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Sentiment and stock prices: The case of aviation disasters ☆

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ABSTRACT

Behavioral economic studies reveal that negative sentiment driven by bad mood and anxiety affects investment decisions and may hence affect asset pricing. In this study we examine the effect of aviation disasters on stock prices. We find evidence of a significant negative event effect with an average market loss of more than $60 billion per aviation disaster, whereas the estimated actual loss is no more than $1 billion. In two days a price reversal occurs. We find the effect to be greater in small and riskier stocks and in firms belonging to less stable industries. This event effect is also accompanied by an increase in the perceived risk: implied volatility increases after aviation disasters without an increase in actual volatility.

1. Introduction

Bad mood and anxiety may affect investor decisions; anxious people may be more pessimistic regarding future returns, tend to take less risk, or both. Anxiety creates a negative sentiment that can affect investment decisions and corresponding asset returns.[1] In this study we examine large-scale aviation disasters. Our hypothesis is that aviation disasters affect people's mood and increase their anxiety which negatively affects the investment in risky assets. Therefore, we expect to observe negative rates of return in the stock market following aviation disasters. Indeed, we find significant evidence that aviation disasters negatively affect stock prices for a short period of a few days.

The effect found in this study encompasses both an event effect and a mean-reverting reversal effect two days after the event. There is more than one possible

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[1] Market sentiment, mood, and emotions are sometimes used in the literature interchangeably. However, market sentiment is a broader notion as it includes any misperception that can cause mispricing. It is broadly defined as "investors' belief about future cash flows and risk not justified by the facts at hand" (Baker and Wurgler, 2007, p. 129). The mood effect is therefore a special case of market sentiment. Also, as we

(*footnote continued*)
shall see in this study, people misperceived risk—which falls also in the category of market sentiment. To avoid confusion in the rest of the paper, we use the terms mood, anxiety, and fear interchangeably, as all these factors affect sentiment and can change investors' attitude toward risk.

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interpretation of the investors' reaction to news of aviation disasters:

1. Investors who are "not fully rational" (see, e.g., Lee, Shleifer, and Thaler, 1991) react irrationally to the immediate news on aviation disasters and after two days revert back to their normal behavior. It is also possible that sophisticated investors exploit the relatively low prices; hence, a price reversal occurs.
2. Investors have a state dependent utility function of the type $U(C,X)$, where C stands for consumption and $X=0,1$ indicates the presence of negative sentiment following aviation disasters ($X=1$) or the absence of negative sentiment (X=0). Thus, if for example $U(C,1)$ is characterized by a higher degree of risk aversion than $U(C,0)$, our results can be explained within the expected utility framework. Yet, even in this case the switch between $U(C,1)$ and $U(C,0)$ falls in the category of behavioral economics, as mood affects preference and, in particular, it affects the degree of risk aversion.

Both the event effect and the reversal effect are examined in this study in various ways. This study shows that the effect is highly significant and remains intact under rigorous robustness checks. Fig. 1 presents the main findings of this study, the statistical analysis of which appears in the following sections.

Fig. 1 depicts the cumulative average residuals (CARs) around the dates when aviation disasters occurred. The figure shows that on the first day after a disaster ($t=1$), when the media are typically flooded with disturbing pictures about the event and horrible stories about casualties (rather than when the occurrence of the disaster is known to some people), there is a sharp decline in average rates of return. This decline is almost 10 times larger in absolute terms than the average daily rate of return during the observed period. This decline represents an average market loss of more than \$60 billion per aviation disaster, whereas the upper bound on the actual economic loss involved with these events is roughly estimated at \$1 billion per disaster. Moreover, we find that the event effect is followed by a reversal effect. On the third day after the event occurs ($t=3$), there is an increase in returns that is about half the magnitude of the first day's decline. This reversal tendency persists for several days afterwards; the market fully reverts back to its mean average about 10 days after the decline.

What can one learn from the coexistence of the event effect and the reversal effect? If the market loss were due to the actual economic loss resulting from the disaster rather than due to the mood and anxiety effect, we would not expect to find a reversal effect at all. The fact that there is almost a complete price reversal is one more element in favor of our hypothesis asserting that excess anxiety induces the effect, and presumably when anxiety subsides or when sophisticated investors exploit the effect, a price reversal occurs.

