250 trading days [−250, −1]. The daily abnormal returns for each firm are calculated as the difference between the expected and realized daily returns. In event windows with different lengths, *CAR*[1, *d2*] is calculated as the sum of daily abnormal returns over a *d2* days event window after earthquakes, where $d2 = 5$, 15, 25.

After dismissing firm-earthquake observations with days less than 150 trading days in the estimation windows, we obtain 327 and 2031 firm-earthquake observations for 265 disaster zone firms and 1028 neighborhood area firms, respectively. Table 6 reports the *CARs* of firms that are possibly affected by earthquakes within the event windows.

Panels A and B of Table 6 present the *CAR* of disaster zone and neighborhood area firms after earthquakes, respectively, and show that the stock returns of these firms are not significantly affected by earthquakes in the short term. The *t*-tests for *CAR* values are insignificant in three gradually extended event windows regardless of the distance to epicenters. Earthquakes do not have any negative effect on short-term stock returns, especially for neighborhood area firms to which analysts show irrational pessimism after earthquakes. Therefore, we can rule out the argument that the post-earthquake analyst pessimism for neighborhood area firms is a rational judgment based on these analysts' concerns over short-term stock returns after earthquakes.

We then check for significant differences in the alpha of the portfolios of firms that are possibly affected by earthquakes and those of control group firms by using the Fama–French 3 factors model (Fama and French (1992) and Fama and French (1993)) to determine the impact of earthquakes on long-term stock returns. We form three exclusive portfolios based on the three groups of firms (disaster zone, neighborhood area, and control group firms) and then calculate the value–weight monthly returns of each group. We also check for differences in the alpha of these firms' portfolios 12, 24, and 36 months after an earthquake. For each portfolio, we estimate the coefficients of the regression as follows:

$$R_m - Rf_m = \alpha + \beta_1 (RM_m - Rf_m) + \beta_2 SMB_m + \beta_3 HML_m + \varepsilon_{im} \quad (4)$$

where *R* is the portfolio return at month *m*, *Rf* is the monthly risk-free rate at month *m*, *Alpha* is the coefficient that represents an excess return, and β_1 is the beta coefficient that represents systematic risks. (*RM-Rf*), *SMB,* and *HML* measure the excess returns of market risks, small- over large-cap stocks, and value stocks over growth stocks, respectively, as defined by Fama and French (1992) and Fama and French (1993). If the occurrence of earthquakes reduces the long-term returns of affected firms, then the alpha (α in Eq. (4)) of the portfolio of disaster zone and neighborhood area firms should be lower than that of the control group firms. Table 7 reports the results for the portfolios regressed on the Fama–French 3 factor model.

Columns (1) to (3) of Table 7 present the estimation results of Eq. (4) for the portfolios of the disaster zone, neighborhood area, and control group firms, respectively. Meanwhile, panels A, B, and C report the estimation results of Eq. (4) by using the returns of portfolios 12, 24, and 36 months after the occurrence of earthquakes. If analyst pessimism is based on a rational concern over stock returns, then the portfolio of the disaster zone or neighborhood area firms should obtain a lower alpha in the long term. However, the estimation results reported in Table 7 do not present enough evidence to support this claim. Neither the portfolio of the disaster group (Column (4), Table 7) nor that of the neighborhood group (Column (5), Table 7) has a significantly lower alpha compared with the portfolio of the control group whether 12 or 36 months after an earthquake. Therefore, the occurrence of earthquakes has no negative impact on the long-term stock returns of possibly affected firms. In this case, we can rule out the argument that post-earthquake analyst

Table 6
The CAR of firms possibly affected by earthquakes.

Event Window	[1,5]	[1,15]	[1,25]
	(1)	(2)	(3)
Panel A. CARs of firms in disaster zones			
CAR	−0.0063	0.0026	0.0067
t-statistics	(−1.11)	(0.22)	(0.34)
Panel B. CARs of firms in neighborhood areas			
CAR	−0.0008	−0.0024	−0.0035
t-statistics	(−0.21)	(−0.32)	(−0.22)

This table presents the short-term changes in stock returns after earthquakes. we focus on the cumulative abnormal return (*CAR*) of firms within 500 km away from epicenters after earthquakes. For each firm, we estimate the market model over days [−250, −1] before the occurrence of earthquakes. Then, the abnormal returns of each firm are constructed as the difference between the realized individual firm returns and the estimated firm returns from the market model. *CAR* of each firm is the sum of daily abnormal returns in different lengths of event windows with 25 trading days in the longest event window. We use T-test to examine whether CARs of firms are significantly unequal to 0. T-stats are reported in parentheses. *, ** and *** measure significance at the 10%, 5%, and 1% levels, respectively.

Table 7
The Alpha of portfolios after earthquakes.

The Group of Firms	Disaster	Neighbor	Control	Disaster-Control	Neighbor-Control
	(1)	(2)	(3)	(4)	(5)
Panel A. 12 months after the earthquake					
Alpha	0.001	0.002	−0.000	0.001	0.002
	(0.14)	(0.34)	(−0.11)		
Rm-Rf	0.774***	0.706***	0.792***	−0.018	−0.086
	(10.01)	(12.73)	(19.20)		
SMB	0.597***	0.365**	−0.028	0.625**	0.393**
	(3.01)	(2.56)	(−0.27)		
HML	−0.405*	−0.041	0.100	−0.505**	−0.141
	(−1.87)	(−0.26)	(0.87)		
Observations	150	150	150		
R-squared	0.465	0.559	0.719		
Panel B. 24 months after the earthquake					
Alpha	0.006	0.008**	0.006**	0.001	0.002
	(1.33)	(2.41)	(2.37)		
Rm-Rf	0.747***	0.712***	0.791***	−0.044	−0.079
	(13.64)	(18.76)	(28.52)		
SMB	0.636***	0.248***	−0.072	0.708***	0.320***
	(4.93)	(2.78)	(−1.10)		
HML	−0.267*	−0.245**	0.055	−0.322**	−0.301***
	(−1.89)	(−2.50)	(0.77)		
Observations	309	309	309		
R-squared	0.446	0.567	0.730		
Panel C. 36 months after the earthquake					
Alpha	0.001	0.008***	0.007***	−0.006	0.002
	(0.23)	(2.93)	(3.26)		
Rm-Rf	0.783***	0.702***	0.781***	−0.001	−0.080
	(16.70)	(21.90)	(33.62)		
SMB	0.703***	0.190***	−0.116**	0.819***	0.306***
	(7.03)	(2.78)	(−2.34)		
HML	−0.227*	−0.221***	0.055	0.282**	−0.276***
	(−1.91)	(−2.72)	(0.93)		
Observations	451	451	451		
R-squared	0.476	0.552	0.721		

This table presents the long-term changes in stock returns after earthquakes. We examine whether there exists a significant difference in Alpha between portfolios of firms possibly affected by earthquakes and portfolios of firms in the control group by using Fama–French 3 factors model (Fama and French (1992, 1993)). Three groups of firms, the disaster group, the neighborhood group, and the control group, are assigned after the occurrence of each earthquake. We then form three exclusive portfolios and calculate the value-weight monthly returns of each group. For each portfolio, we estimate coefficients of the Fama-French 3 factors model and examine whether there exist significant differences in Alpha in 12 months, 24 months and 36 months after earthquakes. The data of Fama-French 3 factors in the Chinese A-share market is obtained from CSMAR. T-stats are reported in parentheses. *, ** and *** measure significance at the 10%, 5%, and 1% levels, respectively.

pessimism is a rational judgment based on concerns over the long-term stock returns of neighbor firms.

We discuss the reasonability of the idea that post-earthquake analyst pessimism is driven by rational concerns over the profitability or stock returns of neighborhood area firms. On the one hand, the significant reduction in corporate earnings was limited to disaster zone firms, while neighborhood area firms do not show any significant reductions in their earnings. On the other hand, earthquakes do not produce negative shocks to the stock returns of possibly affected firms. In this case, there is no sufficient evidence to support the claim that post-earthquake analyst pessimism is based on rational judgments.

4.3. Underlying mechanism: heuristic bias

4.3.1. The impact of media attention on the post-earthquake analyst pessimism

The post-earthquake analyst pessimism for neighborhood firms might stem from the heuristic bias since earthquakes haven't significantly damaged the earnings of these firms. If the post-earthquake analyst pessimism is due to the availability bias, we expect the media coverage to play an important role. We assign earthquakes into two groups according to the media attention and investigate whether the media attention influences the post-earthquake analyst pessimism. We use two variables to measure media attention on earthquakes. The first is the Baidu index of earthquake keywords. The Baidu index is a search frequency index based on the search volume of certain keywords on Baidu, which is the largest Chinese search engine in China (Kong et al. (2019)).[8] A high Baidu index value means high media attention. In terms of keywords, we combine the Chinese name of administrative regions where earthquakes occurred and the Chinese word "earthquake", such as "Wenchuan earthquake." Such keywords are often used in Chinese official documents to identify earthquake events. If the Baidu index excludes this keyword format of certain earthquakes, we use the Chinese name of administrative regions where these earthquakes occurred as search keywords, such as "Wenchuan County." If neither of these two keyword formats of an earthquake can be obtained in the index, the earthquake event is deleted from the sample. We delete the earthquake with ID 1 because its Baidu index value is not available, and we obtain Baidu indices of 17 earthquakes. We use the manually collected daily average index values within one week after the earthquake to measure media attention. The nine earthquakes with high daily average index values are marked as "strong information availability," and the eight earthquakes with low daily average index values are marked as "weak information availability."

The second variable to measure media attention is the number of newspaper articles about earthquakes. These data come from China Core Newspapers Full-text Database (CCND), which has collected academic and informational literature from core newspapers in China since 2000 and is updated continuously. We use the combination of the Chinese name of administrative regions shocked by earthquakes and the Chinese word "earthquake" as keywords to search newspaper articles and count the number of articles. According to the number of relevant newspaper articles in the week following earthquakes, the nine earthquakes with a large number of articles are labeled as "strong information availability," whereas the remaining nine earthquakes were labeled as "weak information availability." We present the Baidu index values and the number of newspaper articles about earthquakes in Appendix B.

We set two dummy variables, *Disaster_Highattention and Neighborhood_Highattention*. If *Disaster* equals 1 and corresponding earthquakes are "strong information availability", *Disaster_Highattention* is equal to 1, otherwise equal to 0. Then, we define *Neighborhood_Highattention* in a similar way. We include these two variables into Eq. (1) and re-estimate it. Table 8 reports the results.

