Natural disasters and market manipulation

Akter, Maimuna; Cumming, Douglas; Ji, Shan

DOI:
10.1016/j.jbankfin.2023.106883

Journal of Banking and Finance 153 (2023) 106883

Contents lists available at ScienceDirect

Journal of Banking and Finance

journal homepage: www.elsevier.com/locate/jbf

Natural disasters and market manipulation

Maimuna Akter[a,1], Douglas Cumming[b,c,1], Shan Ji[d,1,*]

[a] School of Business Administration, Gonzaga University, 502 E Boone Ave, Spokane, WA 99258, USA
[b] College of Business, Florida Atlantic University, 777 Glades Road, Boca Raton, FL 33431, USA
[c] Birmingham Business School, University of Birmingham, University House, 116 Edgbaston Park Rd, Birmingham B15 2TY, UK
[d] Zhejiang Gongshang University Hangzhou College of Commerce, 66 Huan Cheng Nan Road, Tonglu, Hangzhou, Zhejiang 311599, China

ARTICLE INFO

Article history:
Received 27 July 2022
Accepted 15 May 2023
Available online 16 May 2023

JEL Classification:
G14
G18
Q54

Keywords:
Market manipulation
Natural disasters

ABSTRACT

Natural disasters exacerbate swings in investor sentiment and information asymmetry. As such, we propose natural disasters enable more frequent and severe market manipulation. We test this proposition using the securities listed in the NYSE and NASDAQ, disaster data from the National Oceanic and Atmospheric Administration, and surveillance industry-provided manipulation data from SMARTS, Inc. The data indicate the frequency and severity of market manipulation increases during disaster periods. Community resilience, hazard mitigation programs, and operational location moderate the effect of natural disasters on manipulation. These effects are not mechanically driven by spikes in volatility in disaster-county months. These effects are more pronounced for certain industries, including agricultural, health, and manufacturing industries. Finally, these findings are robust to alternative proxies of manipulation and various model specifications that include but are not limited to using difference-in-differences analysis.

1. Introduction

Every year, several natural disasters are observed in the U.S. and around the world that cause structural damage, deaths, and many weeks of chaos and destruction that diverts peoples' attention. Natural disasters exacerbate information uncertainty and distort investor sentiment; as such, during a natural disaster period, there is potentially more scope to manipulate markets. For example, there were allegations of manipulation around the start of Covid in the U.S. in March 2020.[2] In this study, we consider for the first time whether there is a systematic relation between natural disasters more generally (floods, hurricanes, and ice storms) and stock market manipulation.

Natural disasters have varying impacts on investors that include exacerbating information asymmetries and overestimating of risks (Alok et al., 2020; Gao et al., 2020; Shan and Gong, 2012). These varying impacts may translate into different favorable and unfavorable movements, which may cause the firms to take compatible actions in corporate decisions such as earnings forecasts and acquisitions (Kedia and Panchapagesan, 2011; Malloy, 2005). Studies confirm the presence of local bias among local investors (Coval and Moskowitz, 2001; Massa and Simonov, 2006; Nielsson and Wójcik, 2016). Pirinsky and Wang (2006) find evidence that the stock returns of firms headquartered in the same location show strong comovement. A growing body of literature shows how the sentiments and emotions of local investors caused by different events such as personal accidents, deaths, or natural disasters impact their actions (Alok et al., 2020; Bernile et al., 2017; Do et al., 2023; Fiordelisi et al., 2023; Gao et al., 2020; Shan and Gong, 2012). The effect is strong for firms with higher individual investors and regions with less financially sophisticated investors. We build on this prior work to investigate for the first time whether disasters influence the frequency and severity of market manipulation. We predict that natural disasters in the headquarter locations may play a critical role in stock market manipulation in the local firms.

By 'market manipulation,' we mean unusual price and volume patterns that trigger 'alerts' or messages that are sent to securities authorities about illegal trading patterns designed to distort market efficiency and fairness (Alexander and Cumming, 2022; Allen and Gale, 1992; Comerton-Forde and Putniņš, 2011, 2014; Cumming et al., 2011; Griffin and Shams, 2018). We discuss definitions of market manipulation in Section 3 of this paper and base the definitions of market manipulation on actual surveillance authorities, and likewise use data from actual surveillance authorities in the industry. We use both continuous trading manipulation and

* Corresponding author.
E-mail addresses: maimuna.akt1@gmail.com (M. Akter), ji@datafareast.com (S. Ji).

[1] CREDIT Statement, The authors contributed equally

[2] https://www.theguardian.com/commentisfree/2021/mar/21/us-senators-accused-coronavirus-insider-trading-are-a-symbol-moral-bankruptcy

https://doi.org/10.1016/j.jbankfin.2023.106883

end-of-day dislocation as proxies for stock market manipulation.[2] We hypothesize that market manipulation is more pronounced during months of natural disasters. Furthermore, we propose that the effect is heterogenous depending on the types of industries. We also hypothesize that disaster hazard mitigation programs, community sentiment, and operational location can moderate the association between natural disasters and market manipulation. Using 4847 listed firms for 2007–2018, we show that for a 1 standard deviation increase in deaths and injuries caused by natural disasters, there is a 1.68 and 1.08% increase in market manipulation. We add several firm and county-level variables such as information asymmetry, return volatility, firm size, market-to-book etc., and control for time and industry-fixed effects. Moreover, we show that the disaster impact depends on the industry type. We verify these findings by conducting numerous robustness checks, including but not limited to a quasi-natural experiment based on two recent major disasters: Hurricane Irma and Hurricane Harvey; the results from this experiment show a large economic significance of an 18.69% increase in manipulation during the disasters relative to normal times. Using community resilience, hazard mitigation programs, and operational location, we find that these programs moderate the impact of natural disasters on market manipulation. Furthermore, we show that the effect of natural disasters is more prevalent among young firms with more information asymmetry. Finally, we address the concern that our results may be driven by disaster-led volatility by showing the difference in the volatility movements of our treatment and control sample during disasters.

We contribute to the literature on market manipulation (Aggarwal and Wu, 2006; Comerton-Forde and Putniņš, 2011, 2014; Cumming et al., 2020; Hillion and Suominen, 2004) by proposing a new determinant of market manipulation: natural disasters. The existing literature finds many firm-specific and market-related factors that influence market manipulation (Aggarwal and Wu, 2006; Comerton-Forde and Putniņš, 2011). However, the application of any exogenous shock as a determinant of market manipulation is still unexplored. Motivated by this gap in the literature, the current paper focuses on how natural disasters, as exogenous shocks, work as a determinant of market manipulation, which is an entirely new area for exploration. Although studies increasingly focus on the impact of climate disasters on a firm's decisions, very few studies analyze the impact of natural disasters on a firm's information environment. Hence, to our knowledge, our study is the first to show natural disasters' impact on market manipulation. The sample used in our study exhibits considerable variations across the types of disasters, disaster damages, and the amount of continuous trading manipulation. The results of this paper have significant policy implications for regulatory bodies and policymakers. Hence, using the connections between natural disasters and market manipulation, regulators may implement different trading rules and increase their oversight during exogenous shocks such as natural disasters. Moreover, the findings also have implications for investors, mainly to make them aware of price movements during natural disasters.

The remainder of the paper is organized as follows. Section 2 discusses the theories that connect natural disasters to market manipulation and the hypotheses. Section 3 describes our sample. In Section 4, we discuss the research design. Section 5 reports the multivariate results that begin with the descriptive statistics, followed by the results on the relation between natural disasters and continuous trading manipulation. Here, we also provide analyses of how our findings are sensitive to different industry classifications. Section 6 describes different robustness tests showing how our findings are consistent in different scenarios. Finally, Section 7 concludes the study.

[2] We consider suspected manipulation, not prosecuted manipulation. Prosecuted manipulation may occur with a long gap from when it was suspected, and many cases will not be proscuted unless there is a clear expected outcome from obvious patterns of repated manipulation.

2. Literature review and hypotheses development

Disasters, as exogenous shocks, show increasing and significant impacts on the changes in stock market behavior. Policymakers and market players worldwide are increasingly concerned about the impacts of climate change that can affect the financial market. Alok et al. (2020) show in their research that climate disasters cause risk aversion among fund managers, which ultimately proves costly to fund investors. In a similar study, Krueger et al. (2020) find that institutional investors believe climate risks have profound financial implications for their portfolios. Using REITs example, Rehse et al. (2019) show in their study that disaster-affected REITs have relatively less trading and wide bid-ask spread than unaffected REITs. They show that a simultaneous increase in the market price of uncertainty leads to an overestimation of the effects of uncertainty. Hence, it affects the bid-ask spread. Extreme climatic conditions create different systematic risks for the firms. Firms with a high likelihood of loss from extreme weather events are associated with lower but more volatile earnings and cash flows (Huang et al., 2018). The salience of the negative impacts leads people to overestimate the risk and present risk aversion. Using the analysts' sample, Kong et al. (2021) show in their paper that the salience of earthquakes may lead analysts to overestimate the negative impacts of earthquakes. Due to an overreaction to climate disasters, we expect a tendency to be prevalent among market participants to manipulate stock market elements, such as closing price, opening price, information, and trading information. Hence, we propose that disasters may impact firms' propensity to engage in market manipulation. We propose natural disasters as a determinant of market manipulation.

The study of market manipulation is still limited due to the scarcity and complexity of data. Studies show that detecting market manipulation is difficult because trading ahead of information announcements may be attributable to issues such as market anticipation, volatility, or end-of-day market activity (Cumming et al., 2020, 2011). Hence, only a fraction of manipulation is detected. Due to the complexity of calculating manipulation, we focus on continuous trading manipulation. Continuous trading manipulation addresses the abnormal movements of different dimensions of security trading–trading volume, value, liquidity, transaction costs, and returns at a time. The metric detects the abnormal 30 min change of liquidity, returns, and transaction costs based on specific rules. The rules are explained in the Appendix A. Under this metric, the paper uses the number of alerts security i face for continuous trading manipulation during a month, the trading value of security i under continuous trading manipulation during the same month, and its ratio to the total trading value of security i during the same month. The calculation of continuous trading manipulation is explained in the Appendix A.

Most of the market manipulation studies focus on how manipulation impacts corporate decisions (Comerton-Forde and Putniņš, 2014; Cumming et al., 2020). However, there is very little research addressing the determinants of market manipulation. Comerton-Forde and Putniņš (2011) and Comerton-Forde and Putniņš (2014) construct an index of closing price manipulation and find that ~1% of closing prices are manipulated. A better understanding of the role of natural disasters in the information environment can provide some critical findings on the determinant of market manipulation. Extreme climatic conditions create different systematic risks for the firms. Consequently, investors hold a conservative perception of the firms exposed to climate disasters. Studies find the conservatism of the market participants during natural disasters (Alok et al., 2020; Rehse et al., 2019). The main issue of such movement in the markets is the pricing of information. Lee et al. (2002) explain in their study that the effect of any event is well-understood by the reactions of the market participants. Studies reflect that investors often overestimate or underestimate the impacts of natural disasters. Alok et al. (2020) find that mutual fund managers overestimate the impacts of disasters when exposed to a rare but devastating disaster. Consequently, they devalue stocks recently exposed to climatic events in their portfolios.

One important aspect of these studies is the emotional reaction or fear among investors caused by disasters. The idea of using emotional reactions to explain stock market behavior is not new. Bernile et al. (2017) find in their research that professional investors' risk attitudes are affected by catastrophic experiences. Due to an overreaction to climate disasters, we expect a tendency to be prevalent among market participants to manipulate stock market elements, such as closing price, opening price, information, and trading information. Market manipulation creates several incentives during times of uncertainty, such as before, during, and after natural disasters. Comerton-Forde and Putniņš (2014) explain that fund managers are involved in market manipulation to keep their funds' performance high relative to their competitors. Such market manipulation causes a lack of market efficiency and investors' confidence. These studies indicate a high likelihood that the parties try to mitigate the impacts of these uncertainties/reactions by manipulating the closing price, returns, transaction costs, and trading values. Hence, we assume that market manipulation is more prevalent during natural disasters. We propose our first hypothesis,

H1 *Market manipulation is more pronounced during months of natural disasters.*

Prior studies suggest that some industries are more susceptible to climate disasters than others. Hong et al. (2019) find in their study that the stock prices of firms in the food sector do not accurately reflect the underlying climate risks. Krueger et al. (2020) ask investors across various industries whether they believe that current equity valuations correctly reflect the risks and opportunities related to climate change. The authors find that the average investors believe that the equity valuations of the most exposed sectors to climate risk do not fully reflect this risk. Thus, investors may perceive a firm's climatic uncertainties differently depending on its industry. Such uncertainties among the investors may accelerate market manipulation, such as manipulating trade volume, value, or returns, among the parties during the disasters. Based on the above discussion, we present our second hypothesis

H2. The association between natural disasters and market manipulation varies between industries.