To further study the event effect, we conduct several complementary analyses. First, we show that the decline in stock prices after aviation disasters is accompanied by a corresponding increase in perceived volatility, as measured by the VIX and VXO versions of the Fear Index, which has been proposed by Baker and Wurgler (2007) as a potential proxy for market sentiment. As we do not find a similar increase in actual volatility, this suggests that anxiety following aviation disasters affects the perception of volatility. Second, motivated by the prediction of Baker and Wurgler (2006) that a sentiment effect will be larger in stocks with valuations that are highly subjective and difficult to arbitrage, we test whether there is a difference in the magnitude of the effect in portfolios constructed by volatility, size, and industry. Indeed, we not only find the effect to be highly robust and to exist in all studied portfolios, but the results also conform to Baker and Wurgler's (2006) theory; a relatively larger event effect is

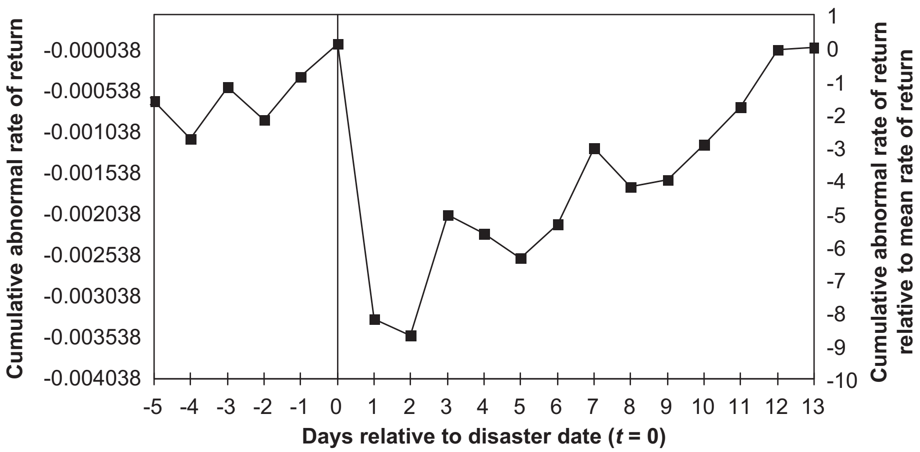

Fig. 1. Cumulative abnormal return. The figure depicts the cumulative average residuals (CAR) around the event date (t=0). The average residual on day t is calculated as the average rate of return on day t, minus the mean rate of return on all days (i.e., minus the average rate of return on all days from t=−5 to t=13) on the NYSE Composite Value-Weighted Index, which is equal to 0.0004038. For presentation purposes, the axis on the left-hand side corresponds to the abnormal rate of return, while the axis on the right-hand side corresponds to the abnormal rate of return relative to the mean rate of return (i.e., the values on the left-hand side are divided by the mean rate of return of 0.0004038). The events occurred during a 58-year period from January 1950 to December 2007 and include 170 event days of disasters of American and European airline companies.

found in small firms, in more volatile stocks, and in the stocks of firms belonging to less stable industries.

If investors' response to the event induces a flight to safety, it can take place in various ways. It may be confined to holding cash intended for stock purchases for a few more days, or it can also induce a shift of a portion of the investments from risky assets toward safer assets such as short-term U.S. Treasury securities and the safe haven of the U.S. dollar. To test whether the effect spills over to the bond and currency markets, we search for possible effects on U.S. Treasury securities with various maturities and on the U.S. dollar exchange rates. Although we find price changes in the expected direction, the changes are insignificant. One possible explanation for this is that the flight to safety is executed through a variety of assets; hence, the event effect on each asset is diluted. An alternative explanation is that investors postpone investing in risky assets and hold more cash in their normal daily trading activity.

Our findings shed new light on the role of information inflow, its psychological effect on investors' decision-making processes, and on the way this process is corrected, i.e., the way markets become more efficient over time. The event effect is found one day after an aviation disaster has occurred and it lasts for two days. On the third day a market correction process begins and this process continues for several days. We also find a clear association between the relevancy of the disasters to U.S. investors and the magnitude of the event effect. Namely, the strongest effect is found in American-oriented disasters; a relatively weaker effect is found in European-oriented disasters, and the weakest effect is found in all other disasters. This association may also be related to the extent of public attention, media coverage, and the speed of information inflow.