Table 8 supports H3a that the post-earthquake analyst pessimism is more pronounced if the media attention is high. We obtain consistent results by using the Baidu index and the number of newspaper articles to measure media attention. The coefficients of *Neighborhood_Highattention* are significantly negative, indicating that analysts are more pessimistic when making earnings forecasts for neighbor firms after earthquakes if media attention is high. Therefore, the difference in information availability caused by media attention affects the intensity of psychological shocks of earthquakes on analysts. High media coverage increases the likelihood of analysts to exhibit heuristic biases by issuing more pessimistic forecasts after earthquakes, which is consistent with the behavioral bias channel.[9]

4.3.2. Persistence of post-earthquake analyst pessimism

Previous studies on heuristics biases suggest that the behavioral bias of individuals is temporary (e.g., Dessaint and Matray (2017)). To investigate whether the behavioral biases of analysts are also temporary, we examine the persistence of post-earthquake analyst pessimism.

Given that both Sichuan Province and Yunnan Province have been ravaged by earthquakes several times during the sample period and some firms may be influenced by these disasters for several successive years, we drop firms located within 500 km from the epicenters of earthquakes occurring in these provinces. We decompose *Disaster* and *Neighborhood* in Eq. (1) into a series of variables to investigate the persistence of post-earthquake analyst pessimism. If the pessimism is caused by the behavioral bias arising from earthquakes, we expect the analyst pessimism to disappear after the first few forecasts according to Dessaint and Matray (2017).

[8] According to the different user terminals, two types of Baidu index exist, Personal computer (PC) search index, which began in 2006, and mobile search index, which began in 2011. The PC search index measures the search volume from the terminals of PCs, whereas the mobile search index measures from the mobile terminals. Given that our sample period started in 2007, we used the PC search index to measure the media attention of earthquakes.

[9] We thank the anonymous reviewer for pointing out that high-attention earthquakes also disrupt a firm's corporate operations or stock returns, thereby prompting analysts to rationally revise their earnings expectations downward. To rule out this alternative explanation, we empirically examine whether high-attention earthquakes statistically disrupt the corporate earnings and stock returns of firms in the Appendix C.

Table 8
The impact of media attention on the post-earthquake analyst pessimism.

	Dependent variable: *Pessimism*					
	Baidu index			the number of newspaper articles		
	Sample #1	Sample #2	Sample #3	Sample #1	Sample #2	Sample #3
	(1)	(2)	(3)	(4)	(5)	(6)
Disaster	−0.135	−0.121	−0.149	−0.156	−0.151	−0.258
	(−0.83)	(−0.78)	(−0.91)	(−0.95)	(−0.86)	(−1.35)
Neighborhood	0.049	0.021	0.056	−0.117**	−0.124**	−0.085
	(0.49)	(0.33)	(0.80)	(−2.02)	(−2.38)	(−0.55)
Disaster_Highattention	−0.063	−0.080	−0.051	−0.177	−0.196	−0.005
	(−0.29)	(−0.47)	(−0.27)	(−0.90)	(−1.00)	(−0.01)
Neighborhood_Highatttention	−0.374***	−0.332***	−0.300***	−0.373***	−0.350**	−0.760*
	(−3.06)	(−4.78)	(−3.89)	(−2.91)	(−2.21)	(−1.86)
Size	−0.365***	−0.354***	−0.334***	−0.387***	−0.381***	−0.333***
	(−8.33)	(−14.71)	(−13.79)	(−8.63)	(−7.46)	(−3.46)
To	0.061***	0.060***	0.059***	0.065***	0.065***	0.059***
	(11.60)	(21.38)	(20.76)	(11.82)	(12.02)	(3.75)
Mom	−0.258***	−0.302***	−0.281***	−0.251***	−0.292***	−0.283***
	(−10.31)	(−18.64)	(−17.22)	(−9.97)	(−9.74)	(−5.25)
Inshold	0.163	−0.065	−0.145**	0.222*	0.001	−0.150
	(1.42)	(−1.05)	(−2.34)	(1.90)	(0.01)	(−0.46)
Exfin	−0.106***	−0.127***	−0.118***	−0.111***	−0.131***	−0.121**
	(−3.88)	(−7.60)	(−7.04)	(−4.05)	(−3.66)	(−1.97)
Groupsize	−0.033	0.007	0.012	−0.032	0.008	0.013
	(−0.92)	(0.30)	(0.55)	(−0.90)	(0.23)	(0.45)
Experience	−0.005	0.004	0.002	−0.004	0.005	0.002
	(−0.35)	(0.36)	(0.21)	(−0.26)	(0.29)	(0.18)
Comnum	−0.000	−0.003	−0.006	0.000	−0.002	−0.006
	(−0.00)	(−0.32)	(−0.69)	(0.04)	(−0.12)	(−0.47)
Female	0.013	0.005	0.009	0.012	0.005	0.009
	(0.64)	(0.33)	(0.59)	(0.61)	(0.25)	(0.42)
Master	−0.037	−0.019	−0.019	−0.038	−0.021	−0.021
	(−1.14)	(−0.85)	(−0.84)	(−1.15)	(−0.66)	(−0.80)
Interval	0.000*	0.000**	−0.002***	−0.000	−0.000	−0.003**
	(1.90)	(2.13)	(−2.99)	(−0.68)	(−0.53)	(−2.22)
AnalystCoverage	−0.178***	−0.202***	−0.189***	−0.171***	−0.193***	−0.188***
	(−5.25)	(−11.55)	(−10.68)	(−5.06)	(−4.76)	(−3.28)
ConFeps	0.280***	0.208***	0.216***	0.290***	0.220***	0.219***
	(10.54)	(16.57)	(16.07)	(10.66)	(8.46)	(4.65)
Death	0.048***	0.048***	0.056***	0.067***	0.068**	0.128
	(2.70)	(4.59)	(4.34)	(2.82)	(2.44)	(1.44)
Broker FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	176,641	154,113	147,161	176,796	154,251	147,212
R-squared	0.254	0.287	0.305	0.256	0.289	0.304

For *Neighborhood* in Eq. (1), we decompose it into six variables, namely *Neighborhood_1*, *Neighborhood_2*, *Neighborhood_3*, *Neighborhood_4*, *Neighborhood_5*, *and Neighborhood_6+*, indicating the first, second, third, fourth, fifth, and sixth and subsequent forecasts for a neighborhood firm issued within a year after the earthquake, respectively. Similarly, we decompose *Disaster* in Eq. (1) into six variables to indicate successive forecasts for a firm in the disaster zone. These twelve variables help us examine whether post-earthquake analyst pessimism will last beyond the initial forecast.

Table 9 presents related results. In Column (1), the coefficients are significantly negative from *Neighborhood_1* to *Neighborhood_5* but insignificant for *Neighborhood_6+*. Similar patterns are also observed in the last two columns, that is, the coefficients are significantly negative from *Neighborhood_1* to *Neighborhood_3* but insignificant for the subsequent three variables. The results indicate that post-earthquake analyst pessimism only exists in the short term. Analysts will eventually get rid of their initial irrationality, but it will not happen immediately after the initial forecast. On average, it takes about three subsequent forecasts to eliminate their over-pessimism. The results support *H2b* that the post-earthquake analyst pessimism arising from earthquakes is temporary and analysts can correct their behavioral biases, which is also consistent with Dessaint and Matray (2017).

4.3.3. The impact of information transparency on the post-earthquake analyst pessimism

Previous studies offer supporting evidence that the information transparency of firms influences analyst forecasts (e.g., Lang, Lundholm, and Lang et al. (1996) and Hope (2003)). Following these studies, we examine whether less information transparency of

Table 9
The persistence of post-earthquake analyst pessimism.

	Dependent variable: *Pessimism*		
	Sample #1	Sample #2	Sample #3
	(1)	(2)	(3)
Disaster_1	−0.304	−0.484	−0.274
	(−0.73)	(−1.04)	(−1.57)
Disaster_2	−0.550	−0.435	−0.234
	(−1.12)	(−0.76)	(−1.31)
Disaster_3	0.249	0.343	0.128
	(0.37)	(0.36)	(1.05)
Disaster_4	0.527	0.879	0.483**
	(0.46)	(0.76)	(2.05)
Disaster_5	0.211	0.926	0.657
	(0.21)	(0.80)	(1.40)
Disaster_6+	0.318	0.708	0.175*
	(0.37)	(0.99)	(1.73)
Neighborhood_1	−0.240*	−0.264*	−0.214***
	(−1.76)	(−1.77)	(−3.24)
Neighborhood_2	−0.291**	−0.308*	−0.177***
	(−2.00)	(−1.88)	(−2.62)
Neighborhood_3	−0.259*	−0.272*	−0.156**
	(−1.87)	(−1.75)	(−2.23)
Neighborhood_4	−0.328**	−0.212	−0.145
	(−2.11)	(−1.22)	(−1.55)
Neighborhood_5	−0.310*	−0.293	0.007
	(−1.66)	(−1.33)	(0.09)
Neighborhood_6+	−0.295	−0.242	−0.026
	(−1.55)	(−1.07)	(−0.21)
Size	−0.396***	−0.365***	−0.315***
	(−4.38)	(−3.66)	(−7.39)
To	0.052***	0.052***	0.052***
	(3.27)	(2.88)	(8.83)
Mom	−0.235***	−0.286***	−0.275***
	(−4.54)	(−4.67)	(−10.02)
Inshold	−0.055	−0.254	−0.321**
	(−0.16)	(−0.67)	(−2.56)
Exfin	−0.091	−0.116	−0.114***
	(−1.32)	(−1.49)	(−3.72)
Groupsize	−0.028	0.012	0.017
	(−1.05)	(0.39)	(0.49)
Experience	−0.002	0.005	0.006
	(−0.16)	(0.35)	(0.40)
Comnum	−0.009	−0.016	−0.018
	(−0.72)	(−1.12)	(−1.23)
Female	0.008	−0.001	−0.001
	(0.35)	(−0.03)	(−0.04)
Master	−0.034	−0.014	−0.010
	(−1.27)	(−0.48)	(−0.28)
Interval	0.001	0.001	−0.000
	(0.81)	(0.67)	(−0.12)
AnalystCoverage	−0.212***	−0.240***	−0.220***
	(−3.75)	(−3.82)	(−6.56)
ConFeps	0.462***	0.341***	0.312***
	(4.85)	(3.45)	(7.99)
Death	−0.039	−0.030	−0.085*
	(−0.47)	(−0.30)	(−1.71)
Broker FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Observations	164,211	143,110	138,527
R-squared	0.247	0.282	0.296