We propose that community resilience moderates the impact of natural disasters on market manipulation. Studies show that a local community's disaster preparedness and resilience mitigate the impact of disasters (Javadi and Masum, 2021; Kahn, 2005; Kellenberg and Mobarak, 2011; Toya and Skidmore, 2007). Toya and Skidmore (2007) show in their study that higher education attainment and a strong financial sector have a negative impact on the number of people killed by natural disasters. Finance studies also find evidence of the mitigating roles of strong community resilience and a strong financial market on the impact of natural disasters. Javadi and Masum (2021) show in their paper that insurance has a moderating impact on the effect of climate change on the cost of bank loans. Likewise, we expect that disaster preparedness, hazard mitigation programs, and community resilience regarding anticipated natural hazards, changing climatic conditions, and disruptions will moderate the relations between natural disasters and market manipulation. Furthermore, we propose that the operational location of a firm may influence the association between natural disasters and market manipulation. The home bias theory says that local investors have a strong location-related preference (Brown et al., 2008; Pirinsky and Wang, 2006). Brown et al. (2008) find that the proximity to publicly traded firms increases the probability of equity market participation and that individuals strongly influence each other's investment decisions in the locality. Therefore, domestic firms are more likely to be affected by the disasters hit in the locality than those that run operations internationally. We assume that the effect of disaster-related damages on market manipulation will be strong for domestically-operated firms. Hence, we suggest two hypotheses describing the moderating roles of hazard programs, community resilience, and operational locations in our proposed association.

H3a *Disaster hazard mitigation programs and community resilience mitigate the association between natural disasters and market manipulation.*

H3b *Operational location of a firm moderates the association between natural disasters and market manipulation.*

3. Data and sample

Our paper uses the securities listed in the NYSE and NASDAQ. We obtain a sample of manipulation data from SMARTS, Inc. (a firm purchased by NASD in 2010) and Capital Markets CRC (CMCRC) in Sydney. We do not change the manipulation measures for our own purposes here but instead use the ones provided by industry surveillance authorities. SMARTS and CMCRC collect data on suspected manipulation cases for over 50 stock exchanges worldwide and are used by regulators in those countries.

The SMARTS surveillance software was developed in the late 1980s. The software is used in more than 50 of the leading exchanges around the world. The system was purchased by NASD in 2010. The SMARTS system does not merely identify irregular trading activity; rather, it detects manipulation (otherwise, the major stock exchanges around the world would not use it to detect manipulation). It is a leading industry standard for detecting manipulative trading. The SMARTS algorithms are not manipulation measures created for this paper; instead, they are measures used by the leading surveillance authorities developed from over 30 years of industry surveillance experience.

The manipulation cases we examine are suspected cases and not actual enforced cases. Enforcement actions can take many years after a suspected case, and many cases will not be brought forward depending on the expected costs and uncertainties in litigation. Repeated cases are more likely to be enforced than single cases due to higher chances of success in litigation. In terms of the intuition as to why these are suspected manipulation cases, the SMARTS system sets parameters where something so egregiously changes over a short window (by at least 3 standard deviations relative to the past 30 days) and then immediately reverts back to normal activity. For a continuous manipulation alert, this information is calculated on a 30 min rolling window. For the end-of-day (EOD) alert, this information looks at the closing period and then how stock prices revert to normal in the following morning. If these alerts were merely abnormal trading activity then there would be proximate changes in nearby periods (say the other 30 min windows close to the identified period) and it would not be isolated to a single 30 min window, and it would not revert back to normal activity.

We use industry-identified manipulations aided by SMARTS from 2007 through 2018. The Continuous Trading Manipulation metric detects an abnormal 30 min change of liquidity, returns, and transaction costs based on specific rules explained in the Appendix A. For robustness, we consider the four specifications of the continuous trading manipulation alert: (1) Continuous Trad-

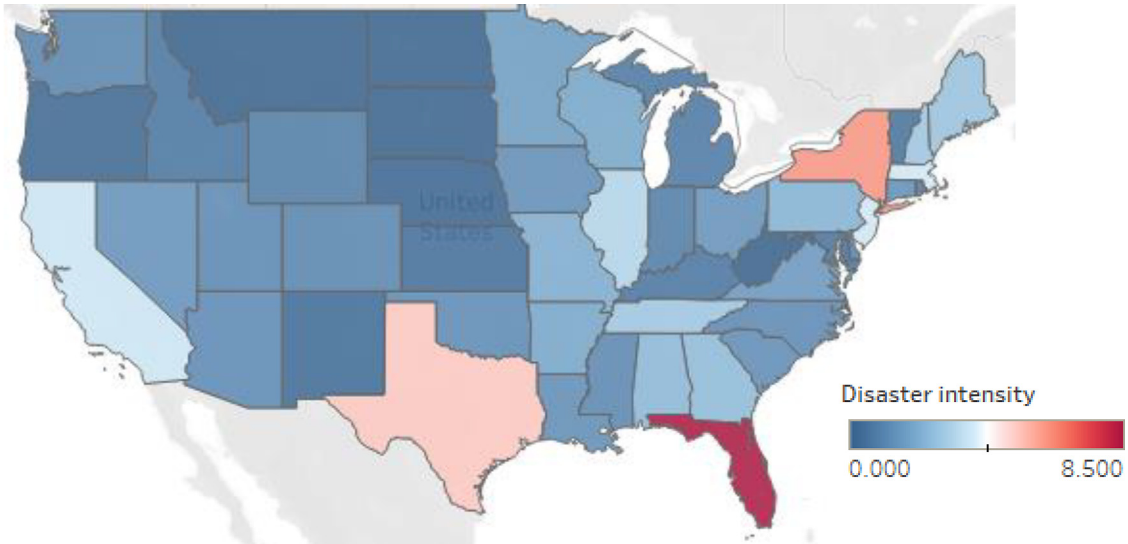

Fig. 1. The figure shows the distribution of disasters in the states of the U.S. This figure presents the average number of disasters throughout the sample period around the states.

ing Manipulation 30 min Number of Alerts, (2) Continuous Trading Manipulation 30 min Number of Alerts to Number of Intervals Ratio (bps), (3) Continuous Trading Manipulation 30 min Total Trade Value, and (4) Continuous Trading Manipulation 30 min Value Ratio (bps). The continuous trading manipulation of 30 min total trade value is further scaled by market capitalization and winsorized at the 95% level. For our robustness analysis, we use the presence of continuous trading manipulation as a categorical variable and EOD price manipulation as the alternative proxies of market manipulation. These variables are defined in the Appendix A.

The disaster data are from the National Oceanic and Atmospheric Administration's (NOAA's) National Weather Service (NWS). The database provides data on different storm events. Our paper records every storm event in the United States from 2007 through 2018. We use direct deaths, direct injuries, crop damage, and property damage caused by different disaster events and use these damages as the main explanatory variables. Fig. 1 shows the distribution of disasters across the U.S. We take the average number of disasters throughout the sample period. It shows that disasters across the years mostly hit Florida, Texas, and New York. We use the monthly panel to combine the total manipulation and disaster damage values every month. Likewise, we sum up the firm-level manipulation and county-level disaster damage for each month. We merge manipulation data with disaster data using the firms' headquarter locations in a county, year, and month, following the study by Shan and Gong (2012). There is a reasonable concern that a firm's headquarter location may not represent actual exposure to disasters. However, studies show that there is a strong relationship between stock market movement and headquarter location (Kellenberg and Mobarak, 2011; Malloy, 2005; Pirinsky and Wang, 2006). Huynh et al. (2020) show evidence that the firm's headquarter location is a reasonable proxy for its operating and business location. Hence, we believe that the headquarter location serves as a quality proxy to measure disaster exposure. Our sample includes all the firms with and without manipulation and firms that were and were not exposed to any disaster events during the study period. We exclude the firms that belong to the financial services industry (SIC 6000–6999) and utilities (SIC 4900-4949). The manipulation among these highly regulated firms may be stimulated by factors that are out of the scope of the study. Hence, our study has a sample of 252,250 firm-month observations.

We use the losses from county-level disaster events as the main explanatory variables. However, measuring the actual losses of a disaster is challenging because it often involves some psychological costs. Hence, we focus on damage to property, damage to crops, direct deaths, and injuries caused by natural disasters as the proxies of disaster loss. Moreover, since our analyses include disasters within all categories all over the United States, the damages follow a highly skewed distribution. We believe that the severity of a disaster event is well understood by the loss compared to its local GDP. Therefore, we scale the damages to property and crops by the county-level GDP.

For controls, we use many firm, county, and industry-level variables. We conduct a rigorous review of the literature to select the controls that are proven to correlate with manipulation (Comerton-Forde and Putniņš, 2014; Cumming et al., 2020, 2011; Hillion and Suominen, 2004; Imisiker and Tas, 2013). Studies show that firms with less information asymmetry, effective corporate governance, and higher idiosyncratic volatility are likely to have fewer market manipulation records (Nguyen et al., 2016, 2022). Moreover, firms with higher returns and share trade volume are likely to be followed by more manipulation. Hence, we include these controls in our model along with other firms, county, and industry-level controls. Data on the controls are collected from I/B/E/S, Compustat, CRSP, and Beta Suite by WRDS. Moreover, if there is no monthly information for the firm for any month, we use the median value across all firms. For robustness, we further use an alternative proxy of market manipulation, EOD price manipulation, which is also collected from SMARTS, Inc. and Capital Markets CRC (CMCRC) in Sydney. Furthermore, to connect to local sentiments and emotional channels, the study incorporates disaster preparedness, operational location, and community resilience data to see if these variables mitigate or aggravate the influence of manipulation.

4. Research design

We employ a number of model specifications to show the association between natural disasters and continuous market manipulation. Firstly, we use a baseline regression where we estimate the following panel regression model

$$Continuous\,Trading\,Manipulation_{it} = \beta_0 + \beta_{1t} Disaster_{ijt} + \beta_{2t} E_{it} + \delta_n FE + \varepsilon_{it} \quad (1)$$

The dependent variable involves four proxies of manipulation: (1) continuous trading manipulation 30 min number of alerts, (2) continuous trading manipulation 30 min number of alerts to the number of intervals ratio (bps), 3) continuous trading manipulation 30 min value ratio (bps), and (4) continuous trading manipulation 30 min total trade value scaled by market capitalization and winsorized at the 95% level, of firm i during month t. $Disaster_{it}$ indicates the continuous value that indicates the damages from disasters, including damage to property, crops, deaths, and injuries of county j, where firm i is located during month t. It considers all the disasters that occurred in month t. To address the outliers and severity of disasters, we scale damage to property and crop by county-level GDP. This provides us with a relative measure of damage. E_{it} includes all the firms, county, and industry-level controls.

In terms of firm-level controls, we follow Comerton-Forde and Putniņš (2014), who discuss that firms with higher information asymmetry are more prone to stock manipulation. Following their study, we use the number of analysts as a proxy for information asymmetry. Studies show that corporate governance greatly influences manipulation (Bedard and Johnstone, 2004; Lambert and Sponem, 2005). We add CEO duality, the percentage of independent directors, and the number of directors as corporate governance proxies. Following the study by Faleye and Krishnan (2017), we develop a score with these proxies. The score ranges from 0 to 3, where a higher value indicates good corporate governance. Comerton-Forde and Putniņš (2014) also explain idiosyncratic volatility as an essential determinant of manipulation since it increases the risk of manipulation being unsuccessful, and the stock regulators pay attention. Hence, we use idiosyncratic volatility in our model as proxies for volatility. Studies find that manipulators use price, returns, and trade volume to attract information seekers/investors. Comerton-Forde and Putniņš (2014) find in their study that manipulation involves less liquid stocks that can be characterized by lower market capitalization and lower turnover. When manipulators sell, prices rise, and trade volume rises (Aggarwal and Wu, 2006). Hence, we use market capitalization, returns, and trade volumes in our model as controls. We also use firm size and firm age as additional controls. We take the natural logarithms of the variables with extreme outliers. The definitions of the controls are provided in the Appendix A. We also include year- and industry-fixed effects.