With regard to the speed of information inflow, we find that the event effect is seen more rapidly over the last three decades than in the previous three decades. This result is consistent with the fact that over the last three decades detailed news has become available much more quickly than in the period before that. Similarly, we find that the event effect of disasters occurring on U.S. soil has a quicker impact on the U.S. market than when the effect corresponds to faraway disasters. Finally, we show that the effect is substantially weaker in transport, industrial, and miscellaneous disasters (see Appendix A), most likely because these disasters lack some psychological resonance that we see in the case of aviation disasters.

The remainder of the paper is organized as follows. Section 2 provides the theoretical background and justification for the selected variables. Section 3 describes the data, presents the events and the corresponding hypotheses tested in this study, and explains the methodology used in the empirical analysis. Section 4 presents the empirical results and the robustness tests. Section 5 concludes the paper.

2. Theoretical background

Several studies show that mood and anxiety affect asset pricing. Saunders (1993) and Hirshleifer and Shumway (2003), for example, study the impact of sunshine on stock prices, finding that sunshine, which is associated with a person's mood, is positively correlated with daily stock returns. Kamstra, Kramer, and Levi (2003) show that the return on risky assets is significantly lower when the daylight period is shorter, due to seasonal characteristics.

The main hypothesis tested in this study asserts that a large-scale aviation disaster increases investors' fear and anxiety, which in turn negatively affects stock prices. This hypothesis relies on the observed relations between the media coverage of disasters, the fear and anxiety that aviation disasters provoke, and the reduced willingness of investors to take risks when fear and anxiety increase. Thus, we require three crucial elements for the event effect to exist: (i) widespread media coverage of the disasters; (ii) coverage that is sufficiently emotionally compelling to provoke fear and anxiety; and (iii) with increased levels of fear and anxiety, investors are more pessimistic regarding stock prices, tend to take less risks, or both. We show below that all three of these elements are present in aviation disasters.

(i) With regard to media coverage, Singer and Endreny (1987) provide the following heuristic that explains the tendency in the media to disproportionately cover aviation disasters: "a rare hazard is more newsworthy than a common one, other things being equal; a new hazard is more newsworthy than an old one; and a dramatic hazard—one that kills many people at once, suddenly or mysteriously—is more newsworthy than a long-familiar illness" (p. 13). Kitzinger and Reilly (1997) note that once a topic gains a certain level of attention in the media, it attracts more attention, and because it attracts more attention, it becomes more newsworthy. According to Vasterman, Yzermans, and Dirkzwager (2005), this self-referential system creates positive feedback loops, expanding the news wave.[2] Thus, as shown by Kepplinger, Brosius, and Staab (1991), when an unusual or shocking event occurs, the media shift into a higher gear, hunting for "newer" news on the topic.

Garner (1993) analyzes the media coverage of Delta Flight 1141 in 1998, which is a relatively small-scale disaster with 13 casualties. Garner finds 351 news stories about the disaster in six daily papers in a period of only three days. She describes this unusual coverage as "a developing news status process in which the media shifts from unscheduled status to a status where the unexpected becomes the routine" (p. 9). Barnett (1990) reports clear evidence of the disproportionate media coverage corresponding to aviation disasters. He finds that the number of *New York Times* front-page stories regarding aviation disasters is much larger than the number of stories regarding any other kind of loss of life. On a per capita death basis, the number of stories about aviation disasters is about 60 times higher than stories about AIDS, about 80

[2] In fact, this phenomenon may be long-lasting. Analyzing the 1992 Bijlmermeer disaster where Flight 199 crashed in Amsterdam killing 39 residents, Vasterman, Yzermans, and Dirkzwager (2005) find that in 1998 and 1999, i.e., six years after the event, two additional media hypes occurred with regard to the disaster investigation, producing more than 1,000 articles in Dutch dailies during the two-year period.

times higher than homicide stories, and several thousand times higher than articles relating to automobile accidents, suicide, and cancer.