In this table, we investigate whether post-earthquake analyst pessimism is temporary. Sichuan Province and Yunnan Province have been attacked by earthquakes many times. For convenience to identify, we exclude earthquakes occurred in these two provinces and forecasts focusing on firms within 500 km away from the epicenters of these earthquakes. We decompose Neighborhood in Eq. (1) into six variables to indicate successive forecasts of an analyst for a given firm in neighborhood area, namely, *Neighborhood_1*, *Neighborhood_2*, *Neighborhood_3*, *Neighborhood_4*, *Neighborhood_5*, and *Neighborhood_6+*. We similarly decompose a series of variables for firms in disaster zone, namely, *Disaster_1*, *Disaster_2*, *Disaster_3*, *Disaster_4*, *Disaster_5*, and *Disaster_6+*. Detailed definitions of variables are presented in Panel A of Appendix A. We control for brokerage, firm, year, quarter, and province fixed effects and cluster the standard errors by analysts. T-stats are reported in parentheses. *, ** and *** measure significance at the 10%, 5%, and 1% levels, respectively.

firms intensifies post-earthquake analyst pessimism. Following Hutton, Marcus, and Tehranian (2009), we use accrual manipulation to measure information transparency. We set *Opaque* as the mean absolute value of discretionary accruals for the past three years, that is, Eq. 6.

$$Opaque_{j,t} = \frac{1}{3}\sum_{l=1}^{3}\left|DisAcc_{j,t-l}\right| \tag{6}$$

where *DisAcc* is the discretionary annual accruals calculated from the modified Jones model (Dechow et al. (1995)) to measure the earnings management of firms. The larger the value of *Opaque*, the lower the transparency of the information. To test the moderating effects of firm transparency, we add *Opaque* as a control variable and an interaction term between *Neighborhood* and *Opaque*, namely, *Neighborhood_Opaque*, into Eq. (1). We drop observations with missing values in the process of calculating *Opaque*. The results are reported in Table 10.

As shown in the table, the coefficients of *Neighborhood_Opaque* are negative at a significance level of 0.01, suggesting that analysts tend to be pessimistic after earthquakes when neighborhood area firms are less transparent. Thereby, we find supporting evidence on H3c that the post-earthquake analyst pessimism is intensified when the information environment of listed firms is less transparent. The result highlights the importance of information transparency in making earnings forecasts and shows that high information transparency reduces the heuristic bias of analysts.[10]

5. Robustness checks and cross-sectional analysis

5.1. Robustness checks

To test the robustness of baseline results, we conduct a series of empirical examinations. First, the baseline results may be driven by outliers of *Pessimism* because it easily obtains an extreme value when the actual EPS is low. We use winsorized and logarithmic *Pessimism* as alternative variables and obtain robust results. Then, we examine the possibility that specific earthquakes drive our baseline results. We use samples respectively excluding the four deadliest earthquakes, earthquakes in Sichuan Province, and earthquakes in Sichuan and Yunnan to re-estimate Eq. (1). The baseline findings keep robust. Finally, to control for the effects of firm operation complexity and time-varying research resources from brokerage firms, we add variables into Eq. (1) and find consistent results in Table 3. Overall, our robust tests suggest that the baseline finding in this study is robust to the outliers of the dependent variable, specific earthquake events, and other influencing factors. The process of robustness checks and empirical results are reported in Appendix E.

5.2. Cross-sectional analyses: analyst sophistication

To improve the understanding of post-earthquake analyst pessimism, we further conduct cross-sectional analyses and we focus on analyst sophistication. The development of the capital market in China has a short history relative to that of developed markets, thus the overall unsophisticated analyst group may promote behavioral biases after extreme events happening. While analyst sophistication or ability is unobservable, previous studies have provided certain helpful measurements. Specifically, we measure analyst sophistication by using two primary variables, namely, the size of brokerage firms and star analysts. A large brokerage firm can provide superior resources (e.g., better access to data sets and administrative support) to their analysts (Clement (1999)), and thereby analysts may obtain more information about the real effect of earthquakes on nearby firms. We expect that analysts employed by large brokerage firms may be less irrationally pessimistic for firms in neighborhood areas. For star analysts, previous studies regarding Chinese analysts show that they know more firm-specific information than non-star analysts (Xu et al. (2013a, 2013b)). Therefore, we also expect that star analysts may keep more rational relative to non-star analysts after earthquakes.

We mark analysts employed by large brokerage firms and star analysts as sophisticated analysts and expect them to be less subject to behavioral biases. To examine the argument, we categorize observations into subsamples. To test the influence of brokerage size, we assign forecasts from brokerage firms whose total asset is larger than the median of total assets into the subsample of large brokerage firms and others into small brokerage firms. Similarly, we assign forecasts from star analysts into the subsample of star analysts and others into non-star analysts to examine the influence. We find that post-earthquake analyst pessimism is generally concentrated in the subsample of small brokerage firms and non-star analysts, supporting our expectations that sophisticated analysts will be less

[10] We thank the anonymous reviewer for raising an alternative explanation that the post-earthquake analyst pessimism for neighborhood area firms may be driven by an upward manipulation of the actual reported earnings after earthquakes. After the occurrence of earthquakes, corporate managers may have a strong incentive to report higher corporate earnings by engaging in earnings management to alleviate their investors' concerns about their corporate performance. Therefore, the upward manipulation of actual reported earnings can lead to relatively low analyst earnings forecasts, which may be interpreted as analyst pessimism. To rule out this alternative explanation, we examine whether managers actually manage their corporate earnings after earthquakes in Appendix D. However, we do not find any supporting evidence on this explanation.

Table 10
The impact of information transparency on the post-earthquake analyst sentiment.

	Dependent variable: *Pessimism*		
	Sample #1	Sample #2	Sample #3
	(1)	(2)	(3)
Disaster	0.098	0.116	−0.209
	(0.84)	(0.91)	(−1.63)
Neighborhood	−0.122*	−0.109	−0.111
	(−1.72)	(−1.44)	(−1.25)
Neighborhood_Opaque	−2.960***	−2.942***	−4.543***
	(−3.99)	(−3.68)	(−4.23)
Opaque	1.335***	1.504***	1.553***
	(3.88)	(4.02)	(4.24)
Size	−0.509***	−0.489***	−0.461***
	(−8.87)	(−8.03)	(−8.04)
To	0.087***	0.082***	0.073***
	(11.30)	(9.70)	(8.92)
Mom	−0.150***	−0.172***	−0.182***
	(−4.77)	(−4.79)	(−5.22)
Inshold	0.061	−0.201	−0.416**
	(0.40)	(−1.18)	(−2.52)
Exfin	−0.134***	−0.141***	−0.121***
	(−3.70)	(−3.40)	(−2.94)
Groupsize	−0.011	0.018	0.018
	(−0.27)	(0.39)	(0.44)
Experience	0.001	0.008	0.007
	(0.06)	(0.49)	(0.45)
Comnum	0.006	0.010	0.006
	(0.41)	(0.59)	(0.37)
Female	0.004	0.003	0.007
	(0.21)	(0.12)	(0.29)
Master	−0.041	−0.022	−0.022
	(−1.10)	(−0.54)	(−0.55)
Interval	0.000	−0.000	−0.002**
	(0.25)	(−0.15)	(−2.24)
AnalystCoverage	−0.142***	−0.151***	−0.159***
	(−3.40)	(−3.33)	(−3.49)
ConFeps	0.252***	0.204***	0.215***
	(8.69)	(7.31)	(7.06)
Death	0.024	0.025	0.049*
	(1.35)	(1.32)	(1.79)
Broker FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Observations	137,706	121,733	116,669
R-squared	0.310	0.337	0.351

In this table, we investigate how information transparency influences the post-earthquake analyst sentiment. We use accrual manipulation to measure information transparency. We set *Opaque* as the mean absolute value of discretionary accruals for the past three years. *Neighborhood_Opaque* is constructed by *Neighborhood* and *Opaque*. Detailed definitions of variables are presented in Panel A of Appendix A. We control for brokerage, firm, year, quarter, and province fixed effects and cluster the standard errors by analysts. T-stats are reported in parentheses. *, ** and *** measure significance at the 10%, 5%, and 1% levels, respectively.

influenced by behavioral biases. Empirical results in detail are reported in Appendix F.

6. Conclusion

This study examines the effect of natural disasters on analyst sentiment or behavioral bias. We focus on those earthquakes that occur in China and find evidence to support the causal relationship between earthquakes and analyst pessimism. Despite the difficulty in directly investigating how earthquakes drive analyst pessimism, our empirical design offers evidence to support that post-earthquake pessimism is driven by the use of heuristics in making forecasts. The features of analyst behavior in forecasting earnings are consistent with the features of heuristic bias documented in the existing literature. The availability heuristics driven by excessive media attention has been identified as a source of post-earthquake analyst pessimism.

Our investigations on the economic impact of earthquakes reveal that these disasters can influence listed firms to some extent, but their negative effects on corporate earnings and stock returns are limited to those firms that are located in a very close range from the epicenter. Analysts do not show over-pessimism for disaster zone firms yet show irrational pessimism for neighborhood area firms. A discussion regarding the influence of earthquakes on the profitability and stock returns of neighborhood area firms does not produce any evidence to support that post-earthquake analyst pessimism is based on rational judgments.

In line with our hypotheses, the salience of an earthquake event prompts analysts to use heuristics in forecasting earnings and induces irrational pessimism. While previous studies have ignored the pessimism of analysts, our research partly fills this gap by proving that heuristic bias is among the reasons why analysts show pessimism after natural disasters.

Declaration of Competing Interest

None.