Table 1 provides summary statistics for the main variables in the data. The table shows the descriptive results of the dependent variables. The mean value of the monthly continuous trading manipulation 30 min number of alerts is 0.676, whereas the maximum and the minimum number of alerts are 26 and 0, respectively. The number of alerts to interval ratio ranges from 0 to 2, indicating that the maximum number of alerts is almost 2 times higher than the total number of 30 min windows of a day. Moreover, the continuous trading manipulation value (scaled by market capitalization) ranges from 0 to 2.458. This indicates that the sample includes securities with no manipulation and securities with the maximum total manipulation value of 2.458 (scaled by market capitalization and winsorized). In terms of the independent variables, the table shows that the maximum monthly property damage is 575.53 times higher than the GDP. Moreover, it is 4.56 times higher for crop damage. The maximum number of deaths caused by different disaster events in a county is 43. The number of injuries is even higher, with a value of 941. In terms of controls, the monthly average number of analysts for each sample firm ranges from 1 to 54. Most of the controls, such as current assets, trade volume, market capitalization, debt to equity ratio, sales turnover, net income to sales, R&D intensity, and market to book follow a highly skewed distribution, as our sample includes firms of different sizes and from various industry backgrounds. Therefore, we take the natural logarithms of those controls for our analyses.

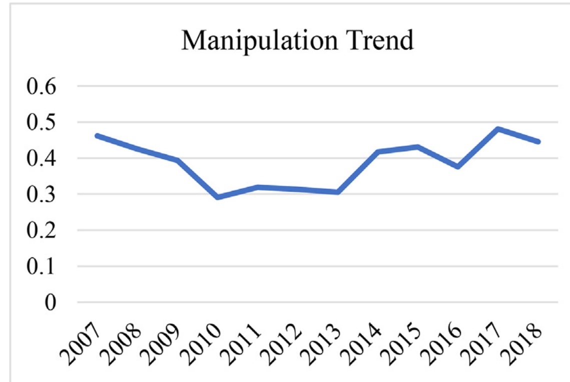

Fig. 2. The figure shows the trend of market manipulation over the sample period. The trend is created by calculating the average value of manipulation that occurred during each year in the U.S.

Fig. 2 shows the trend of manipulation over the study period. We use our main measure of market manipulation, winsorized continuous trading manipulation scaled by market capitalization. This shows that manipulation is more likely in the crisis years, but there is no discernable learning pattern over time. However, the trend of manipulation has been increasing in recent years. Fig. 3 also shows this upward trend; however, we divide the total period into slots ranging from 4 months before the disasters to 5 months after. The figure shows that there is a sharp increase in manipulation during the disaster period. The number of manipulation alerts, the ratio of alerts to the number of intervals, and the manipulation value ratio increased during the disaster months. However, it gradually decreases in the following years, indicating market-correcting behavior. Table 2 compares mean and median tests for natural disasters and continuous trading manipulation variables. The analysis is limited to the firms in the top 50th percentile regarding trading volume. We also limit the sample to the firms exposed to manipulation and disasters at least once during our sample period. Limiting the sample helps us understand how disaster-affected firms react to manipulation during disaster periods relative to non-disaster periods. Table 2 Panel A shows a significant difference in continuous trading manipulation between the firms with and without disasters. All our manipulation variables indicate a higher manipulation during the disaster periods, consistent with the hypothesis *(H1)*. We explore whether the difference is significant depending on the type of disaster damage. Panel B shows that the manipulation is significant for disasters that involve property damage, direct deaths, and injuries.

5. Multivariate results

5.1. Baseline estimates

Table 3 reports the baseline regression results. The paper uses a panel regression that covers all the firms in our sample. We scale the property damage and the crop damage by the county-level GDP. The standard errors are clustered by county. We cluster the standard errors by counties because whenever there is reason to believe that both the regressors and the errors might be correlated within a cluster, we need to think about clustering defined broadly enough to account for that clustering. The results show that disasters involving deaths and injuries significantly and positively impact continuous trading manipulations. The positive and statistically significant effect for all of our manipulation variables supports our hypothesis *(H1)*. In terms of economic significance, we find that for a 1 standard deviation increase in deaths and injuries, there is a 1.68 and 1.08% increase, respectively, in manipu-

Table 1
Summary Statistics.
This table presents summary statistics for the main variables in the data. Variables and sources are as defined in the Appendix.

Variable	Observations	Mean	Median	Std. Dev	Min	Max
Dependent Variables						
Continuous Trading Manipulation 30 min Number of Alerts to Number of Intervals Ratio (bps)	252,250	0.0547	0.0000	0.1041	0.0000	2
Continuous Trading Manipulation 30 min Value Ratio (bps)	252,250	0.0989	0.0000	0.1871	0.0000	2.3671
Continuous Trading Manipulation 30 min Number of Alerts	252,250	0.6763	0.0000	1.2933	0.0000	26
Continuous Trading Manipulation 30 min Total Trade Value / Market Capitalization Winsorized 5/95	252,247	0.3915	0.0000	0.7311	0.0000	2.4579
Disaster Variables						
Damage Property Direct scaled by GDP	252,250	0.0184	0.0000	2.1118	0.0000	575.5312
Damage Crops Direct scaled by GDP	252,250	0.0001	0.0000	0.0215	0.0000	4.5609
Deaths Direct	252,250	0.0313	0.0000	0.3982	0.0000	43
Injuries Direct	252,250	0.1686	0.0000	8.8273	0.0000	941.0000
Firm-level Variables						
Analyst Coverage	252,250	4.9646	4.6667	2.4508	1.0000	54.7500
Returns	252,250	0.0092	0.0045	0.1640	-0.9936	8.3365
Idiosyncratic Risk	252,250	0.1336	0.1079	0.0631	0.0158	1.2067
Current Ratio	252,250	3.2042	2.1227	12.8975	0.0000	4036
Share Trade Volume	252,250	287,344	68,844.50	897,026.80	0.0000	59,700,000
Market Capitalization	252,250	4,099,700	529,119.6	21,700,000	0.0000	1,100,000,000
Debt to Equity	252,250	292,502.5	0.5696	5533,236	0.0000	426,000,000
Sales Turnover	252,250	4622.19	595.6540	17,810.27	0.0000	496,785
Market to Book	252,250	948.1108	102.3126	7721.376	0.0000	1,020,718
Total Asset	252,250	5198.79	950.9043	22,405.14	0.0000	797,769
Company Age	252,250	11.5531	11	6.2139	0.0000	50
Governance score	252,250	1.7001	1.7484	0.8282	0.0000	3
Acquisitions	252,250	0.0962	0.0000	0.2948	0.0000	1

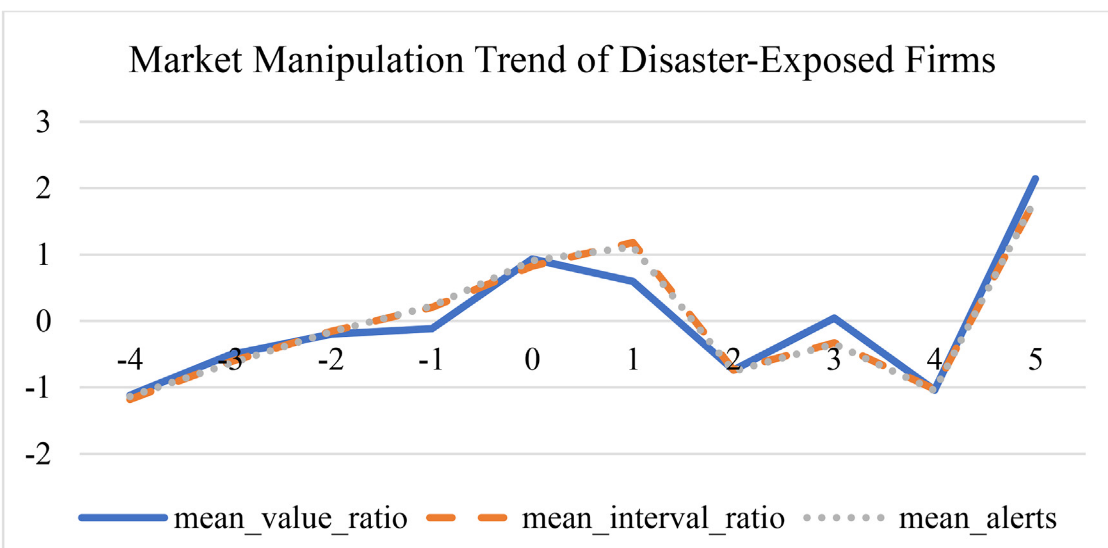

Fig. 3. The trend of market manipulation over the sample period. It includes three types of manipulation used in the study. The manipulation variables are standardized here. We divide our total sample period into different segments. The period ranges from 4 months prior to 5 months after the disaster.

lation. The table also shows the baseline regression results for the firm- and county-level controls and uses time- and industry-fixed effects to control for time and industry-level heterogeneity in manipulation.

In terms of controls, the number of analysts is negatively associated with continuous trading manipulation, which indicates that the higher the number of analysts, the lower the level of information asymmetry. Consequently, this discourages market manipulation. A 1 standard deviation increase in analysts reduces the manipulation by approximately 0.24%. On the other hand, idiosyncratic risk (a proxy of volatility) is negatively associated with continuous trading manipulation. As volatile stocks are less likely to move with the market, manipulation becomes less common for those stocks. These stocks are likely to catch regulators' attention, which eventually increases the probability of manipulation being unsuccessful. This supports the idea that manipulation in the disaster months is not driven by any possible rise in volatility in these months.[3] Thus, our findings are consistent with those of Comerton-Forde and Putniņš (2014). We find trade volume to be positively associated with manipulation. This is also consistent

[3] See also Fig. 4 and accompanying text, below.

Table 2
Comparison of Mean and Median Tests.
This table presents a comparison of means and median tests for natural disasters and continuous trading manipulation. The sample is restricted to the top 50 percentile of share trade volume, which was exposed to natural disasters and manipulation. *, **, *** significant at the 10%, 5%, and 1% levels, respectively.

		Continuous Trading Manipulation 30 min Number of Alerts to Number of Intervals Ratio (bps) (I)		Continuous Trading Manipulation 30 min Value Ratio (bps) (II)		Continuous Trading Manipulation 30 min Number of Alerts (III)		Continuous Trading Manipulation 30 Value (IV)		
		Mean	Median	Mean	Median	Mean	Median	Mean	Median	Sample Size
Panel A										
Disaster	1	0.0937	0.0769	0.1554	0.0762	1.1693	1	0.6371	0.1814	6965
	0	0.0843	0.0769	0.1387	0.0429	1.0446	1	0.6224	0.0840	86,105
Difference	0.0094***	0	0.01667***	0.0333***	1.0537***	0	0.0147	0.0974***		
Panel B										
Disaster=1										
Damage Property	>0	0.0928	0.0769	0.1563	0.0796	1.1624	1	0.6256	0.1967	4070
	0	0.0846	0.0769	0.1392	0.0445	1.0490	1	0.6234	0.0873	89,000
Difference	0.0082***	0	0.0171***	0.0351***	0.1134***	0	0.0022	0.1094***		
Damage Crops	>0	0.1019	0.0769	0.1716	0.0854	1.3036	1	0.6088	0.2984	112
	=0	0.0850	0.0769	0.1399	0.0474	1.0536	1	0.6235	0.0967	92,958
Difference	0.0169	0	0.0317	0.038	0.2400*	0	(0.0147)	0.2017		
Direct Deaths	>0	0.0949	0.0769	0.1552	0.0705	1.1761	1	0.6853	0.1744	2146
	=0	0.0848	0.0769	0.1396	0.0468	1.0510	1	0.6221	0.0938	90,924
Difference	0.0101***	0	0.0156***	0.0237***	0.1251***	0	0.0632***	0.0806**		
Direct Injuries	>0	0.1010	0.0769	0.1631	0.0850	1.2607	1	0.6826	0.1783	1400
	=0	0.0847	0.0769	0.1396	0.0468	1.0507	1	0.6226	0.0941	91,670
Difference	0.0163***	0	0.0235***	0.0382***	0.2099***	0	0.0600**	0.0842***		

with Aggarwal and Wu (2006) findings, which provide evidence that manipulation corresponds to higher volatility and returns of the stock. Returns have a significant positive association with manipulation. However, market capitalization shows an inverse relationship with our main variable of interest, market manipulation scaled by capitalization, indicating that high-capitalization shares are less likely to engage in market manipulation. Finally, we find that acquisitions are negatively associated with market manipulation, indicating that firms which engage in M&A are less likely to be involved in market manipulation.

Next, our study shows the association between disaster damage and continuous trading manipulations, limiting the sample to the manipulation-exposed firms only. Hence, the main objective of this analysis is to show if the manipulation tendency changes from the disaster to the non-disaster months. Table 4 shows the results of the panel regression. We follow the same controls and fixed effects from the baseline regression. The table shows that disasters involving direct injuries and deaths influence manipulation significantly for the firms involved in continuous trading manipulation. All of our manipulation variables are statistically significant for the deaths and direct injuries. The effect is economically significant, showing that a 1 standard deviation increase in deaths and injuries is associated with a 1.35 and 0.85% increase in manipulation. However, we fail to find a significant relationship with disasters involving damage to property and crops. The coefficient estimates for the controls are consistent with the literature and baseline regression findings. Overall, our regression results indicate that disasters that involve deaths and injuries are more likely to affect market manipulation behavior. Therefore, we can conclude that disasters with deaths and injuries significantly impact market manipulation behavior.