Following Barnett's findings, and to obtain a sense regarding the proportion of this coverage, we search *The New York Times* on days following aviation disasters. We examine two groups: aviation disasters of American and European non-U.S. companies, and separately, aviation disasters of U.S. companies. For all 12 non-U.S. aviation disasters that occurred in the last seven years (2001–2007), we find that in each disaster, at least one full page of the main section (Section A) was dedicated to the disaster. Specifically, the aviation disasters usually received a small reference on the first page and 50–100% of the upper area of the first page of the international section, indicating it was the main international story. In addition, in some cases roughly the same coverage is observed on the second day after the disaster.

Focusing on U.S. companies, we look at 10 disasters randomly selected from the entire period (from the 1960s to the 2000s). In all cases the disasters received the first page main headline accompanied by articles that cover 20–90% of the first page plus additional coverage within the first section ranging from half a page to five pages. Moreover, in nine out of the 10 disasters, the event also received the front-page headline on the next day plus an additional one to five inside pages. Thus, in all cases the event was a main story on the first day and, in nine out of 10 disasters, it was also the most prominent story the next day. This supports the result of Fig. 1 that the event effect also continues on the second day after the event.

Finally, all the aviation disasters discussed above include dramatic pictures. Indeed, the widespread media coverage is often accused of being specifically emotionally provoking. Anzur (2000) summarizes public health officials' criticisms of media coverage of disasters, accusing the media of being "dominated by sensational images that may frighten rather than inform the public; having a potential for psychological damage to viewers when frightening images are shown repeatedly in the days and weeks of the disaster; and placing too much emphasis on crime, property damage, and loss of life, giving a relatively low priority to disaster preparedness and to public health issues in the aftermath of a disaster" (p. 196).

(ii) Does the media coverage of aviation disasters provoke excess fear and anxiety? Generally speaking, it has been shown that the media affect people's mood and emotions. Forgas and Moylan (1987) and Chou, Lee, and Ho (2007), for example, show that a change in mood induced by viewing happy, neutral, or sad movie clips, is sufficient to alter social judgments and risk-taking tendency, respectively.[3] In the context of disasters, Collimore, McCabe, Carleton, and Asmundsona (2008) find that exposure to media coverage of traumatic events provokes an anxiety level that is so strong that it may be associated with post traumatic stress disorder (PTSD) symptomatology. Similarly, Schuster, Stein, Jaycox, Collins, Marshall, and Elliott (2001), Schlenger, Caddell, Ebert, Jordan, Rourke, and Wilson (2002), and Silver, Holman, McIntosh, Poulin, and Gil-Rivas (2002) find that watching television coverage of 9/11 is positively correlated with substantial symptoms of post traumatic stress. Additional findings demonstrate that people who were exposed to television coverage during the week following the attacks—when significantly more dramatic coverage was aired[4]—were more likely to meet diagnostic criteria for PTSD (see also Ahern, Galea, Resnick, Kilpatrick, Bucuvalas, and Gold, 2002; Ahern, Galea, Resnick, and Vlahov, 2004; Bernstein, Ahern, Tracy, Boscarino, Vlahov, and Galea, 2007).[5]

Similarly, in the event of the Oklahoma City bombing, Pfefferbaum, Doughty, Reddy, Patel, Gurwitch, Nixon, and Tivis (2002) find that peritraumatic response and television exposure accounted for 25% of the total variance in a measure of post traumatic stress symptomatology among Oklahoma City's child population. Vasterman, Yzermans, and Dirkzwager (2005) show that the media coverage of the 1992 Bijlmermeer aviation disaster resulted in an increasing number of people who attribute their health problems to the disaster. Vasterman, Yzermans, and Dirkzwager (2005) claim that news coverage can fuel fear and anxiety among people involved in one way or another in the aftermath of disasters and conclude that media can indeed have an important impact on health problems and on how people view their health problems in the aftermath of disasters.[6]

Anxiety may also affect the perceived risk. Slovic (1987) finds that the most important factor affecting risk perception, generally defined as people's subjective judgments of risk, is "dread risk"—that is, risk that is perceived as uncontrollable, involuntary, and which has catastrophic potential or fatal consequences. Since aviation disasters incorporate all these characteristics and many people fly occasionally, it is not surprising that fear of flying affects a larger proportion of the population relative to any other phobia, affecting an estimated 10–25% of the population (Agras, Sylvester, and Oliveau, 1969), or more than 25 million adults in the U.S. (Deran and Whitaker, 1980). Moreover, Zuckerman (2001) and Greist and Greist (1981)