Appendix A. Variable definitions

Measure	Description
Panel A: Forecast-level	
Pessimism	The difference between analysts' forecasted EPS and actual EPS divided by the absolute value of actual EPS.
WPessimism	A variable equaling to the winsorized *Pessimism* at 5th and 95th quantiles.
LogPessimism	The nature logarithm of 1 plus *Pessimism.*
Disaster	A dummy variable equal to 1 if the forecast is for a firm in the disaster zone and released within a year after the occurrence of the earthquake; otherwise, 0.
Neighborhood	A dummy variable equal to 1 if the forecast is for a firm in the neighborhood area and released within a year after the occurrence of the earthquake; otherwise, 0.
SIZE	The natural logarithm of the firms' total assets last year.
TO	The ratio of the trading volume of firms and the tradeable market value last year.
MOM	Annual stock return last year.
Inshold	The ratio of institutional holdings on outstanding shares last year. Institutional holdings include holdings from mutual funds, brokerage firms, insurance firms, social insurance funds, and qualified foreign institutional investors (QFII).
Exfin	External financing needs for a firm last year. The definition is referred to Demirgüç-Kunt and Maksimovic (1998).
Groupsize	The natural logarithm of the number of members of an analyst team. If the analyst forecast is issued by a single analyst, then, *Groupsize* equals 0.
Experience	The natural logarithm of 1 plus the number of years since the analyst released their first forecast.
Comnum	The natural logarithm of the total number of firms that the analyst focuses on in the year when their forecast is released.
Female	The ratio of female analysts in an analyst team. If the forecast is issued by a single analyst, then, *Female* becomes a dummy variable equal to 1 if the analyst is a female analyst.
Master	The ratio of analysts with a Master's degree or a doctorate degree in an analyst team. If the forecast is issued by a single analyst, then, *Master* becomes a dummy variable equal to 1 if the analyst owns a Master's degree or a doctorate degree.
Interval	The number of days between the latest earthquake and the issue date of forecasts within a year, where the value would be zero for all pre-earthquake forecasts and forecasts for the control group.
ConFeps	The median of all forecasted EPS for the same targeted year issued within a year before the forecast of a listed firm.
AnalystCoverage	The natural logarithm of the number of brokerage firms focusing on the same listed firm.
Death	Variable equaling to the natural logarithm of 1 plus the number of casualties caused by the earthquake if the forecast is an earthquake-exposed forecast; otherwise, 0.
R&D	The ratio of R&D expenditures on corporate income last year.
Brokerasset	The natural logarithm of the total assets of brokerage firms last year.
Opaque	The mean absolute values of discretionary accruals for the past three years. The calculation process of discretionary accruals is referred to Dechow et al. (1995).
Panel B: Firm-level	
EPS	Earnings per share defined as total net earnings divided by the number of outstanding shares.
Disaster_Firm	A dummy variable equaling 1 if the firm is in the disaster zone in the earthquake-occurring year.
Neighborhood_Firm	A dummy variable equaling 1 if the firm is in the neighborhood area in the earthquake-occurring year.
Size	The natural logarithm of total assets.
Leverage	The ratio of leverage defined as total debts divided by total assets.
Ppe	The total assets ratio defined as the value of total assets divided by total assets.
Inshold	The ratio of institutional holdings on outstanding shares.
Indratio	The ratio of independent directors to the board of firms.
Boardsize	The natural logarithm of the number of board members of firms.
Cashratio	The ratio of cash holdings defined as the value of cash and cash equivalent divided by the value of total assets.
NWC	The ratio of net working capital defined as the net working capital divided by the value of total assets.
IntervalToEnd	The number of days between the earthquake date and the end of the fiscal year. If a firm is located 500 km away from epicenters, *IntervalToEnd* equals 0.

Appendix B. Media attention for each earthquake

ID	Quake date	Measure media attention by Baidu Index	Measure media attention by newspaper articles in CNKI

(continued on next page)

(*continued*)

ID	Quake date	Measure media attention by Baidu Index			Measure media attention by newspaper articles in CNKI		
		Keywords	Baidu Index	High attention	Keywords	The number of articles	High attention
		Keywords	Baidu Index	High attention	Keywords	The number of articles	High attention
1	6/2/2007	–	–	–	Puer earthquake (普洱地震)	0	0
2	8/21/2008	Yingjiang earthquake (盈江地震)	135.5	0	Yingjiang earthquake (盈江地震)	5	1
3	7/9/2009	Yaoan county (姚安县)	196.9	0	Yaoan earthquake (姚安地震)	10	1
4	5/10/2011	Yingjiang earthquake(盈江地震)	176.3	0	Yingjiang earthquake (盈江地震)	0	0
5	9/7/2012	Yiliang earthquake (彝良地震)	3132.6	1	Yiliang earthquake (彝良地震)	40	1
6	8/3/2014	Lulian earthquake (鲁甸地震)	8252.3	1	Lulian earthquake (鲁甸地震)	55	1
7	5/18/2016	Yulong county (云龙县)	151.3	0	Yulong earthquake (云龙地震)	1	0
8	5/12/2008	Wenchuan earthquake (汶川地震)	173,451.0	1	Wenchuan earthquake (汶川地震)	197	1
9	1/30/2010	Suining city (遂宁市)	151.4	0	Suining earthquake (遂宁地震)	2	0
10	6/24/2012	Yanyuan earthquake (盐源地震)	310.6	0	Yanyuan earthquake (盐源地震)	3	0
11	4/20/2013	Yaan earthquake (雅安地震)	446,110.8	1	Yaan earthquake (雅安地震)	171	1
12	11/22/2014	Kangding earthquake (康定地震)	4060.3	1	Kangding earthquake (康定地震)	27	1
13	7/3/2015	Hetian earthquake (和田地震)	454.6	0	Hetian earthquake (和田地震)	2	0
15	7/20/2012	Gaoyou earthquake (高邮地震)	7871.4	1	Gaoyou earthquake (高邮地震)	0	0
16	7/22/2013	Minxian earthquake (岷县地震)	2157.9	1	Minxian earthquake (岷县地震)	8	1
17	10/6/2008	Lasa earthquake (拉萨地震)	850.0	1	Lasa earthquake (拉萨地震)	1	0
18	1/17/2010	Anshun city (安顺市)	163.5	0	Anshun earthquake (安顺地震)	0	0
19	4/14/2010	Yushu earthquake (玉树地震)	77,797.0	1	Yushu earthquake (玉树地震)	205	1

Appendix C. Alternative explanations: earthquakes that receive high media attention cause more damage

Although earthquakes that receive high media attention are more salient to analysts under the heuristic bias channel, these "high attention earthquakes" also disrupt a firm's corporate operations or stock returns and prompt analysts to rationally revise their earnings expectations downward. To rule out this alternative explanation, we empirically examine whether high attention earthquakes statistically disrupt the corporate earnings and stock returns of firms.

First, we examine the impact of high attention earthquakes on corporate earnings. We add *Disaster_Attention_Firm* and *Neighborhood_Attention_Firm* to Eq. (3) to examine the effects of high attention earthquakes on corporate earnings. *Disaster_Attention_Firm* and *Neighborhood_Attention_Firm* are dummy variables equal to 1 if a firm is located in the disaster zone of a high attention earthquake or the neighborhood area, respectively.

Table AC1 presents the estimation results, where columns (1) and (2) measure media attention based on the Baidu index and the number of newspaper articles, respectively. In Table 9, the coefficients of *Disaster_Firm* remain significantly negative, thereby suggesting that earthquakes reduce the earnings of disaster zone firms. This finding is consistent with the results reported in Table 5. Interestingly, the high media attention for earthquakes can alleviate the negative impact of earthquakes on corporate earnings because having more media coverage may translate to higher public attention, which in turn leads to increased financial or material support from the public.[11] As for neighborhood area firms, the coefficients of *Neighborhood_Firm* and *Neighborhood_Attention_Firm* remain insignificant, thereby suggesting that high attention earthquakes do not significantly damage the profitability of these firms.

[11] For example, after the high attention Wenchuan earthquake, the policy document entitled "Guideline from People's Bank of China, China Banking Regulatory Commission, China Securities Regulatory Commission and China Insurance Regulatory Commission on Financial Support and Service Measures for Post-Wenchuan Earthquake Reconstruction" was issued to support the reconstruction of the affected areas. This document brought extensive financial support to those areas significantly affected by earthquakes, thereby alleviating the negative effects of earthquakes on local firms.

We also examine the market reactions to earthquakes with different media attention levels. We initially examine short-term market reactions by calculating *CARs* after earthquakes. Specifically, apart from studying the changes in the stock returns of firms located different distances away from epicenters, we further separate the firms in each group based on their levels of media attention. As shown in Table AC2, almost all *CARs* are insignificant, except for that in Column (10) of Panel A, thereby indicating the absence of any obvious market reaction, especially for neighborhood area firms, after earthquakes regardless of the level of media attention. Therefore, we find no evidence that the post-earthquake analyst pessimism for neighborhood area firms results from concerns over short-term stock returns.

To compare the long-term changes in the stock returns of firms located different distances away from epicenters and across different levels of media attention, we categorize these firms into five groups. We calculate the value-weight portfolio returns of firms in the disaster zone, the neighborhood area, and the control group after the occurrence of high and low attention earthquakes and then check whether the differences in their alpha (as reported by the Fama-French 3 factors model) are statistically significant. Table AC3 presents the results. The last 4 columns of Table AC3 show that despite considering the effects of media attention and calculating the corresponding portfolio returns, the alphas of disaster zone or neighborhood area firms are not significantly lower than that of control group firms.

Collectively, we rule out the possibility that the post-earthquake analyst pessimism for neighborhood area firms is induced by high attention earthquakes because these earthquakes negatively affect these firms' corporate earnings or stock returns. Our findings suggest that even high attention earthquakes do not statistically affect the corporate earnings and stock returns of neighborhood area firms. Therefore, *H3a* is supported because of the heuristic bias.

Table AC1
The impact of earthquakes on corporate earnings across different levels of media attention.