Some industries, such as agriculture and energy, are more sensitive to location than others. As such, we investigate four industry categories: agricultural production–crops, energy and transportation, health, and manufacturing industries. Table 5 shows the regression results. Notably, our regression results vary significantly based on the industry exposure, indicating that the disaster-related damage's effect depends on the firm's industry.

Table 5 uses only continuous trading manipulation scaled by market capitalization as the main dependent variable since it is adjusted for the outliers and significantly associated with the damage variables in the previous analyses. The data indicate a significant and positive association of property, crop damage, and deaths with manipulation for the firms that belong to agricultural production. In terms of economic significance, a 1 standard deviation increase in property and crop damage scaled by GDP and deaths is associated with a 1.77, 2.93, and 1.95% increase in manipulation, respectively. Since the agriculture industry is more prone to disaster-related property and crop damage, manipulation is more prevalent when the damage is greater. Hence, the firms in these industries are more likely to manipulate trade to minimize the uncertainties among the investors. Moreover, for the firms that belong to the energy industry, it is interesting to see that disasters involving crop damage and injuries influence market manipulation. Likewise, the manipulation in the health sector shows a significant association with disasters that involve property, crop damage, and death. Moreover, for manufacturing firms, disasters involving deaths and injuries are positively associated with manipulation. In all cases, there is a high economic significance. However, it is interesting that property damage is negatively associated with manipulation in the health and manufacturing sectors. Hence, it may be possible that disasters involving property damage may not immediately impact those industries. Overall, the results from Table 5 are consistent with Hypothesis (*H2*). In addition, our controls are still significant and consistent with previous findings.

5.2. Moderating roles of disaster mitigation program and community resilience

A county's disaster preparedness strongly impacts how the community reacts to disaster-related damage. To test if county-level disaster preparedness influences our findings, we have a sub-

Table 3
Baseline Regressions.
This table presents panel regression results of the determinants of continuous trading manipulation with industry- and year-fixed effects. The dependent variable is continuous trading manipulation, which is measured by alerts, alerts to interval ratio, value to trade volume ratio, and scaled by market capitalization in Columns I, II, III, and IV, respectively. The main independent variables are the damages to property and crops scaled by county-level GDP and deaths and injuries caused by disaster events. Firm- and county-level controls are explained in the Appendix. The model controls for industry and time-fixed effects. The standard errors are clustered by county. The full sample is used in each regression in this table. *, **, *** significant at the 10%, 5%, and 1% levels, respectively.

	Continuous Trading Manipulation 30 min Number of Alerts to Number of Intervals Ratio (bps) (I)	Continuous Trading Manipulation 30 min Value Ratio (bps) (II)	Continuous Trading Manipulation 30 min Number of Alerts (III)	Continuous Trading Manipulation 30 min Total Trade Value / Market Capitalization Winsorized 5/95 (IV)
Damage Property Direct scaled by GDP	0.00001	0.00011	0.00012	−0.00021
	(0.17495)	(0.64468)	(0.12459)	(−0.42952)
Damage Crops Direct scaled by GDP	0.01233	0.02524	0.15473	0.07205
	(0.58854)	(0.61671)	(0.57455)	(0.52935)
Deaths Direct	0.00182*	0.00314***	0.02253*	0.01658***
	(1.86401)	(2.63753)	(1.90291)	(4.17746)
Injuries Direct	0.00009***	0.00011***	0.00107***	0.00048***
	(5.89014)	(5.87261)	(5.86360)	(6.14142)
ln_Analyst Coverage	−0.00951***	−0.01068***	−0.11869***	−0.03758**
	(−4.27629)	(−2.75527)	(−4.30656)	(−2.38156)
ln_Returns	0.00331***	0.00381***	0.04063***	0.02315***
	(19.03575)	(10.08005)	(18.92816)	(15.43791)
Idiosyncratic Risk	−0.07873***	−0.14614***	−0.97368***	−0.53668***
	(−5.59145)	(−5.52224)	(−5.61248)	(−4.56987)
ln_Share Trade Volume	0.01093***	0.01545***	0.13397***	0.14103***
	(18.92697)	(16.32637)	(18.71092)	(27.91503)
ln_Market Capitalization	0.00353***	0.00238**	0.04408***	−0.02127***
	(5.34500)	(2.11745)	(5.38898)	(−4.06209)
ln_Debt to Equity	0.00028	0.00113***	0.00334	−0.00284*
	(1.25422)	(2.81534)	(1.22425)	(−1.67352)
ln_Sales Turnover	0.00229***	0.00265**	0.02901***	0.01807***
	(3.38463)	(2.29364)	(3.44698)	(3.33757)
ln_Market to Book	−0.00130***	−0.00191***	−0.01589***	−0.02211***
	(−3.56403)	(−2.81483)	(−3.51015)	(−7.77736)
ln_Asset	0.00053	0.00552***	0.00732	−0.00699
	(0.59170)	(3.76167)	(0.65726)	(−1.02137)
Company Age	−0.00011	−0.00060**	−0.00160	−0.00035
	(−0.80155)	(−2.56150)	(−0.91610)	(−0.32730)
Current Ratio	−0.00001	−0.00004	−0.00018	−0.00013
	(−1.22515)	(−1.41979)	(−1.18115)	(−1.26581)
Acquisitions	−0.01404***	−0.01465***	−0.17246***	−0.08263***
	(−15.96185)	(−9.35513)	(−15.84211)	(−13.25769)
Governance Score	0.00012	0.00162	0.00060	0.00906
	(0.11936)	(0.90900)	(0.04894)	(1.24364)
Intercept	−0.10003***	−0.11248***	−1.25183***	−0.60745***
	(−10.65393)	(−6.86538)	(−10.70553)	(−9.25582)
adj. R-sq	0.11564	0.08542	0.11699	0.12388
No. of observations	252,250	252,250	252,250	252,247
Year-fixed effects	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes

sample of counties that receive the Hazard Mitigation Assistance (HMA) Grant Program. The data on the Hazard Mitigation program is available on the Federal Emergency Management Agency (FEMA) website. Hazard mitigation is any sustainable action that reduces or eliminates long-term risk to people and property from future damage. Thus, it is expected that the presence of a hazard mitigation program will reduce the impact of disaster-related damage on manipulation. We interact the damage variables with a categorical variable that indicates 1, if the county is covered under the program and 0 otherwise. The results are shown in Table 6, Column I. The results show that the interaction variable with crop damage has a statistically significant negative coefficient. Counties with the HMA grant incur 10.07% less manipulation than counties without the HMA grant when there is a 1 standard deviation increase in disaster damages to crops. Therefore, our research indicates that the grant program mitigates the impact of crop damage on manipulation, which is consistent with our prediction.

Furthermore, the study of disaster and location impacts requires controlling for location attributes. Records indicate that disasters repeatedly hit the same area. Therefore, the people of those areas

Table 4
Regressions with Subsample of Firms that have Experienced Manipulation.
This table presents panel regression results of the determinants of continuous trading manipulation with industry- and year-fixed effects. The sample includes firms that have had a suspected manipulation event to illustrate the results with disaster versus non-disaster months. The dependent variable is continuous trading manipulation, which is measured by alerts, alerts to interval ratio, value to trade volume ratio, and scaled by market capitalization. The main independent variables are the damages to property and crops scaled by county-level GDP and deaths and injuries caused by disaster events. Firm- and county-level controls are explained in the Appendix. The model controls for industry - and time-fixed effects. The standard errors are clustered by county. *, **, *** significant at the 10%, 5%, and 1% levels, respectively. The standard errors are clustered by counties.

	Continuous Trading Manipulation 30 min Number of Alerts to Number of Intervals Ratio (bps) (I)	Continuous Trading Manipulation 30 min Value Ratio (bps) (II)	Continuous Trading Manipulation 30 min Number of Alerts (III)	Continuous Trading Manipulation 30 min Total Trade Value / Market Capitalization Winsorized 5/95 (IV)
Damage Property Direct scaled by GDP	0.00002	0.00014	0.00015	−0.00022
	(0.18303)	(0.66708)	(0.12893)	(−0.37326)
Damage Crops Direct scaled by GDP	0.01323	0.02759	0.16568	0.07618
	(0.56231)	(0.60645)	(0.54779)	(0.49684)
Deaths Direct	0.00170*	0.00295***	0.02103*	0.01561***
	(1.76873)	(2.61916)	(1.81506)	(3.89058)
Injuries Direct	0.00009***	0.00010***	0.00106***	0.00042***
	(6.02690)	(5.83941)	(5.98766)	(5.23263)
ln_Analyst Coverage	−0.00797***	−0.00857***	−0.09961***	−0.01966***
	(−9.37252)	(−5.02914)	(−9.41122)	(−2.89788)
ln_Returns	0.00271***	0.00175***	0.03322***	0.01747***
	(17.66341)	(6.16983)	(17.53772)	(13.39163)
Idiosyncratic Risk	−0.10948***	−0.20574***	−1.35354***	−0.76953***
	(−6.02575)	(−5.91404)	(−6.05400)	(−4.90129)
ln_Share Trade Volume	0.01299***	0.01675***	0.15941***	0.17482***
	(16.92454)	(13.00433)	(16.73449)	(29.59228)
ln_Market Capitalization	0.00175**	−0.00155	0.02237**	−0.04764***
	(2.20165)	(−1.11638)	(2.26562)	(−7.62453)
ln_Debt to Equity	0.00027	0.00124***	0.00324	−0.00337*
	(1.10043)	(2.74471)	(1.05538)	(−1.80567)
ln_Sales Turnover	0.00203**	0.00125	0.02564**	0.02101**
	(1.98013)	(0.72235)	(2.00176)	(2.47825)
ln_Market to Book	−0.00135***	−0.00187**	−0.01653***	−0.02388***
	(−3.29602)	(−2.48014)	(−3.25514)	(−7.52724)
ln_Asset	0.00051	0.00660***	0.00751	−0.01379
	(0.39241)	(3.10590)	(0.46535)	(−1.35127)
Company Age	0.00001	−0.00039	−0.00018	0.00094
	(0.05327)	(−1.56720)	(−0.09585)	(0.85408)
Current Ratio	−0.00015	−0.00040	−0.00229	0.00397
	(−0.52210)	(−0.74156)	(−0.62848)	(1.64066)
Acquisitions	−0.01567***	−0.01532***	−0.19231***	−0.08997***
	(−16.12643)	(−8.42009)	(−15.98562)	(−13.00283)
Governance Score	0.00026	0.00112	0.00247	0.00954
	(0.24357)	(0.57570)	(0.18544)	(1.20652)
Intercept	−0.09284***	−0.05977***	−1.17031***	−0.55320***
	(−7.64547)	(−2.77620)	(−7.73464)	(−6.55242)
adj. R-sq	0.09278	0.06184	0.09455	0.10983
No. of observations	215,081	215,081	215,081	215,078
Year-fixed effects	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes

are expected to be more resilient to disaster-related damage. Our theory assumes that market participants such as firm managers, hedge funds, and mutual funds may increase trade manipulation to exploit the benefits from investors' distraction or overestimation of disasters. Hence, we can assume that community-based resilience can minimize disaster-related sentiments and, thus, reduce the impact of disasters on manipulation. We get the community resilience data from the FEMA National Risk Index. The community resilience score indicates the ability of a community to prepare for anticipated natural hazards, adapt to changing conditions, and withstand and recover rapidly from disruptions. FEMA collects these data from the University of South Carolina's Hazards and Vulnerability Research Institute. The higher the score is, the more resilient the community is. The data provide county-level data for the years 2010 and 2015. Therefore, we apply the score of 2010 to the years from 2007 to 2014 and 2015 to the years from 2015 to 2018. We create a dummy variable using the resilient score, where 1 indicates higher than the median score and 0 otherwise. Hence, we interact the variable with our variables of interest. Table 6, Column II shows that the interacted variable with damages to property is negative and highly significant. It shows that the manipulation is 7.98% less (relative to the average value of manipulation) in the areas where the community is more resilient than other communities when there is a 1 standard deviation increase in property damage. Therefore, the more resilient the community's people are to the hazards, the less likely the damage to property influences the manipulation behavior. However, our results show the opposite result for the disasters that cause crop damage. We fail to find any significant influence of resilience on other variables. One possible interpretation of our results is that the death damages are too extreme to be offset by community resilience. Overall, we can say that hazard preparedness and community resilience act as moder-

Table 5
Regressions with Subsample of Firms in Different Sectors.
This table presents panel regressions with firm- and year-fixed effects for the determinants of continuous trading manipulation. Variables are as defined in the Appendix. The subsamples of firms in different sectors are used in each regression in this table. In all regressions, the dependent variable is Continuous Trading Manipulation 30 min Total Trade Value / Market Capitalization Winsorized 5/95. *, **, *** significant at the 10%, 5%, and 1% levels, respectively.