	Dependent variable: *EPS*	
	(1)	(2)
Disaster_Firm	−0.119***	−0.086**
	(−3.31)	(−2.26)
Neighobrhood_Firm	0.030	−0.032
	(0.47)	(−0.55)
Disaster_Attention_Firm	0.112**	0.074***
	(2.09)	(2.91)
Neighobrhood_Attention_Firm	−0.034	−0.025
	(−1.07)	(−0.83)
Size	−0.002	−0.002
	(−0.18)	(−0.15)
Leverage	0.125***	0.119***
	(3.28)	(2.94)
Ppe	−0.611***	−0.605***
	(−12.68)	(−12.58)
Inshold	0.834***	0.837***
	(15.21)	(15.23)
Indratio	0.104	0.102
	(1.05)	(1.02)
Boardsize	0.046	0.047
	(1.45)	(1.47)
Cashratio	0.208***	0.208***
	(6.48)	(6.46)
NWC	−0.136***	−0.135***
	(−2.98)	(−2.99)
IntervalToEnd	−0.000	0.000
	(−0.26)	(0.50)
Firm FE	Yes	Yes
Year FE	Yes	Yes
Province FE	Yes	Yes
Observations	19,207	19,251
R-squared	0.608	0.606

This table presents results from regressions examining whether earthquakes with high media attention would cause more severe damage to corporate earnings of firms in neighborhood areas. Results with media attention measured by the Baidu Index and the number of newspaper articles are presented in column (1) and (2) respectively. *EPS* is earnings per share of a firm at the end of the year. *Disaster_Firm* is a dummy variable equaling 1 if the firm is in the disaster zone in the year when the earthquake occurs. Similarly, *Neigborhood_Firm* is a dummy variable indicating neighbor firms in the earthquake-occurring year. *Disaster_Attention_Firm* is a dummy variable equal to 1 if a firm locates in the disaster zone of a high attention earthquake in the earthquake-occurring year. *Neighborhood_Attention_Firm* similarly indicates firms in neighborhood areas. We control for some firms' features and fixed effects including *Firm, Year*, and *Province* representing firm, year, and province fixed effects. Detailed definitions of variables are in Panel B of Appendix A. The standard errors are clustered by firms. T-stats are reported in parentheses. *, ** and *** measure significance at the 10%, 5%, and 1% levels, respectively.

Table AC2
CAR after earthquakes occurring across different levels of media attention.

Measurement	Baidu Index						Newspaper articles					
	Low attention			High attention			Low attention			High attention		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Event windows	[1,5]	[1,15]	[1,25]	[1,5]	[1,15]	[1,25]	[1,5]	[1,15]	[1,25]	[1,5]	[1,15]	[1,25]
Panel A CARs of firms in disaster zones												
CAR	−0.0086	0.0262	0.0076	−0.0052	−0.0032	0.0072	−0.0005	0.0163	0.0269**	−0.0149***	−0.0175	−0.0228
t-value	(−0.84)	(1.31)	(0.93)	(−0.75)	(−0.24)	(0.28)	(−0.09)	(1.72)	(2.63)	(−7.16)	(−0.92)	(−0.64)
Panel B. CARs of firms in neighborhood areas												
CAR	−0.0062	−0.0037	−0.0060	0.0006	−0.0020	−0.0031	−0.0031	0.0001	0.0099	0.0022	−0.0056	−0.0208
t-value	(−1.19)	(−0.47)	(−1.06)	(0.13)	(−0.21)	(−0.15)	(−1.47)	(0.02)	(1.46)	(0.29)	(−0.34)	(−0.69)

This table examines whether earthquakes with high media attention would cause a negative short-term change in stock returns after earthquakes. We use Baidu Index and the number of newspaper articles to measure media attention. We focus on the cumulative abnormal return (*CAR*) of firms within 500 km away from epicenters after earthquakes. For each firm, we estimate the market model over days [−250, −1] before the occurrence of earthquakes. Then, the abnormal returns of each firm are constructed as the difference between the realized individual firm returns and the estimated firm returns from the market model. *CAR* of each firm is the sum of daily abnormal returns in different lengths of event windows with 25 trading days in the longest event window. For groups with different levels of media attention, we use *t*-test to examine whether CARs of firms are significantly unequal to 0. Panel A reports the results for firms in disaster zones and Panel B reports for firms in neighborhood areas. In Column (1) to Column (6) the media attention is measured by Baidu Index, and in Column (7) to Column (12) the media attention is measured by the number of newspaper articles. T-stats are reported in parentheses. *, ** and *** measure significance at the 10%, 5%, and 1% levels, respectively.

Table AC3
The Alpha of portfolios after earthquakes across different levels of media attention.

	Disaster Zones		Neighborhood areas		Control	Disaster-Control	Disaster-Control	Neighbor-Control	Neighbor-Control
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	High attention	Low attention	High attention	Low attention		(1)–(5)	(2)–(5)	(3)–(5)	(4)–(5)
Panel A Portfolio returns for 12 months after the earthquakes and media attention measured by Baidu Index									
Alpha	−0.001	−0.003	0.000	0.001	−0.001	−0.001	−0.002	0.001	0.002
	(−0.12)	(−0.38)	(0.03)	(0.19)	(−0.18)				
Rm-Rf	0.805***	0.646***	0.643***	0.682***	0.769***	0.036	−0.124	−0.126	−0.0870
	(7.16)	(6.78)	(9.66)	(8.38)	(19.57)				
SMB	0.661**	0.049	0.294*	0.348*	−0.051	0.712**	0.100	0.345*	0.400
	(2.36)	(0.20)	(1.78)	(1.69)	(−0.52)				
HML	−0.384	−0.183	−0.081	−0.146	0.028	−0.412	−0.210	−0.109	−0.174
	(−1.10)	(−0.84)	(−0.39)	(−0.78)	(0.26)				
Obs	72	66	72	66	138				
R^2	0.496	0.407	0.610	0.539	0.742				
Panel B Portfolio returns for 12 months after the earthquakes and media attention measured by the number of newspaper articles									
Alpha	0.000	0.001	0.001	0.003	−0.000	0.001	0.002	0.002	0.004
	(0.03)	(0.14)	(0.20)	(0.43)	(−0.11)				
Rm-Rf	0.742***	0.817***	0.686***	0.745***	0.792***	−0.050	0.025	−0.106	−0.047
	(6.44)	(7.58)	(10.53)	(7.97)	(19.20)				
SMB	0.642**	0.538*	0.264	0.488*	−0.028	0.670*	0.566*	0.292	0.517*
	(2.17)	(1.90)	(1.58)	(1.99)	(−0.27)				
HML	−0.366	−0.468*	0.121	−0.202	0.100	−0.466	−0.568**	0.021	−0.302
	(−1.05)	(−1.67)	(0.61)	(−0.83)	(0.87)				
Obs	72	78	72	78	150				
R^2	0.446	0.465	0.645	0.484	0.719				
Panel C Portfolio returns for 24 months after the earthquakes and media attention measured by Baidu Index									
Alpha	0.009	0.002	0.010**	0.005	0.005**	0.004	−0.003	0.005	0.000
	(1.18)	(0.29)	(2.27)	(1.11)	(2.17)				
Rm-Rf	0.751***	0.753***	0.731***	0.703***	0.779***	−0.028	−0.026	−0.048	−0.0770
	(9.34)	(9.39)	(15.57)	(10.76)	(27.32)				
SMB	0.573***	0.495***	0.180*	0.237*	−0.089	0.663**	0.585***	0.270**	0.326
	(3.22)	(2.88)	(1.73)	(1.69)	(−1.42)				
HML	−0.289	−0.469***	−0.045	−0.547***	−0.004	−0.284	−0.465**	−0.041	−0.543***
	(−1.33)	(−2.68)	(−0.36)	(−3.84)	(−0.06)				

(*continued on next page*)

Table AC3 (*continued*)

	Disaster Zones		Neighborhood areas		Control	Disaster-Control	Disaster-Control	Neighbor-Control	Neighbor-Control
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	High attention	Low attention	High attention	Low attention		(1)–(5)	(2)–(5)	(3)–(5)	(4)–(5)
Obs	144	141	144	141	285				
R^2	0.460	0.414	0.661	0.468	0.727				
Panel D Portfolio returns for 24 months after the earthquakes and media attention measured by the number of newspaper articles									
Alpha	0.010	0.004	0.011**	0.007	0.006**	0.005	−0.002	0.005	0.001
	(1.33)	(0.60)	(2.49)	(1.39)	(2.37)				
Rm-Rf	0.704***	0.795***	0.760***	0.677***	0.791***	−0.087	0.004	−0.032	−0.114
	(8.31)	(11.03)	(16.26)	(11.51)	(28.52)				
SMB	0.584***	0.705***	0.158	0.285*	−0.072	0.656**	0.777***	0.230*	0.357
	(3.07)	(3.85)	(1.51)	(1.91)	(−1.10)				
HML	−0.228	−0.299	0.039	−0.489***	0.055	−0.284	−0.355	−0.017	−0.545***
	(−1.03)	(−1.64)	(0.31)	(−3.28)	(0.77)				
Obs	144	165	144	165	309				
R^2	0.409	0.470	0.678	0.477	0.730				
Panel E Portfolio returns for 36 months after the earthquakes and media attention measured by Baidu Index									
Alpha	0.004	−0.003	0.012***	0.004	0.007***	−0.003	−0.009	0.006	−0.003
	(0.54)	(−0.52)	(3.38)	(1.00)	(3.24)				
Rm-Rf	0.806***	0.794***	0.758***	0.610***	0.762***	0.044	0.031	−0.005	−0.153**
	(11.32)	(11.58)	(18.98)	(11.59)	(31.86)				
SMB	0.665***	0.610***	0.138*	0.176*	−0.117**	0.782***	0.727***	0.255***	0.292**
	(4.60)	(4.47)	(1.71)	(1.67)	(−2.40)				
HML	−0.123	−0.439***	−0.083	−0.505***	0.001	−0.123	−0.440**	−0.084	−0.506***
	(−0.66)	(−2.72)	(−0.80)	(−4.07)	(0.01)				
Obs	214	201	214	201	415				
R^2	0.486	0.458	0.670	0.422	0.716				
Panel F Portfolio returns for 36 months after the earthquakes and media attention measured by the number of newspaper articles									
Alpha	−0.000	0.002	0.011***	0.007	0.007***	−0.007	−0.004	0.004	0.000
	(−0.03)	(0.44)	(2.99)	(1.59)	(3.26)				
Rm-Rf	0.803***	0.766***	0.771***	0.643***	0.781***	0.022	−0.015	−0.010	−0.138**
	(10.71)	(12.99)	(19.22)	(13.04)	(33.62)				
SMB	0.748***	0.648***	0.142*	0.204*	−0.116**	0.864***	0.764***	0.258***	0.320***
	(4.74)	(5.07)	(1.68)	(1.91)	(−2.34)				
HML	−0.126	−0.317**	−0.101	−0.297**	0.055	−0.181	−0.372**	−0.156	−0.352**
	(−0.67)	(−2.11)	(−0.99)	(−2.36)	(0.93)				
Obs	214	237	214	237	451				
R^2	0.463	0.488	0.672	0.444	0.721				

Appendix D. Alternative explanations: the role of earnings management

After the occurrence of earthquakes, corporate managers may engage in earnings management to alleviate their investors' concerns about their corporate performance. Therefore, post-earthquake analyst pessimism can be a result of relatively high reported earnings of firms in the neighborhood area. To examine the alternative explanation, we run the following regression by using firm-level data:

$$DisAcc_{jt} = \alpha + \beta_1 Disaster\_Firm_{jt} + \beta_2 Neighborhood\_Firm_{jt} + \gamma Control_{j,t-1} + Firm\ FE_j + Year\ FE_t + Province\ FE_{jt} + \varepsilon_{jt} \tag{A1}$$

where *DisAcc* is the discretionary annual accruals calculated from the modified Jones model (Dechow et al. (1995)) to measure the earnings management of firms. Specifically, we estimate the following cross-sectional regression (i.e., Eq. A2) using the firms in each industry for each year between 2007 and 2016.

$$\frac{TA_{j,t}}{Asset_{j,t-1}} = k_1 \frac{1}{Asset_{j,t-1}} + k_2 \frac{\Delta Sales_{j,t}}{Asset_{j,t-1}} + k_3 \frac{PPE_{j,t}}{Asset_{j,t-1}} + \varepsilon_{j,t} \tag{A2}$$

where *j* indexes firms and *t* indexes year. *TA* is total accruals equal to the difference between the net income and the net cash flow from operating activities; *ΔSales* is the change in sales; and *PPE* is property, plant, and equipment for firms. The classification of the industry is based on the Guidelines for Industry Classification of Firms published by China Securities Regulatory Commission in 2012. Then, we use the estimated k_1, k_2, and k_3, marked as $\widehat{k}_1$, $\widehat{k}_2$, and $\widehat{k}_3$, respectively, to calculate the discretionary annual accruals (*DisAcc*) as follows (Eq. A3):

$$DisAcc_{j,t} = \frac{TA_{j,t}}{Asset_{j,t-1}} - \left(\widehat{k}_1 \frac{1}{Asset_{j,t-1}} + \widehat{k}_2 \frac{\Delta Sales_{j,t} - \Delta REC_{j,t}}{Asset_{j,t-1}} + \widehat{k}_3 \frac{PPE_{j,t}}{Asset_{j,t-1}} \right) \tag{A3}$$

where *ΔREC* is the change in account receivables. A larger *DisAcc* denotes upward managing earnings. We drop those observations with missing values in calculating earnings management and then estimate Eq. (A1). The results are presented in Table AD1.

The coefficients of *Neighborhood_Firm* are insignificant, thereby suggesting that managers of neighborhood area firms do not significantly manipulate their corporate earnings after earthquakes even if they have the incentives to engage in such activity. Therefore, we can rule out the alternative explanation that post-earthquake analyst pessimism is caused by corporate earnings management.

Table AD1
The impact of earthquakes on earnings management.

	Dependent variable: *DisAcc*	
	(1)	(2)
Disaster_Firm	−0.012	−0.021
	(−1.54)	(−1.20)
Neighborhood_Firm	0.002	−0.009
	(0.66)	(−0.46)
Size		−0.007
		(−1.25)
Leverage		0.020*
		(2.04)
Ppe		−0.074***
		(−4.79)
Inshold		0.053***
		(4.79)
Indratio		0.021
		(0.64)
Boardsize		0.026**
		(2.45)
Cashratio		0.044***
		(2.90)
NWC		−0.119***
		(−10.10)
IntervalToEnd		0.000
		(0.58)
Firm FE	Yes	Yes
Year FE	Yes	Yes
Province FE	Yes	Yes
Observations	19,209	19,209
R-squared	0.188	0.201

This table examines the impact of earthquakes on earnings management of firms possibly affected by earthquakes. We estimate the Eq. (A1) using firm-year data and report the results in this table. *DisAcc* is the discretionary annual accruals. Other settings are the same as Table 5 in the paper. T-stats are reported in parentheses. *, ** and *** measure significance at the 10%, 5%, and 1% levels, respectively.

Appendix E. Robustness checks

We test the robustness of our baseline finding. First, we examine the possibility that our baseline finding is driven by outliers of the dependent variable. *Pessimism* easily obtains an extreme value when the actual EPS is very low according to Eq. (2). We replaced the dependent variables with other specifications to alleviate the influence of the outliers of *Pessimism* on our results. For the first variable, we winsorize *Pessimism* at the 5th and 95th quantiles and mark it as *Wpessimism*. The second variable, *LogPessimism*, denotes the nature logarithm of 1 plus *Pessimism*. The maximum of *Wpessimism* and *LogPessimism* respectively are 2.57 and 3.52, which are far smaller than that of *Pessimism* reported in Table 2. We replace *Pessimism* in Eq. (1) with *WPessimism* and *LogPessimism* and then re-estimate the equation. Table AE1 reports the results. The coefficients of *Neighborhood* remain significantly negative even if we use the new dependent variables in Eq. (1). Therefore, our baseline finding is not driven by the extreme values of *Pessimism*.

Second, we examine the possibility that specific earthquake events drive our baseline finding. The first concern is that our baseline results may be driven by certain of the most severe earthquakes. Although all earthquakes in our sample have caused casualties, they show significant differences in their number of casualties, and analyst pessimism is likely to be caused by those earthquakes that have caused the fewest deaths. The second concern may be that firms in those provinces that are most severely affected by earthquakes drive our baseline finding. Sichuan Province has reported the highest number of earthquake-related casualties in our sample period. Among the four earthquakes with the highest number of deaths, two took place in Sichuan Province. Therefore, our baseline finding may be driven only by those earthquakes that have occurred in this province. The third concern may be that firms in earthquake-prone provinces drive our baseline finding. The majority of the earthquakes in our sample have occurred in either Sichuan Province or Yunnan Province (12/18). Our baseline finding may be driven by the analysts' concerns that these two provinces are more vulnerable to earthquakes compared with other provinces.

We remove the corresponding analysts' forecast observations from our sample to rule out the possibility that specific earthquake events drive our baseline finding. The estimations of Eq. (1) are reported in Table AE2, where column (1) to (3) exclude the observations related to the four deadliest earthquakes (earthquake IDs 6, 8, 11, and 19), column (4) to (6) exclude the observations related to earthquakes in Sichuan Province, and column (7) to column (9) exclude the observations related to earthquakes in both Sichuan Province and Yunnan Province. The coefficients of *Neighborhood* are all significantly negative in Table AE2, thereby suggesting that our baseline finding is not driven by specific earthquake events.

Finally, to control for the potential effects of firm operation complexity and time-varying research resources from brokerage firms, we include R&D expenditures and brokerage size as our control variables. We obtain our data on R&D expenditures from CSMAR and calculate the ratio of R&D expenditures to corporate income. We also obtain data on the total asset of brokerage firms from the Chinese Research Data Services (CNRDS) to control for the effects of brokerage size. However, the data of R&D expenditures are seriously missed before 2011 due to the disclosure of R&D expenditures is mostly voluntary. Missing values are also observed in the brokerage size data because some unlisted brokerage firms are not required to disclose their financial information. Controlling for R&D expenditures and brokerage size will inevitably reduce the sample size. Therefore, we only control for the effect of R&D expenditures (*R&D*) and *Brokerasset* in the robustness tests and present the results in Table AE3, where column (1) to (3) present the results based on the observations over the entire sample period, and column (4) to (6) present the results over the sample period after 2011. The coefficients of *Neighborhood* are significantly negative in all columns, thereby suggesting that our baseline results remain robust after controlling for the effects of *R&D* and *Brokerasset*.

Table AE1
Robustness test I: Alternative measurements of analyst pessimism.

	Dependent variables					
	Wpessimism			*Logpessimism*		
	Sample #1	Sample #2	Sample #3	Sample #1	Sample #2	Sample #3
	(1)	(2)	(3)	(4)	(5)	(6)
Disaster	−0.012	0.009	−0.006	−0.014	−0.003	−0.015
	(−0.50)	(0.32)	(−0.28)	(−0.67)	(−0.15)	(−0.67)
Neighborhood	−0.046***	−0.044***	−0.029**	−0.039***	−0.038***	−0.025**
	(−3.26)	(−2.97)	(−2.31)	(−3.69)	(−3.45)	(−1.99)
Size	−0.120***	−0.122***	−0.128***	−0.080***	−0.076***	−0.078***
	(−10.32)	(−9.73)	(−19.81)	(−8.40)	(−7.53)	(−7.72)
To	0.021***	0.020***	0.018***	0.016***	0.015***	0.014***
	(14.89)	(13.43)	(24.21)	(15.08)	(13.51)	(12.43)
Mom	−0.109***	−0.126***	−0.119***	−0.099***	−0.112***	−0.107***
	(−14.21)	(−13.56)	(−27.33)	(−15.90)	(−15.23)	(−14.66)
Inshold	0.111***	0.001	−0.010	0.085***	0.008	−0.010
	(4.35)	(0.05)	(−0.58)	(4.06)	(0.32)	(−0.41)
Exfin	−0.017**	−0.022***	−0.025***	−0.020***	−0.025***	−0.025***
	(−2.55)	(−2.90)	(−5.66)	(−3.95)	(−4.39)	(−4.49)
Groupsize	−0.003	0.022*	0.022***	−0.005	0.010	0.011
	(−0.29)	(1.92)	(3.59)	(−0.64)	(1.21)	(1.32)
Experience	−0.001	0.004	0.004	−0.001	0.002	0.001
	(−0.23)	(0.81)	(1.34)	(−0.43)	(0.43)	(0.38)
Comnum	−0.003	−0.004	−0.004*	−0.001	−0.002	−0.003
	(−0.99)	(−0.92)	(−1.91)	(−0.55)	(−0.72)	(−0.87)
Female	−0.007	−0.012*	−0.009**	−0.001	−0.004	−0.002
	(−1.10)	(−1.83)	(−2.16)	(−0.16)	(−0.83)	(−0.40)
Master	−0.017*	−0.010	−0.011*	−0.011	−0.004	−0.005
	(−1.87)	(−0.95)	(−1.77)	(−1.47)	(−0.56)	(−0.65)
Interval	−0.000	−0.000	−0.001**	0.000	−0.000	−0.000***
	(−0.11)	(−0.85)	(−2.50)	(0.16)	(−0.23)	(−3.52)
AnalystCoverage	−0.085***	−0.089***	−0.080***	−0.054***	−0.055***	−0.050***
	(−9.47)	(−9.01)	(−17.00)	(−7.42)	(−7.18)	(−6.41)
ConFeps	0.163***	0.127***	0.140***	0.127***	0.101***	0.110***
	(14.08)	(12.86)	(39.24)	(14.29)	(13.31)	(14.82)
Death	−0.001	−0.001	0.003	0.000	−0.000	0.005
	(−0.16)	(−0.29)	(0.88)	(0.02)	(−0.10)	(1.26)
Broker FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	176,796	154,251	147,212	176,796	154,251	147,212
R-squared	0.342	0.406	0.411	0.323	0.380	0.388

Table AE2
Robustness test II: Excluding some specific earthquakes.