	Agricultural Production - Crops, and Industries in the Office of Life Sciences (I)	Industries in the Office of Energy and Transportation (II)	Health Sector Industries (III)	Manufacturing Sector Industries (IV)
Damage Property Direct scaled by GDP	0.02313***	0.00052	−0.50266***	−0.00148***
	(2.69770)	(0.93559)	(−6.63033)	(−7.78252)
Damage Crops Direct scaled by GDP	0.71632***	−1.92023***	1.133e+05***	0.00773
	(89.70163)	(−12.30835)	(12.68276)	(0.09317)
Deaths Direct	0.02399***	−0.01389	0.12830***	0.02819***
	(3.09637)	(−1.04090)	(3.69097)	(2.84652)
Injuries Direct	0.00058	0.00121***	−0.03016	0.00081***
	(1.44408)	(2.93678)	(−0.57696)	(3.21653)
ln_Analyst Coverage	−0.02336	−0.00797	0.04740	−0.07072*
	(−1.01840)	(−0.29208)	(0.66635)	(−1.70856)
ln_Returns	0.02433***	0.02935***	0.01639*	0.01819***
	(9.17365)	(8.23217)	(1.92910)	(5.60378)
Idiosyncratic Risk	−0.04584	−1.02329**	−2.11948**	−0.74198***
	(−0.22981)	(−2.59760)	(−2.43526)	(−3.66025)
ln_Share Trade Volume	0.11288***	0.15966***	0.10656***	0.15514***
	(16.68057)	(11.81256)	(3.10889)	(14.60203)
ln_Market Capitalization	0.01180	−0.05818***	0.07753*	−0.03075**
	(1.49604)	(−4.06432)	(1.74068)	(−2.18897)
ln_Debt to Equity	−0.00153	−0.01020*	0.02687	0.00144
	(−0.53679)	(−1.84143)	(1.61386)	(0.28835)
ln_Sales Turnover	0.01705***	0.00291	−0.07125	0.05801**
	(2.82982)	(0.18252)	(−0.65881)	(2.33753)
ln_Market to Book	−0.02163***	−0.03410***	0.02122	−0.02240***
	(−4.22568)	(−4.16778)	(0.81884)	(−3.13943)
ln_Asset	−0.00185	0.02927	−0.05484	−0.05682**
	(−0.23181)	(1.53923)	(−0.55236)	(−2.09204)
Company Age	−0.00229	0.00125	0.00999	0.00208
	(−1.18608)	(0.38641)	(1.30826)	(0.86431)
Current Ratio	0.00517***	−0.00239	0.00874	−0.01058**
	(3.25395)	(−1.56037)	(0.38437)	(−2.18151)
Acquisitions	−0.07222***	−0.07136***	−0.07255*	−0.09021***
	(−8.20766)	(−4.25740)	(−1.96581)	(−6.98169)
Governance Score	0.01139	0.02900	0.00293	−0.01321
	(0.93589)	(1.33528)	(0.06690)	(−0.74577)
Intercept	−0.97367***	−0.55400***	−0.95985**	−0.49008***
	(−8.71194)	(−3.47985)	(−2.19034)	(−3.38654)
adj. R-sq	0.12204	0.13845	0.12324	0.12587
No. of observations	63,020	28,184	1957	55,286
Year-fixed effects	Yes	Yes	Yes	Yes

ating factors to the association between natural disasters and manipulation in some aspects, which supports our hypothesis *H3a*.

The operational location of a firm often influences how it reacts to different events, such as natural shocks. Hence, we assume that the operational location may influence the impact of disaster-related damages on manipulation. Domestic firms are more likely to be affected by local disasters than firms that run internationally. It is also consistent with the home bias theory proposed in the literature (Kellenberg and Mobarak, 2011; Malloy, 2005; Pirinsky and Wang, 2006). International firms can diversify operations globally, reducing their chance of being directly affected by domestic disasters. Thus, investors of international firms are less sensitive to the effects of domestic disasters. To test if the association between disaster and manipulation is directed by the firm's operational status (domestic or international), we run an analysis where a firm's operational status interacts with the damage variables. The operational status information is collected from the Compustat database. The operational status is an indicator variable, where 1 denotes a firm that operates internationally, and 0 denotes a firm that operates domestically. The results are shown in Table 6, Column III, which shows that the interaction variables are negative and statistically significant for the disasters that involve injuries. Moreover, the table shows that disasters involving deaths and property damage do not make any difference in the market manipulation of the firms that operate internationally. Overall, it shows that disasters have an opposite or no influence on the market manipulation of international firms. Hence, the data are consistent with *H3b*.

6. Cross-sectional analyzes

We propose information asymmetry and sentiment as two channels through which natural disaster is expected to influence market manipulation. In this section, we conduct two cross-sectional analyses to show the influence of information asymmetry and sentiment on our findings.

The literature finds that continuous trading manipulation is less pronounced among firms with less information asymmetry (Comerton-Forde and Putniņš, 2014). They explain that informa-

Table 6
Moderating Roles of Disaster Mitigation Program and Community Resilience.
This table presents panel regression results of the determinants of manipulation with industry- and year-fixed effects. The dependent variable is continuous trading manipulation, which is measured by alerts, alerts to interval ratio, value to trade volume ratio, and scaled by market capitalization. The main independent variables are property, crop damages scaled by county-level GDP, and deaths and injuries caused by disaster events. Column I uses the interaction of the damage, death, and injury variables with the county's disaster preparedness. Column II uses the interaction of the damage, death, and injury variables with the community's resilience status. Column III uses the interaction of the damage, death, and injury variables with the firm's operation status. Firm- and county-level controls are explained in the Appendix. The model controls for industry- and time-fixed effects. The standard errors are clustered by county. The sample includes the firms which were involved in manipulation at least once during the sample period. The sample includes the firms that experienced manipulation at least once. *, **, *** significant at the 10%, 5%, and 1% levels, respectively.

	Continuous Trading Manipulation (I)	Continuous Trading Manipulation (II)	Continuous Trading Manipulation (III)
Damage Property Direct scaled by GDP	−0.00029	0.01399**	0.00045
	(−0.32500)	(2.05559)	(0.40477)
Damage Crops Direct scaled by GDP	0.07481	−0.09136***	0.06966
	(0.54939)	(−2.82748)	(0.52364)
Deaths Direct	0.01764***	0.01144***	0.01449***
	(4.19828)	(3.43625)	(2.84517)
Injuries Direct	0.00046***	0.00075	0.00072***
	(5.74877)	(1.18265)	(6.86507)
HMA_Program	0.00380		
	(0.17571)		
Damage Property Direct scaled by GDP*HMA_Program	0.00082		
	(0.80375)		
Damage Crops Direct scaled by GDP*HMA_Program	−1.83420***		
	(−4.11045)		
Deaths Direct*HMA_Program	−0.05542*		
	(−1.71460)		
Injuries Direct*HMA_Program	0.00337*		
	(1.91037)		
Community Resilience		0.01273	
		(0.50896)	
Damage Property Direct scaled by GDP*Community Resilience		−0.01460**	
		(−2.14088)	
Damage Crops Direct scaled by GDP*Community Resilience		0.45465***	
		(3.05391)	
Deaths Direct*Community Resilience		0.01181*	
		(1.72946)	
Injuries Direct*Community Resilience		−0.00035	
		(−0.54687)	
International			−0.12620***
			(−4.81807)
Damage Property Direct scaled by GDP*International			−0.00119
			(−0.97143)
Damage Crops Direct scaled by GDP*International			−2.37064
			(−0.78351)
Deaths Direct*International			0.02708
			(0.87197)
Injuries Direct*International			−0.00152***
			(−3.41074)
Intercept	−0.60752***	−0.61956***	−0.66899***
	(−9.26098)	(−9.81036)	(−11.10893)
adj. R-sq/ Psudo R-sq	0.12389	0.12400	0.13095
No. of observations	252,247	252,247	236,906
Controls	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes

tion asymmetry makes it difficult for the market participants to understand whether the parties in the market (e.g., buyers, brokers, and fund managers) are informed traders or manipulators. As a part of robustness analyses, we want to see if the impact of a disaster on manipulation is strong when there is high information asymmetry. According to the theory, it is expected that the relationship will be stronger when there is high information asymmetry. Hence, we use information asymmetry as an interaction variable with our main variables of interest. Here, we use the number of analysts as a proxy for information asymmetry, where a higher value means lower information asymmetry. Table 7, Column I shows that the interaction variable is negative and statistically significant for damage to property. Therefore, a strong information environment minimizes the effect of disasters that involve property damage on manipulation, consistent with the theory that information asymmetry between firms and investors provides more opportunities for manipulation. However, we fail to find any such relationship with other variables of interest. To further investigate the impact of information asymmetry, we use a different proxy for information asymmetry. We use the age of a firm calculated by the years from IPO. The younger a firm, the more information asymmetry. Column II of Table 7 uses age as an interaction variable

Table 7
Channel analysis.
This table presents panel regression results of the determinants of manipulation with industry- and year-fixed effects. The dependent variable is Continuous Trading Manipulation 30 min Total Trade Value / Market Capitalization Winsorized 5/95. The main independent variables are the damages to property and crops scaled by county-level GDP and deaths and injuries caused by disaster events. Columns I and II use information asymmetry and company age as interaction variables with the main independent variables. Columns III and IV include the results for subsample with a high sentiment (higher than the median score) and a low sentiment (lower than the median score). The model controls for industry- and time-fixed effects. The standard errors are clustered by county. The sample includes the firms which were involved in manipulation at least once during the sample period. The sample includes the firms that experienced manipulation at least once. *, **, *** significant at the 10%, 5%, and 1% levels, respectively.

	Continuous Trading Manipulation (I)	Continuous Trading Manipulation (II)	Continuous Trading Manipulation (III)	Continuous Trading Manipulation (IV)
Damage Property Direct scaled by GDP	0.00818**	0.00052	−0.00080**	0.00219
	(2.37344)	(0.32945)	(−2.35846)	(0.97939)
Damage Crops Direct scaled by GDP	−0.09165	0.17518	0.07956	−0.01045
	(−0.67224)	(0.77520)	(0.53419)	(−0.18088)
Death Direct	−0.01062	0.01178*	0.02054***	0.00502
	(−0.49183)	(1.85899)	(3.04455)	(1.00054)
Injuries Direct	0.00445**	0.00112***	0.00049***	−0.00050
	(1.97347)	(5.58633)	(4.25618)	(−0.85936)
ln_Analyst Coverage	−0.03779**	−0.03759**	−0.03956**	−0.03363**
	(−2.38693)	(−2.38259)	(−2.36445)	(−2.03014)
Damage Property Direct scaled by GDP * ln_Analyst Coverage	−0.00531***			
	(−2.63780)			
Damage Crops Direct scaled by GDP * ln_Analyst Coverage	0.11148			
	(0.75490)			
Deaths Direct * ln_Analyst Coverage	0.01735			
	(1.37780)			
Injuries Direct * ln_Analyst Coverage	−0.00257*			
	(−1.75678)			
Company Age	−0.00034	−0.00035	−0.00080	0.00052
	(−0.32616)	(−0.32705)	(−0.68526)	(0.49047)
Damage Property Direct scaled by GDP * Company Age		−0.00006		
		(−0.41042)		
Damage Crops Direct scaled by GDP * Company Age		−0.00718		
		(−1.02810)		
Deaths Direct*Company Age		0.00046		
		(0.74995)		
Injuries Direct*Company Age		−0.00006***		
		(−3.03510)		
Intercept	−0.60712***	−0.60735***	−0.72691***	−0.51958***
	(−9.24616)	(−9.25209)	(−10.06460)	(−8.07406)
adj. R-sq	0.12388	0.12388	0.12081	0.12968
No. of observations	252,247	252,247	136,956	115,291
Controls	Yes	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes

with the main variables of interest. The coefficient of the interaction variables is negative and statistically significant for the disasters that cause injuries. Although the coefficients for other damages are negative, they are not statistically significant. Hence, the findings from information asymmetry are consistent with the local bias hypothesis, as documented by Bernile et al. (2015). They find that local bias especially applies to younger firms. Consistent with their findings, we find that younger local firms are more susceptible to manipulation when there is a local natural disaster.