	Dependent variables: *Pessimism*								
	Exclude the four deadliest earthquakes			Exclude earthquakes in Sichuan			Exclude earthquakes in Sichuan and Yunnan		
	Sample #1	Sample #2	Sample #3	Sample #1	Sample #2	Sample #3	Sample #1	Sample #2	Sample #3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Disaster	−0.173	−0.182	−0.210	−0.132	−0.151	−0.151	−0.076	−0.083	−0.053
	(−1.18)	(−1.10)	(−1.50)	(−0.94)	(−0.95)	(−1.35)	(−0.46)	(−0.45)	(−0.40)
Neighborhood	−0.165***	−0.160**	−0.275***	−0.143***	−0.127*	−0.204***	−0.150**	−0.167**	−0.177***
	(−3.11)	(−1.98)	(−3.48)	(−3.39)	(−1.86)	(−3.26)	(−2.32)	(−2.33)	(−3.02)
Size	−0.384***	−0.369***	−0.319***	−0.396***	−0.387***	−0.318***	−0.391***	−0.374***	−0.333***
	(−8.75)	(−7.71)	(−7.06)	(−8.80)	(−7.93)	(−6.93)	(−9.40)	(−8.39)	(−7.66)
To	0.063***	0.063***	0.058***	0.064***	0.063***	0.057***	0.057***	0.056***	0.056***
	(11.42)	(10.24)	(9.68)	(11.41)	(10.16)	(9.60)	(10.71)	(9.46)	(9.45)
Mom	−0.250***	−0.292***	−0.288***	−0.256***	−0.297***	−0.291***	−0.245***	−0.290***	−0.277***
	(−9.94)	(−9.73)	(−10.13)	(−9.97)	(−9.63)	(−10.13)	(−9.97)	(−9.96)	(−9.97)
Inshold	0.170	−0.048	−0.205	0.180	−0.041	−0.205	0.107	−0.116	−0.182
	(1.48)	(−0.37)	(−1.62)	(1.54)	(−0.31)	(−1.60)	(0.95)	(−0.90)	(−1.45)
Exfin	−0.104***	−0.123***	−0.105***	−0.094***	−0.116***	−0.113***	−0.091***	−0.112***	−0.108***
	(−3.80)	(−3.95)	(−3.49)	(−3.47)	(−3.78)	(−3.76)	(−3.36)	(−3.62)	(−3.60)
Groupsize	−0.030	0.002	0.018	−0.020	0.004	0.022	−0.027	0.002	0.018
	(−0.85)	(0.11)	(0.50)	(−0.61)	(0.25)	(0.61)	(−0.86)	(0.11)	(0.50)
Experience	−0.006	−0.004	0.003	−0.002	−0.005	0.004	−0.005	−0.009	0.003
	(−0.41)	(−0.26)	(0.16)	(−0.13)	(−0.33)	(0.26)	(−0.36)	(−0.62)	(0.17)
Comnum	−0.001	−0.000	−0.008	−0.001	−0.000	−0.009	−0.004	−0.000	−0.009
	(−0.05)	(−0.79)	(−0.54)	(−0.09)	(−1.06)	(−0.60)	(−0.31)	(−0.35)	(−0.63)
Female	0.013	−0.208***	0.008	0.012	−0.204***	0.008	0.017	−0.234***	0.009
	(0.64)	(−5.66)	(0.37)	(0.60)	(−5.52)	(0.36)	(0.86)	(−6.79)	(0.40)
Master	−0.030	0.244***	−0.013	−0.034	0.242***	−0.015	−0.039	0.263***	−0.019
	(−0.92)	(8.58)	(−0.37)	(−1.06)	(8.61)	(−0.42)	(−1.24)	(8.63)	(−0.54)
Interval	−0.004**	0.061	−0.003*	−0.005***	0.033	−0.004**	−0.000	0.002	−0.003
	(−2.38)	(1.29)	(−1.80)	(−3.03)	(1.51)	(−2.08)	(−0.70)	(0.05)	(−1.57)
AnalystCoverage	−0.182***	−0.182	−0.199***	−0.179***	−0.151	−0.192***	−0.208***	−0.083	−0.212***
	(−5.37)	(−1.10)	(−5.38)	(−5.22)	(−0.95)	(−5.08)	(−6.56)	(−0.45)	(−6.12)
ConFeps	0.326***	−0.160**	0.237***	0.319***	−0.127*	0.233***	0.350***	−0.167**	0.241***
	(11.15)	(−1.98)	(8.37)	(10.97)	(−1.86)	(8.41)	(11.39)	(−2.33)	(8.37)
Death	0.051	−0.369***	0.107	0.026	−0.387***	0.039*	0.003	−0.374***	−0.007
	(1.25)	(−7.71)	(1.63)	(1.26)	(−7.93)	(1.66)	(0.09)	(−8.39)	(−0.18)
Broker FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	174,794	152,448	145,914	173,109	151,044	145,492	170,985	149,130	144,248
R-squared	0.259	0.293	0.309	0.264	0.297	0.313	0.254	0.290	0.302

This table examines whether our baseline results are driven by certain specific earthquakes. We use the subsamples excluding some specific earthquakes to tests this possibility. From column (1) to (3), we remove observations related to the four deadliest earthquakes with Earthquake ID equal to 6, 8, 11, and 19. From column (4) to (6), we remove observations related to earthquakes occurring in Sichuan Province with Earthquake ID ranging from 8 to 12. From column (7) to (9), we remove observations related to earthquakes occurring in Sichuan Province and Yunnan Province with Earthquake ID ranging from 1 to 12. We use these three subsamples to re-estimate Eq. (1). Other settings are the same as Table 3 in the paper. T-stats are reported in parentheses. *, ** and *** measure significance at the 10%, 5%, and 1% levels, respectively.

Table AE3
Robustness test III: Control for the potential effects of R&D expenditure and brokerage size.

	Dependent variable: *Pessimism*					
	Period: 2007–2016			Period: 2011–2016		
	Sample #1	Sample #2	Sample #3	Sample #1	Sample #2	Sample #3
	(1)	(2)	(3)	(4)	(5)	(6)
Disaster	−0.160	−0.164	−0.101	−0.115	−0.101	0.112
	(−1.14)	(−1.06)	(−0.82)	(−0.79)	(−0.62)	(1.14)
Neighborhood	−0.144**	−0.148**	−0.223***	−0.214***	−0.206***	−0.213***
	(−2.20)	(−2.17)	(−2.96)	(−3.48)	(−3.11)	(−3.54)
Size	−0.350***	−0.354***	−0.326***	−0.220***	−0.208***	−0.184***
	(−7.23)	(−6.69)	(−6.34)	(−4.07)	(−3.70)	(−3.35)
To	0.058***	0.056***	0.054***	0.056***	0.053***	0.053***
	(9.82)	(8.68)	(8.39)	(8.59)	(7.50)	(7.55)

(continued on next page)

Table AE3 (*continued*)

	Dependent variable: *Pessimism*					
	Period: 2007–2016			Period: 2011–2016		
	Sample #1	Sample #2	Sample #3	Sample #1	Sample #2	Sample #3
	(1)	(2)	(3)	(4)	(5)	(6)
Mom	−0.259***	−0.305***	−0.288***	−0.273***	−0.338***	−0.315***
	(−9.20)	(−9.16)	(−9.05)	(−8.10)	(−8.55)	(−8.13)
Inshold	0.033	−0.217	−0.333**	−0.424***	−0.737***	−0.886***
	(0.25)	(−1.44)	(−2.26)	(−2.96)	(−4.37)	(−5.52)
Exfin	−0.106***	−0.114***	−0.099***	−0.105***	−0.114***	−0.086**
	(−3.45)	(−3.24)	(−2.86)	(−3.00)	(−2.82)	(−2.21)
R&D	2.702	3.672*	5.073**	1.732	2.826	4.984*
	(1.44)	(1.68)	(2.08)	(0.83)	(1.13)	(1.77)
Groupsize	−0.034	0.011	0.022	−0.015	0.033	0.046
	(−0.88)	(0.25)	(0.55)	(−0.36)	(0.76)	(1.10)
Experience	−0.010	0.001	0.000	−0.002	0.010	0.008
	(−0.63)	(0.06)	(0.00)	(−0.13)	(0.54)	(0.46)
Comnum	0.019	0.012	0.008	0.029*	0.019	0.018
	(1.34)	(0.68)	(0.45)	(1.95)	(1.06)	(1.02)
Female	0.013	0.001	0.004	0.013	−0.003	0.002
	(0.58)	(0.03)	(0.15)	(0.59)	(−0.10)	(0.07)
Master	−0.015	−0.009	−0.019	−0.026	−0.019	−0.034
	(−0.43)	(−0.23)	(−0.49)	(−0.74)	(−0.48)	(−0.85)
Brokerasset	−0.207***	0.096**	−0.004**	−0.217***	0.109**	−0.003*
	(−2.99)	(2.21)	(−2.33)	(−2.71)	(2.35)	(−1.78)
Interval	−0.000	−0.000	0.075*	0.000	0.000	0.091**
	(−0.84)	(−0.77)	(1.81)	(0.32)	(0.11)	(2.12)
AnalystCoverage	−0.183***	−0.197***	−0.185***	−0.162***	−0.181***	−0.154***
	(−5.21)	(−5.24)	(−4.94)	(−4.08)	(−4.43)	(−3.76)
ConFeps	0.291***	0.219***	0.224***	0.492***	0.397***	0.405***
	(10.26)	(8.24)	(8.46)	(12.91)	(10.97)	(12.05)
Death	0.043**	0.047**	0.076**	0.034*	0.037*	0.036*
	(2.19)	(2.27)	(2.58)	(1.88)	(1.83)	(1.66)
Broker FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	145,991	127,184	120,981	125,947	109,843	103,803
R-squared	0.258	0.291	0.309	0.295	0.328	0.351

This table examines whether the baseline results can be robust when including *R&D* and *Brokerasset* as control variables. From column (1) to (3), we use the sample with the complete sample period. From column (4) to (6), we use the sample over the period after 2011. Other settings are the same as Table 3 in the paper. T-stats are reported in parentheses. *, ** and *** measure significance at the 10%, 5%, and 1% levels, respectively.