Our theory claims sentiment as one of the drivers of our findings. In line with that, our next analysis shows how overall community sentiment impacts our results. We assume that manipulation can take place in the areas and at times when people are more sensitive to movement in stock price and trade volume. Literature shows that the reactions to disasters are strong for local investors (Alok et al., 2020; Bernile et al., 2017; Gao et al., 2020). Hence, we expect the disaster's effect on manipulation will be strong for the community with a high sentiment. Using the household investors' sentiment index, Khan et al. (2020) find a high causal effect of household investors' sentiment indices on the stock returns of the S&P 500, financials, technology, health care, and consumer discretionary sectors. We follow them to construct a sentiment index based on 15 search terms derived from words of economic sentiment in the Harvard and Lasswell dictionaries.[4] Google Trends gives real-time frequencies of these search terms. These terms are found to have a significant correlation with returns. Each term has a score that ranges from 0 to 100, indicating a high value as a high sentiment. We take the average of the scores of these 15 search terms for each month. We assign the state-level monthly sentiment index to the county groups. We divide our sample into two groups depending on the median value of the sentiment index. A group with a higher than median score is regarded as a high-sentiment group and vice versa. The results are shown in Table 7, Columns III and IV for the high-sentiment and low-sentiment groups, respectively. Disasters that involve property damage, death, and injury have a positive and statistically significant impact on manipulation for the high-sentiment group. In terms of economic significance, for a 1 standard deviation increase

[4] These terms are: The Crisis, Bankrupt, Poverty level, Thrift, Savings, Inflation Rates, Gold, US poverty, Expense, Gold prices, Benefits, Poverty, Recession, Equity fund, Price of gold, and Roth IRA contribution.

in deaths and injuries, there is a 2.24 and 1.43% increase, respectively, in manipulation. However, we fail to find similar results for the low-sentiment group.

We also conduct an analysis using the FEARS index developed by Da et al. (2015), which is a sentiment index.[5] The difference between the FEARS and the sentiment index used in our study using Google Trends is that the FEARS provides the overall U.S.-wide data while we examine county-level data. However, Google Trends provides state-level data, which is more relevant to our study design. Moreover, FEARS offers data from 2004 to 2011, whereas our study period prolongs from 2007 to 2018. Therefore, a substantial sample period is omitted if we use the FEARS index. Since FEARS is U.S.-wide data, we merge the index data based on year and month. When we run the analysis by splitting periods into high versus low FEARS, we see a stronger connection with disasters and manipulation in periods of low FEARS (similar results with quartiles and deciles). One explanation is that investors are more responsive and focused on local disasters in times when national level FEARS are less problematic. However, there could be many other explanations for this finding since the FEARS index is nationwide, and our analyses in this paper focus on localized effects in disaster regions; as such, these results are not presented here but available on request. The data examined are consistent with information asymmetry, firm age, and sentiment as contributors to the relationship between disasters and manipulation.

7. Endogeneity concerns and robustness analyses

7.1. Difference-in-Differences (DiD) analysis

In terms of endogeneity, it is theoretically less likely that manipulation causes disasters. Moreover, since disasters are random, the firm's location choices do not influence the occurrence of disasters. Nevertheless, as a part of the robustness tests, we use a propensity score-matched sample to address the concern that the firm-level characteristics may drive the results. Moreover, there may be concerns that our results are driven by the differences in firm-level characteristics between high and low-disaster-prone areas (Ghoul et al., 2017). Hence, our paper selects two recent disasters to see if any location-specific attributes drive our results. We use hurricane Harvey and Irma as our quasi-natural experiment. We select these two disaster events since these are considered the most recent devastating and costliest disasters, which occurred in two subsequent periods and affected two states. We use August and September of 2017 as the period of our natural experiment. We consider Texas and Florida as our treatment states, as they were the most affected. As controls, our paper uses all other states except these two. For the control group, we consider only those firms located in the counties of the states that were not affected by any disaster during our sample period. However, for treatments, we consider only those firms in Texas and Florida located in the counties affected by Harvey and Irma. Moreover, we confirm that our treatment firms were unaffected by disasters other than Irma and Harvey during the sample period. We consider the year 2017 as our experiment period for this study. The reason behind choosing a single year is to confirm that we have enough observations that were not impacted by any disasters other than Harvey and Irma for our treatment group and were not impacted by any disasters for our control group. We consider the months before August 2017 as a pre-disaster period and the remaining months as a post-disaster period. Firstly, we match the firms from both the control and treatment groups based on firmm level characteristics using the caliper matching technique of the propensity matching score. We confirm no significant differences between the control and treatment firms before the event. Therefore, we use the matched sample for the post-disaster period to perform the DiD regression. Our regression is as follows

$$\begin{aligned} &Continuous\,Trading\,Manipulation_{it} \\ &= \beta_0 + \beta_{1t} Treatment_i + \beta_{2t} After_t + \beta_{3t} Treatment_i \\ &\times After_{t+} \beta_{4t} E_{it} + \delta_n FE + \varepsilon_{it} \end{aligned} \tag{2}$$

We use continuous trading manipulation scaled by market capitalization as our main dependent variable in the DiD analysis. Table 8 shows the results of DiD analysis. Although the treatment sample has no significant difference in manipulation before the event, the sample obtains a significant positive coefficient in the post-disaster period. The economic significance is such that treat*after gives an 18.69% increase in manipulation relative to its average value in the full sample. The economic significance of the effect is much larger here with a more narrowly benchmarked experiment. Hence, we can again infer that the data indicate that disasters lead to more manipulation for disaster-exposed firms than non-exposed firms.

We further consider stock liquidity to see if the results vary. Studies show that liquidity is one of the critical determinants of manipulation (Aggarwal and Wu, 2006; Comerton-Forde and Putniņš, 2009). According to these studies, manipulation is expected for the less liquid stocks since moving a highly-liquid stock by manipulation is difficult without incurring a high cost and risk. We consider the bid-ask spread to measure liquidity. We divide the sample according to their liquidity–more liquid and less liquid stocks. We classify more liquid stocks when the spread is less than the median and less liquid stocks when the spread is more than the median. The results are shown in Columns II and III of Table 8. The table shows that the interaction term is positive and more significant for the less liquid stocks. However, the sample of more liquid stocks does not show any significance. Hence, our results are consistent with the literature that less liquid stocks are more prone to manipulation during disasters.

7.2. Alternative measures of manipulation

We have been showing how disaster-related damage affects the magnitude of manipulation among firms. In our next analysis, we use alternative proxies of manipulation. Firstly, we replace our dependent variable with a dummy indicating if manipulation occurred. The main objective of the analysis is to see how the likelihood of manipulation changes with the occurrence of disasters. The regression results are shown in Table 9, Column I. The results show that when the disaster causes death and injury, the likelihood of manipulation increases by 5.3% and 0.11%, respectively. The result is highly consistent with our baseline regression results. In Column II, we use a different measure for manipulation–EOD price manipulation–as a proxy for the manipulation variable. We consider a categorical variable representing 1, if there is any EOD price dislocation in time t, and 0 otherwise. An EOD price is considered dislocated if it has been four standard deviations away from its mean price change during the past 100-day trading benchmarking period at the end of the trading day and reverts back to the mean price the subsequent morning. A detailed definition of EOD price manipulation is provided in the Appendix A. This shows that EOD price manipulation is strongly associated with disasters that cause crop damage. As well, when the disaster causes crop damage, the likelihood of EOD price manipulation increases by 86.3%. Hence, our alternative proxies of manipulation also show a significant association with disasters.

Furthermore, we consider the probability of disasters in different states to see if there is any systematic difference in disas-

[5] FEARS index is constructed by aggregating the volume of queries related to household concerns (e.g., "recession," "unemployment," and "bankruptcy").

Table 8
Difference-in-Differences Analysis on Harvey and Irma.
This table presents the difference-in-differences regression results on the matched sample of disaster-affected states (treatment) and non-disaster affected states (control) during the year 2017. The sample uses Texas and Florida as the treatment groups, affected by Harvey and Irma, and other states, as the control groups, not affected by Harvey and Irma. The sample is matched based on the continuous trading manipulation scaled by market capitalization and other control variables before the event of Harvey and Irma. Hence, the matched sample is used to observe the difference-in-differences estimates for the post-event period. The sample is further divided into two groups based on the liquidity of stocks. Liquidity is measured by the difference between the bid and ask price. Column II includes the sample stocks that have higher than the median level of liquidity (less spread), and Column III includes the sample stocks that have less than the median level of liquidity (more spread). The main independent variable is continuous trading manipulation scaled by market capitalization. Firm- and county-level controls are explained in the Appendix. The model controls for industry-fixed effects. The standard errors are clustered by counties. The sample includes the firms that experienced manipulation at least once. *, **, *** significant at the 10%, 5%, and 1% levels, respectively.

	Continuous Trading Manipulation Full Sample (I)	Continuous Trading Manipulation High Liquidity Stocks (II)	Continuous Trading Manipulation Low Liquidity Stocks (III)
After	−0.10024**	−0.00211	−0.18441***
	(−2.32187)	(−0.03760)	(−3.10124)
Treatment	−0.02907	−0.03042	−0.02647
	(−0.93463)	(−0.80997)	(−0.58819)
After*Treatment	0.07319**	0.02697	0.09237**
	(2.01557)	(0.58201)	(2.01864)
ln_Analyst Coverage	−0.03726	0.01334	−0.03289
	(−1.37256)	(0.42308)	(−0.81923)
ln_Returns	0.02767***	0.01717***	0.03536***
	(5.95031)	(3.04603)	(5.07463)
Idiosyncratic Risk	−0.24226	0.21482	−0.52144
	(−0.99369)	(0.75990)	(−1.35373)
ln_Share Trade Volume	0.17404***	0.12574***	0.20634***
	(17.73853)	(10.42159)	(11.50387)
ln_Market Capitalization	0.02446*	0.08373***	−0.02459
	(1.82693)	(6.83973)	(−1.16865)
ln_Debt to Equity	−0.00041	−0.00181	−0.00100
	(−0.09517)	(−0.40888)	(−0.17365)
ln_Sales Turnover	0.02278	0.00334	0.04559*
	(1.61705)	(0.31138)	(1.81202)
ln_Market to Book	−0.02573***	−0.02862***	−0.02075**
	(−4.30684)	(−4.07849)	(−2.57180)
ln_Asset	−0.05677**	−0.03624**	−0.08194**
	(−2.58326)	(−1.99498)	(−2.37928)
Company Age	−0.00126	−0.00104	−0.00132
	(−0.68875)	(−0.52785)	(−0.52360)
Current Ratio	0.00298	0.00271	0.00368
	(0.63482)	(0.56907)	(0.52653)
Acquisitions	0.00558	−0.02844	0.03371
	(0.16766)	(−0.66544)	(0.65590)
Governance Score	0.00763	−0.00696	0.00995
	(0.41550)	(−0.39517)	(0.39680)
Intercept	−1.33912***	−1.76964***	−0.95797***
	(−8.81513)	(−11.29679)	(−4.08530)
adj. R-sq	0.15194	0.16875	0.12417
No of observations	7675	3325	4350
Month-fixed effects	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes

ter's impacts on manipulation when the disasters are predictable. There is a possibility that certain hedge funds and professional investors may be tuned into this news and be alert ahead of time once the probability reaches a certain threshold. Hence, we control for the predictability of disasters in regions. We consider the years from 1980 to 2018 disaster data from NOAA to determine the predictability of disasters. We divide the states between high and low-predictable disaster zones.[6] We run two separate analyses with these two groups. The results are reported in Table 9, columns III and IV. It shows that the impact of disasters on manipulation is statistically significant for states where disasters are not predictable; however, the impact is not statistically significant for states where disasters are highly predictable.

7.3. Alternative explanations

Our analysis shows that manipulation increases during the time of disaster. However, there may be concerns that disaster increases volatility, leading to manipulation. Hence, in our next analysis, we graphically show how the volatility changes between the manipulation and non-manipulation firms during the time of the disasters. We use four combinations of our sample: manipulation firms with exposure to disasters, non- manipulation firms with exposure to disasters, manipulation firms with no exposure to disasters, and non-manipulation with no exposure to disasters. We use two proxies for volatility: idiosyncratic risk and total volatility. Idiosyncratic risk is measured by the difference between realized returns and expected returns using the market model. Moreover, total volatility is calculated as the volatility of the realized returns of the underlying security. Fig. 4 shows the results for these two proxies separately and takes the average of the changes in idiosyncratic risk and the changes in total volatility of our sample combinations for the period ranging from three months before the disaster to three months after the disaster. We confirm that manipulation and

[6] High predictable states include AL, AR, CO, FL, GA, IA, IL, IN, KS, KY, LA, MD, MO, MS, NC, NE, NJ, NY, OH, OK, PA, SC, TN, TX, VA, and WI. Low predictable disaster zones include AK, AZ, CA, CT, DC, DE, HI, ID, MA, ME, MI, MN, MT, ND, NH, NM, NV, OR, RI, SD, UT, VT, WA, WV, and WY.

Table 9
Other robustness tests.
This table presents panel regression results using alternative measures of market manipulation and likelihood of disasters. The dependent variable for Column I is the manipulation dummy, which is 1 for manipulation, and 0 otherwise. The dependent variable for Column II is the dummy of EOD price manipulation, which is 1 when there is a manipulation, and 0 otherwise. Column III reports the results for the states that have a low predictability of disaster and column IV reports the results for the states that have a high predictability of disasters. The main independent variables are property, crop damages scaled by county-level GDP, and deaths and injuries caused by disaster events. Firm- and county-level controls are explained in the Appendix. The model controls for industry- and time-fixed effects. The standard errors are clustered by county. The sample includes the firms which were involved in manipulation at least once during the sample period. The sample includes the firms that experienced manipulation at least once. *, **, *** significant at the 10%, 5%, and 1% levels, respectively.

	Presence of continuous trading manipulation (I)	Presence of EOD price manipulation (II)	Continuous Trading Manipulation (III)	Continuous Trading Manipulation (IV)
Damage Property Direct scaled by GDP	1.0016	−0.9733	0.00341**	−0.00002
	(0.54347)	(−0.72712)	(2.19943)	(−0.22087)
Damage Crops Direct scaled by GDP	1.0500	1.8636 ***	4031.83748***	0.01136
	(0.15925)	(3.84590)	(45.87056)	(0.54715)
Deaths Direct	1.0528***	−0.9225	0.00162*	0.00141
	(3.07031)	(−1.48838)	(1.68756)	(1.54032)
Injuries Direct	1.0011***	1.0014	0.00020	0.00008***
	(3.54159)	(1.35444)	(1.27444)	(5.24614)
Intercept	0.0031***	0.0019***	−0.09306***	−0.11438***
	(−11.62974)	(−14.09923)	(−6.66699)	(−13.60174)
adj. R-sq/ Psudo R-sq	0.1468	0.0404	0.11059	0.12359
No. of observations	252,250	252,250	96,173	156,077
Controls	Yes	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes

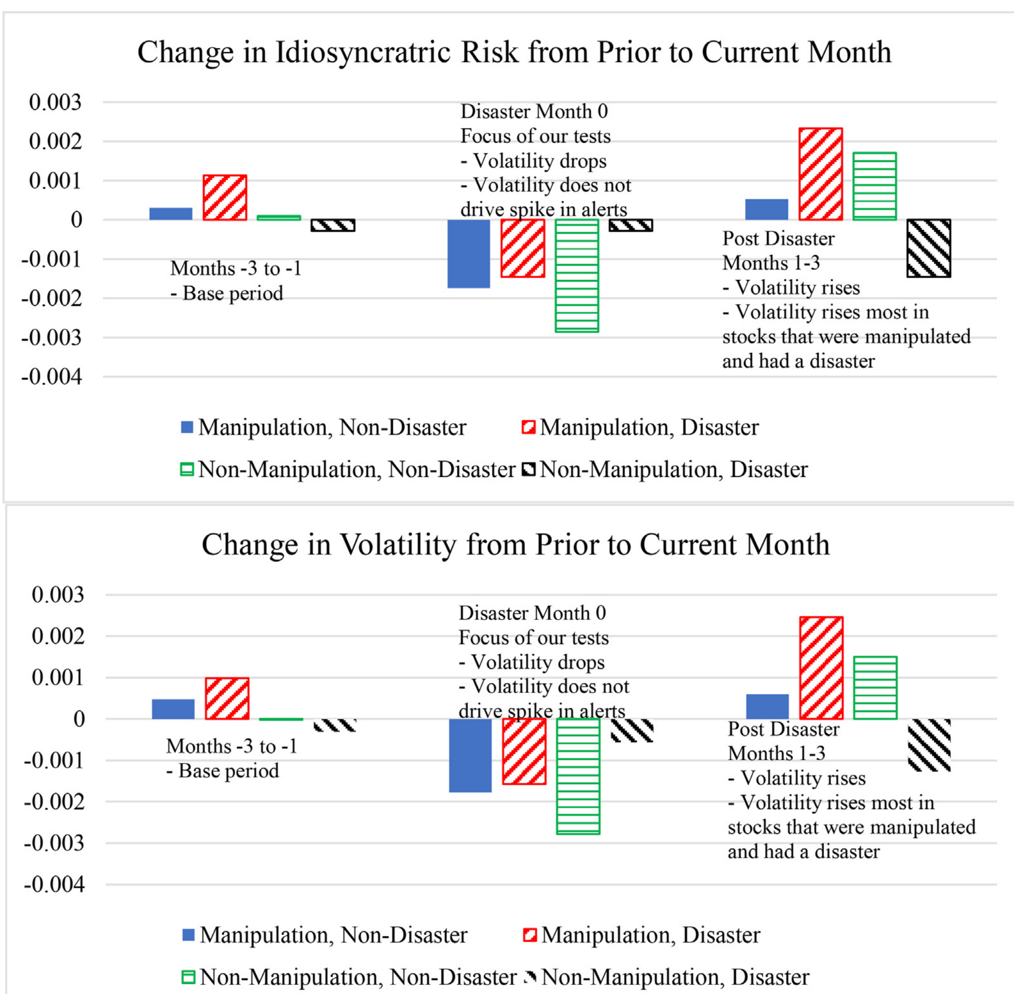

Fig. 4. The trend of volatility among the manipulation and non-manipulation firms around the time of disasters. Firms are matched using size, age, and industry.

non-manipulation firms are similar in size, age, and industry for our disaster-exposed sample. Therefore, we illustrate how volatility moves around disasters. Fig. 4 shows no significant increase in volatility during the time of the disaster; in fact, volatility significantly drops. Moreover, for our non-disaster exposed firms, we confirm that they are similar to our disaster firms in terms of age, size, and industry. In addition, to assign the disaster periods for these non-disaster-exposed firms, we mimic the disaster periods of the disaster-exposed firms. Fig. 4 shows the volatility trends of this sample. No significant increase appears in their volatility during the time of disaster. Thus, these four subsamples do not show any significant increase in their volatility during the disaster period. We can confirm that our results are not driven by an increase in volatility during the disaster periods.

It is noteworthy from Fig. 4 that the firms that have been both the subject of disasters and the subject of manipulations have the greatest rise in volatility in the months +1 to +3 after the disaster. This suggests that manipulation is particularly costly for firms that have been the subject of a disaster, akin to "adding insult to injury." This post-disaster/manipulation period type of analysis is beyond the scope of our paper. Future research could examine in greater detail the harm caused by the combination of disasters and manipulation in terms of volatility, risk, and other microstructure and corporate finance outcome.

Moreover, the literature explains the learning effects of natural disaster experiences on corporate actions (Bernile et al., 2017; Chen et al., 2021; Ouazad and Kahn, 2022). Regarding our study, there may be a concern that repetitive exposures to natural disasters may impact the firm's susceptibility to manipulation. Therefore, we divided the sample into three groups based on their exposure to natural disasters: firms with no exposures to disasters over the period, firms with exposure to one disaster, and firms with exposure to two or more disasters. The data indicate that firms with one disaster exposure are 12.1% more likely to experience a manipulation than firms with two or more disasters during the disaster months, while firms with two or more disasters are 3.6% more likely to experience a manipulation during a disaster month than firms with no disasters; both of these differences are statistically significant at the 1% level. These results are available on request. One explanation for these findings is that there is learning of manipulation during disaster months. Another explanation is that manipulators are less likely to do the exact same thing over time (since pattern behavior is more likely to be successfully prosecuted, and hence it is not a wise strategy to repeatedly rob the same firm under the same circumstances so to speak). Future research could investigate this issue of repeat manipulations, prosecutions, and learning over time, and how companies respond to these manipulation events under different circumstances to improve their long-term performance and corporate outcomes.

8. Conclusions

This paper explores the impact of disaster and disaster-related damage to the continuous trading manipulation measured by the number of alerts, alerts to interval ratio, value to trade volume ratio, and values scaled by market capitalization. The study considers the headquarter of the firms listed in the NYSE and NASDAQ to determine their disaster exposure. Our data indicate that continuous trading manipulation increases during disaster periods. Using the overall sample, the paper provides empirical evidence supporting that disasters involving death and injury trigger manipulation. It is interesting to note that the association between disasters and manipulation varies significantly between industries. We show information asymmetry and sentiment as two channels through which natural disasters cause market manipulation. We find community resilience, operational location, and hazard management programs moderate the impact of disasters on market manipulation. Our results are robust to alternative model specifications, different identification strategies, and adjustments for potential endogeneity.

Our results, thus, add supporting evidence to the documented market reactions to natural disasters in the literature (Alok et al., 2020; Gao et al., 2020; Shan and Gong, 2012). Moreover, it proposes a new market manipulation measure and determinant which adds to the manipulation literature (Aggarwal and Wu, 2006; Comerton-Forde and Putniņš, 2011, 2014; Cumming et al., 2020; Hillion and Suominen, 2004). We show that disasters in the headquarter locations lead to market manipulation in the local firms. The findings provide a new insight for policymakers to monitor the markets during shocks such as natural disasters. Moreover, it suggests that investors carefully estimate the risk and price movement during exogenous shocks. There are some limitations and possible extensions of this paper. Our paper does not classify the type of disasters. It focuses on one type of manipulation: continuous trading manipulation, whereas there are other types, such as wash trades, opening price manipulation, and information leakage. Lastly, since we do not have access to climatic research data, we cannot compare the consequences of predicted versus actual events. Therefore, it is beyond our scope that we can look at this issue relating disasters to market manipulation in this first look.

Future research using different proxies of manipulation can shed light on whether disasters impact other types of manipulation. Moreover, future studies may use other forecasting methods from climatic research to predict future disasters and compare predicted versus actual events. Lastly, extending the study to an international sample setting may provide more insights. As we found in our study that operational diversification may mitigate the impact of natural disasters, it would be a good venue for future studies on how operational diversification of international firms can mitigate the impacts of natural disasters.

Declaration of Competing Interest

None.

Data availability

The authors do not have permission to share data.

Acknowledgments

We are grateful to the seminar participants at the Birmingham Business School, EDHEC, Florida International University, RMIT, Sheffield University Management School, the center for Research into Accounting and Finance in Context (CRAFiC), and the University of Leeds. Also, we thank the conference participants at the Academy of Sustainable Finance, Accounting, Accountability & Governance (ASFAAG) Conference; the Association of Italian Scholars in Banking and Finance; the British Journal of Management Annual Conference; the center for Transnational Commercial Law; National Law University Dehli; Leicester Business School; the Eastern Finance Association Annual Conference; the Eurasian Business and Economics Society Conference, Athens; the Financial Management and Accounting Research Conference, University of Cyprus; the Green Finance Conference, Shanghai; IIM Jammu's International Conference on Sustainable Finance, Economics & Accounting in the Pre- and Post-Pandemic Era; and the University of Southampton Cryptocurrency Research Conference.