Appendix F. Cross-sectional analyses: analyst sophistication

We use brokerage size and star analysts to measure analyst sophistication in cross-sectional analyses. First, we define the brokerage firms whose total asset is larger than the median as the large brokerage firms and others as small brokerage firms. We drop observations with missing value in brokerage total assets. Then we assign forecasts from analysts employed by large brokerage firms into the subsample of large brokerage firms and others into the subsample of small brokerage firms. Results of subsample estimations of Eq. (1) are reported in Table AF1. The coefficients of *Neighborhood* are negative at a significance level of 0.05 in the subsample of small brokerage firms (from column (1) to (3)), while the coefficients of *Neighborhood* are insignificant in the subsample of large brokerage firms (from column (4) to (6)). We conclude that analysts employed by large brokerage firms are less affected by behavioral biases after earthquakes.

We also use the status of star analysts to measure analyst sophistication. We define analysts who win the Best Analyst Award by the *New Fortune* magazine, which is the most influential in the industry in China, as the star analysts. Then we assign forecasts from star analysts into the subsample of star analysts and others into the subsample of non-star analysts. We report related results in Table AF2. The coefficients of *Neighborhood* are consistently negative at the 0.05 significant level in the subsample of Non-star analysts (from column (1) to (3)). However, in the subsample of star analysts, the coefficients of *Neighborhood* are overall insignificant except for Sample #2 in Column (5). Therefore, star analysts are less subject to irrational pessimism after earthquakes.

Consistent with our expectations, sophistication is another factor influencing behavioral biases of analysts in China. Empirical results show that post-earthquake analyst pessimism is generally concentrated in the group of unsophisticated analysts.

Table AF1
The influence of analyst sophistication: brokerage size.

	Dependent variable: *Pessimism*					
	Small brokerage firms			Large brokerage firms		
	Sample #1	Sample #2	Sample #3	Sample #1	Sample #2	Sample #3
	(1)	(2)	(3)	(4)	(5)	(6)
Disaster	0.056	0.048	−0.027	−0.066	−0.318	−0.411
	(0.77)	(0.56)	(−0.24)	(−0.58)	(−1.33)	(−1.45)
Neighborhood	−0.097**	−0.129**	−0.169**	−0.028	−0.053	0.166
	(−2.28)	(−2.18)	(−2.46)	(−0.43)	(−0.44)	(0.49)
Size	−0.400***	−0.439***	−0.378***	−0.312***	−0.345***	−0.342**
	(−9.91)	(−11.30)	(−9.73)	(−7.62)	(−4.50)	(−2.43)
To	0.037***	0.054***	0.049***	0.044***	0.057***	0.058***
	(7.35)	(12.02)	(10.80)	(9.34)	(6.35)	(2.79)
Mom	−0.145***	−0.243***	−0.253***	−0.121***	−0.270***	−0.240***
	(−6.10)	(−9.27)	(−9.68)	(−5.10)	(−5.81)	(−3.50)
Inshold	0.230**	0.460***	0.286***	−0.027	−0.614***	−0.714
	(2.44)	(4.85)	(3.04)	(−0.29)	(−3.02)	(−1.38)
Exfin	−0.050**	−0.070***	−0.091***	−0.050**	−0.128***	−0.112
	(−2.54)	(−2.72)	(−3.58)	(−1.99)	(−2.64)	(−1.22)
Groupsize	−0.044	−0.004	0.023	−0.006	0.016	0.023
	(−1.03)	(−0.09)	(0.57)	(−0.22)	(0.39)	(0.62)
Experience	−0.036***	−0.026*	−0.037**	0.001	−0.001	0.003
	(−2.95)	(−1.66)	(−2.34)	(0.09)	(−0.04)	(0.13)
Commun	0.023**	0.004	0.011	−0.022*	−0.003	−0.019
	(2.12)	(0.32)	(0.86)	(−1.87)	(−0.11)	(−0.81)
Female	0.021	0.051**	0.053**	−0.021	−0.057	−0.038
	(1.22)	(2.26)	(2.32)	(−0.91)	(−1.48)	(−0.81)
Master	−0.008	−0.032	−0.049	−0.055	−0.037	−0.040
	(−0.31)	(−0.91)	(−1.39)	(−1.45)	(−0.59)	(−0.67)
Interval	−0.000	−0.000	−0.001	0.000	−0.000	−0.007*
	(−1.02)	(−1.05)	(−1.46)	(0.20)	(−0.88)	(−1.70)
AnalystCoverage	−0.179***	−0.237***	−0.229***	−0.156***	−0.147***	−0.125
	(−5.84)	(−8.52)	(−8.20)	(−5.91)	(−3.38)	(−1.35)
ConFeps	0.455***	0.172***	0.177***	0.514***	0.293***	0.299***
	(15.81)	(9.14)	(8.75)	(14.60)	(5.97)	(2.88)
Death	0.003	0.037**	0.064***	0.048***	0.070**	0.068
	(0.24)	(2.52)	(3.77)	(3.06)	(2.42)	(0.83)
Broker FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	72,996	63,592	60,491	72,995	63,592	60,490
R-squared	0.339	0.329	0.348	0.355	0.380	0.397

In this table, we conduct cross-sectional analyses by brokerage firm size. Column (1) to (3) report the results using the subsample of small brokerage firms. Column (4) to (5) report the results using the subsample of large brokerage firms. Other settings are the same as Table 3 in the paper. T-stats are reported in parentheses. *, ** and *** measure significance at the 10%, 5%, and 1% levels, respectively.

Table AF2
The influence of analyst sophistication: star analysts.

	Dependent variable: *Pessimism*					
	Non-star analysts			Star analysts		
	Sample #1	Sample #2	Sample #3	Sample #1	Sample #2	Sample #3
	(1)	(2)	(3)	(4)	(5)	(6)
Disaster	0.019	0.021	−0.148	−0.082	−0.555	−0.345
	(0.28)	(0.29)	(−1.10)	(−0.36)	(−1.15)	(−1.58)
Neighborhood	−0.080**	−0.109**	−0.160**	−0.157	−0.264*	−0.161
	(−2.40)	(−2.25)	(−2.07)	(−1.64)	(−1.73)	(−0.86)
Size	−0.361***	−0.438***	−0.367***	−0.348***	−0.344***	−0.356***
	(−12.89)	(−15.12)	(−7.33)	(−5.14)	(−2.90)	(−2.78)
To	0.038***	0.063***	0.057***	0.051***	0.070***	0.069***
	(11.16)	(18.78)	(8.60)	(5.89)	(3.24)	(3.09)
Mom	−0.160***	−0.258***	−0.261***	−0.150***	−0.325***	−0.289***
	(−9.54)	(−13.11)	(−8.75)	(−3.66)	(−4.06)	(−3.38)

(continued on next page)

Table AF2 (*continued*)

	Dependent variable: *Pessimism*					
	Non-star analysts			Star analysts		
	Sample #1	Sample #2	Sample #3	Sample #1	Sample #2	Sample #3
	(1)	(2)	(3)	(4)	(5)	(6)
Inshold	0.175***	0.311***	0.134	−0.106	−0.775*	−0.814*
	(2.60)	(4.24)	(0.94)	(−0.61)	(−1.82)	(−1.70)
Exfin	−0.067***	−0.125***	−0.119***	−0.032	−0.134*	−0.103
	(−4.05)	(−6.27)	(−3.43)	(−0.88)	(−1.79)	(−1.34)
Groupsize	0.004	0.073**	0.075*	0.010	−0.020	−0.017
	(0.17)	(2.34)	(1.65)	(0.31)	(−0.36)	(−0.41)
Experience	0.000	0.013	0.007	0.013	0.002	0.004
	(0.03)	(1.06)	(0.37)	(0.81)	(0.06)	(0.13)
Comnum	−0.004	−0.011	−0.010	0.013	0.041	0.015
	(−0.52)	(−1.05)	(−0.61)	(0.81)	(1.35)	(0.56)
Female	0.006	0.004	0.011	0.001	−0.005	−0.006
	(0.43)	(0.25)	(0.49)	(0.03)	(−0.09)	(−0.07)
Master	−0.029	−0.024	−0.027	−0.048	−0.014	0.009
	(−1.37)	(−0.95)	(−0.70)	(−0.85)	(−0.12)	(0.08)
Interval	−0.000	−0.000	−0.001	0.000	0.000	−0.004**
	(−1.17)	(−1.32)	(−1.58)	(0.80)	(0.45)	(−2.37)
AnalystCoverage	−0.180***	−0.217***	−0.220***	−0.122**	−0.128	−0.094
	(−8.87)	(−10.38)	(−5.71)	(−2.35)	(−1.27)	(−0.81)
ConFeps	0.421***	0.188***	0.186***	0.539***	0.285***	0.280***
	(17.10)	(12.69)	(6.67)	(9.69)	(4.42)	(2.96)
Death	0.001	0.001	0.026	0.050*	0.135***	0.133**
	(0.11)	(0.04)	(0.94)	(1.92)	(2.70)	(2.40)
Broker FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	126,923	111,345	106,411	49,873	42,906	40,801
R-squared	0.312	0.302	0.312	0.353	0.375	0.409

In this table, we conduct cross-sectional analyses by the status of star analysts. Column (1) to (3) report the results using the observations of forecasts issued by non-star analysts. Column (4) to (5) report the results using t the observations of forecasts issued by star analysts. Other settings are the same as Table 3 in the paper. T-stats are reported in parentheses. *, ** and *** measure significance at the 10%, 5%, and 1% levels, respectively.

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