Appendix A. Definitions of the Variables

Variable names	Definitions/ Descriptions	Sources
Continuous Trading Manipulation 30 min Number of Alerts	The Continuous Trading Manipulation metric detects abnormal 30 min changes in liquidity, returns, and transaction costs based on the following rules. (a) For every 30 min window (j) after opening of the current trading day (t), calculate the following metrics for every security in the market. 1. Total trading value over the past 30 min (Val) 2. Total trading volume over the past 30 min (Vol) 3. Return over the past 30 min (Ret) 4. Average effective spread over the past 30 min (EffSpr) 5. Average quoted spread over the past 30 min (QuotedSpr) b) For every security in the market, calculate the average value of the above metrics for each 30 min window (j) over the past 30 trading days (t-1 to t-31). c) For the *j*th 30 min window of the current trading day (t) 1. For security i, calculate the difference ($\text{Security\_Delta}_{i,j,t,m}$) between metric m for the current window (j) and the average metric value for the same window (j) over the past 30 trading days. (Note that for the trading volume and trading value metric, the difference is calculated as the percentage of change.) 2. Calculate the average value of $\text{Delta}_{i,j,t,m}$ across all securities ($\text{Mkt\_Delta}_{j,t,m}$). Note that for the 30 min return metric, index returns are used to calculate the average delta. 3. Calculate the difference between ($\text{Security\_Delta}_{i,j,t,m}$) and ($\text{Mkt\_Delta}_{j,t,m}$) for the current trading day ($\text{Current\_Security\_Delta}_{i,j,t,m}$) and the average daily difference over the past 30 trading days ($\text{Hist\_Security\_Delta}_{i,j,t,m}$) 4. If there are 3 or more metrics with ($\text{Current\_Security\_Delta}_{i,j,t,m}$) that are more than 3 standard deviations away from Hist_Security_Deltai,j,t,m, increase the number of Continuous Trading Manipulation alerts by one. The paper uses the monthly continuous trading manipulation 30 min number of alerts, which sums up the total number of alerts a security incurs during a month..	SMARTS, Inc. and Capital Markets CRC (CMCRC) in Sydney
Continuous Trading Manipulation 30 min Number of Alerts to Number of Intervals Ratio (bps)	Represents the ratio of the number of Continuous Trading Manipulation alerts over the total number of 30 min (j) windows for security i on day t. The paper uses the monthly continuous trading manipulation number of alerts to the number of intervals ratio by summing up the total number of the ratios for each day of a month when security i was exposed to continuous trading manipulation.	SMARTS, Inc. and Capital Markets CRC (CMCRC) in Sydney
Continuous Trading Manipulation 30 min Total Trade Value	Represents the trading value across all 30 min (j) windows with Continuous Trading Manipulation alert triggered for security i on day t. The paper uses the monthly continuous trading manipulation 30 min total trade value by summing up the trading values for each day of a month when security i was exposed to continuous trading manipulation.	SMARTS, Inc. and Capital Markets CRC (CMCRC) in Sydney
Continuous Trading Manipulation 30 min Value Ratio (bps)	Represents the ratio of trading value across all 30 min (j) windows with Continuous Trading Manipulation alert over the total trading value for security i on day t. The paper uses the monthly continuous trading manipulation 30 min value ratio (bps) by summing up the ratios for each day of a month when security i was exposed to continuous trading manipulation.	SMARTS, Inc. and Capital Markets CRC (CMCRC) in Sydney
End-of-day (EOD) price dislocation value ($)	An EOD price is considered dislocated if, in the 15 min before the continuous trading period, it is four standard deviations away from its mean price change during the past 100-trading-day benchmarking period, and then reverts back to the benchmark price range the following morning. Our measure of EOD price dislocation value indicates the severity of EOD price dislocation.	SMARTS, Inc. and Capital Markets CRC (CMCRC) in Sydney
Deaths direct	The number of deaths in a month directly related to the weather event in a county.	National Oceanic and Atmospheric Administration
Injuries direct	The number of injuries in a month directly related to the weather event in a county.	National Oceanic and Atmospheric Administration
Damage property direct scaled by county-level GDP	The estimated amount of damage to property incurred in a month by the weather event in a county (e.g. 10.00 K = \$10,000; 10.00 M = \$10,000,000). The variable is further scaled by GDP to show the relative loss compared to a county's total GDP.	National Oceanic and Atmospheric Administration
Damage crops direct scaled by county-level GDP	The estimated amount of damage to crops incurred in a month by the weather event in a county (e.g. 10.00 K = \$10,000; 10.00 M = \$10,000,000). The variable is further scaled by GDP to show the relative loss compared to a county's total GDP.	National Oceanic and Atmospheric Administration
Analyst Coverage	The number of analysts who are covering a company is the number of analysts who provide an earnings per share estimate (EPS) for the next (to be announced) financial year (FY1)	I/B/E/S
Returns	The change in the total value of an investment in a common stock over some period of time per dollar of initial investment. The paper uses the monthly returns, which are holding period returns from month-end to month-end, not compounded from daily returns, and ordinary dividends are reinvested at month-end.	CRSP

(*continued on next page*)

(*continued*)

Variable names	Definitions/ Descriptions	Sources
Idiosyncratic Risk	Monthly realized idiosyncratic volatility measured using the residuals from a daily market model within the month. Part of the total volatility of the asset's returns that cannot be explained by market returns. Idiosyncratic volatility and total volatility are essentially identical when measured within a month, due to the low explanatory power of the market model regression. In our sample, the average correlation between these variables is 0.9923.	Beta Suite by WRDS.
Current Ratio	Computed as current assets/ current liabilities.	Compustat
Share Trade Volume	Represents the sum of the trading volumes during that month.	CRSP
Market Capitalization	Refers to the total dollar market value of a company's outstanding shares of stock. Calculated as price * shares_outstanding.	Compustat
Debt to Equity	Computed as the total of the long term debt and debt in current liabilities scaled by the stockholder's equity.	Compustat
Sales Turnover	Represents gross sales reduced by cash discounts, trade discounts, and returned sales and allowances.	Compustat
Market to Book	Market value of equity divided by book value of equity.	Compustat
Company Age	Years from the IPO listing.	Compustat
Governance Score	Ranges from 0 to 3. Higher score means higher governance. The score is based on the proportion of independent directors, the number of directors, and CEO duality.	Compustat
Acquisitions	An indicator variable where 1 indicates that the firm underwent an acquisition during the period and vice versa.	Compustat
Hazard Mitigation Program	Mitigation is any sustainable action that reduces or eliminates long-term risk to people and property from future damages.	FEMA
Sentiment Index	Average scores on the Crisis, Bankrupt, Poverty level, Thrift, Savings, Inflation Rates, Gold, U.S. poverty, Expense, Gold prices, Benefits, Poverty, Recession, Equity fund, Price of gold, and Roth IRA contribution	Google Trends
Community Resilience Score	Indicates the ability of a community to prepare for anticipated natural hazards, adapts to changing conditions, and withstands and recover rapidly from disruptions.	FEMA National Risk Index

References

Aggarwal, R.K., Wu, G., 2006. Stock market manipulations. J. Bus. 79 (4), 1915–1953.

Alexander, C., Cumming, D., 2022. Corruption and Fraud in Financial Markets: Malpractice, Misconduct and Manipulation. John Wiley & Sons.

Allen, F., Gale, D., 1992. Stock-price manipulation. Rev. Financ. Stud. 5 (3), 503–529.

Alok, S., Kumar, N., Wermers, R., 2020. Do fund managers misestimate climatic disaster risk. Rev. Financ. Stud. 33 (3), 1146–1183.

Bedard, J.C., Johnstone, K.M., 2004. Earnings manipulation risk, corporate governance risk, and auditors' planning and pricing decisions. Account. Rev. 79 (2), 277–304.

Bernile, G., Bhagwat, V., Rau, P.R., 2017. What doesn't kill you will only make you more risk-loving: early-life disasters and CEO behavior. J. Financ. 72 (1), 167–206.

Bernile, G., Kumar, A., Sulaeman, J., 2015. Home away from home: economic relevance and local investors. Rev. Financ. Stud. 28 (7), 2009–2049.

Brown, J.R., Ivković, Z., Smith, P.A., Weisbenner, S., 2008. Neighbors matter: causal community effects and stock market participation. J. Financ. 63 (3), 1509–1531.

Chen, Y., Fan, Q., Yang, X., Zolotoy, L., 2021. CEO early-life disaster experience and stock price crash risk. J. Corp. Financ. 68, 101928.

Comerton-Forde, C., Putniņš, T.J., 2009. Short Selling: Information or Manipulation. University of Sydney, Sydney. Faculty of Economics and Business Online verfügbar unter.

Comerton-Forde, C., Putniņš, T.J., 2011. Measuring closing price manipulation. J. Financ. Intermed. 20 (2), 135–158.

Comerton-Forde, C., Putniņš, T.J., 2014. Stock price manipulation: prevalence and determinants. Rev. Financ. 18 (1), 23–66.

Coval, J.D., Moskowitz, T.J., 2001. The geography of investment: informed trading and asset prices. J. Pol. Econ. 109 (4), 811–841.

Cumming, D., Ji, S., Peter, R., Tarsalewska, M., 2020. Market manipulation and innovation. J. Bank Financ. 120, 105957.

Cumming, D., Johan, S., Li, D., 2011. Exchange trading rules and stock market liquidity. J. Financ. Econ. 99 (3), 651–671.

Da, Z., Engelberg, J., Gao, P., 2015. The sum of all FEARS investor sentiment and asset prices. Rev. Financ. Stud. 28 (1), 1–32.

Do, Q., Cao, N.D., Gounopoulos, D., Newton, D., 2023. Environmental concern, regulations and board diversity. Rev. Corp. Financ. Forthcom..

Faleye, O., Krishnan, K., 2017. Risky lending: does bank corporate governance matter? J. Bank. Financ. 83, 57–69.

Fiordelisi, F., Galloppo, G., Paimanova, V., 2023. Climate change fears: natural disasters and investor behaviour. Rev. Corp. Financ. Forthcom..

Gao, M., Liu, Y.J., Shi, Y., 2020. Do people feel less at risk? Evidence from disaster experience. J. Financ. Econ. 138 (3), 866–888.

Ghoul, S.E., Guedhami, O., Kim, Y., 2017. Country-level institutions, firm value, and the role of corporate social responsibility initiatives. J. Int. Bus. Stud. 48, 360–385.

Griffin, J.M., Shams, A., 2018. Manipulation in the VIX? Rev. Financ. Stud. 31 (4), 1377–1417.

Hillion, P., Suominen, M., 2004. The manipulation of closing prices. J. Financ. Mark. 7 (4), 351–375.

Hong, H., Li, F.W., Xu, J., 2019. Climate risks and market efficiency. J. Econom. 208 (1), 265–281.

Huang, H.H., Kerstein, J., Wang, C., 2018. The impact of climate risk on firm performance and financing choices: an international comparison. J. Int. Bus. Stud. 49, 633–656.

Huynh, T.D., Nguyen, T.H., Truong, C., 2020. Climate risk: the price of drought. J. Corp. Financ. 65, 101750.

Imisiker, S., Tas, B.K.O., 2013. Which firms are more prone to stock market manipulation? Emerg. Mark. Rev. 16, 119–130.

Javadi, S., Masum, A.A., 2021. The impact of climate change on the cost of bank loans. J. Corp. Financ. 69, 102019.

Kahn, M.E., 2005. The death toll from natural disasters: the role of income, geography, and institutions. Rev. Econ. Stat. 87 (2), 271–284.

Kedia, S., Panchapagesan, V., 2011. Why do only some Nasdaq firms switch to the NYSE? Evidence from corporate transactions. J. Financ. Mark. 14 (1), 109–126.

Kellenberg, D., Mobarak, A.M., 2011. The economics of natural disasters. Annu. Rev. Resour. Econ. 3 (1), 297–312.

Khan, M.A., Hernandez, J.A., Shahzad, S.J.H., 2020. Time and frequency relationship between household investors' sentiment index and US industry stock returns. Financ. Res. Lett. 36, 101318.

Kong, D., Lin, Z., Wang, Y., Xiang, J., 2021. Natural disasters and analysts' earnings forecasts. J. Corp. Financ. 66, 101860.

Krueger, P., Sautner, Z., Starks, L.T., 2020. The importance of climate risks for institutional investors. Rev. Financ. Stud. 33 (3), 1067–1111.

Lambert, C., Sponem, S., 2005. Corporate governance and profit manipulation: a French field study. Crit. Perspect. Account. 16 (6), 717–748.

Lee, W.Y., Jiang, C.X., Indro, D.C., 2002. Stock market volatility, excess returns, and the role of investor sentiment. J. Bank Financ. 26 (12), 2277–2299.

Malloy, C.J., 2005. The geography of equity analysis. J. Financ. 60 (2), 719–755.

Massa, M., Simonov, A, 2006. Hedging, familiarity and portfolio choice. Rev. Financ. Stud. 19 (2), 633–685.

Nielsson, U., Wójcik, D., 2016. Proximity and IPO underpricing. J. Corp. Financ. 38, 92–105.

Nguyen, D.D., Hagendorff, J., Eshraghi, A., 2016. Can bank boards prevent misconduct? Rev. Financ. 20 (1), 1–36.

Nguyen, D.D., Hagendorff, J., Eshraghi, A., Alexander, C., Cumming, D., 2022. Misconduct in banking: governance and the board of directors. Corruption and Fraud in Financial Markets: Malpractice. Misconduct and Manipulation Chapter 11.

Ouazad, A., Kahn, M.E., 2022. Mortgage finance and climate change: securitization dynamics in the aftermath of natural disasters. Rev. Financ. Stud. 35 (8), 3617–3665.

Pirinsky, C., Wang, Q., 2006. Does corporate headquarters location matter for stock returns? J. Financ. 61 (4), 1991–2015.

Rehse, D., Riordan, R., Rottke, N., Zietz, J., 2019. The effects of uncertainty on market liquidity: evidence from Hurricane Sandy. J. Financ. Econ. 134 (2), 318–332.

Shan, L., Gong, S.X., 2012. Investor sentiment and stock returns: wenchuan Earthquake. Financ. Res. Lett. 9 (1), 36–47.

Toya, H., Skidmore, M., 2007. Economic development and the impacts of natural disasters. Econ. Lett. 94 (1), 20–25.