[3] Marketing science has long acknowledged the effect that feelings provoked by advertisements have on their effectiveness. Edell and Chapman (1987) find that exposure to television commercials may provoke both negative and positive emotions; these emotions are important predictors of the advertisement's effectiveness and viewers' beliefs about the brand and the brand's attributes. They also find that the extent to which the advertisement is transformational and informational affects the relative importance of emotions and judgments.

[4] For a discussion on the association between the type of media exposure and its effect on fear and anxiety, see Foa and Kozak (1986). For the specific importance of pictures over written words in affecting audience emotions, see Chemtob, Roitblat, Hamada, Muraoka, Carlson, and Bauer (1999).

[5] Bernstein, Ahern, Tracy, Boscarino, Vlahov, and Galea (2007), for example, show that among people who did not suffer from any PTSD when the 9/11 disaster occurred, 5.6% of the people who watched the 9/11 anniversary news coverage suffered from PTSD. That is, the anniversary coverage provoked PTSD even one year after the event.

[6] Other notorious examples of the effect of the media on public health are mass psychogenic illness (Clements, 2003) and suicide coverage where the media has been seen as a risk factor by itself, mainly because media coverage may create a copycat effect (for a survey, see Stack, 2003).

show that approximately 20% of those who fly at any time suffer from severe anxiety.[7] To understand the emotional factor relative to the rational one in aviation perceived risk, recall that according to the U.S. Department of Transportation, airline travel is 29 times safer than driving an automobile.[8] Thus, if fear of flying were rational, then everyone who is afraid to fly should be even more afraid—29 times more afraid, to be precise—to drive or ride in an automobile. However, this is clearly not the case, implying that people have a wrong perception of aviation disasters' risk.[9]

Holtgrave and Weber (1993) show that two psychological mechanisms determine people's risk perception: the rational mechanism and the experimental thinking that represents risk as a feeling and is characterized by a quick reaction to images and associations, and that is linked to emotions of fear, dread, and anxiety (see also Loewenstein, Weber, Hsee, and Welch, 2001). Slovic and Weber (2002) find that rare events, like aviation disasters in our case, may be weighted too heavily in decision-making processes due to the psychological experimental mechanism (see also Rottenstreich and Hsee, 2001).

(iii) Finally, can transient fear and anxiety affect people's investment decisions? Much evidence can be found in the affirmative. Mood, even if it is only a transient one, can affect people's decisions in many aspects of life. Natale and Hantas (1982) show that a temporary bad mood affects memory; Forgas (1989) shows similar results with regard to social decisions. Mitchell and Phillips (2007), who review numerous previous studies on the cognitive and neural effects of mood on executive functions (control processes, updating, planning, working memory, fluency and creativity, inhibition, and switching), conclude that even mild fluctuations in mood can have a significant influence on neural activation and cognition.

Specifically to risk attitude, numerous psychological studies find that greater anxiety, fear, or depression is associated with a reduced willingness to take risks (see, e.g., Etzioni, 1988; Hanock, 2002; Mehra and Sah, 2002; and many others). Mittal and Ross (1998) show that transient mood affects systematic differences in issue interpretation and risk-taking in a strategic decision-making context. Similarly, Yuen and Lee (2003) find varying risk-taking tendencies in different mood states; people in an induced depressed mood would have a lower willingness to take risks than people in neutral and positive moods. Finally, Lerner and Keltner (2001) and Lerner, Small, and Loewenstein (2004) find that feelings of fear and anger have a significant impact specifically on economic decision-making.

To sum up, the wide media coverage of aviation disasters increases investors' anxiety, which may in turn affect stock prices. Perhaps the best description of this phenomenon is given by Garner (1996): "Airplane crashes shake the peaceful foundation of our everyday life… it reminds us that the system can fail and people die" (pp. 167–168). In the next section we test whether aviation disasters have a significant effect on stock prices and analyze the magnitude of the effect.

3. Data, methodology, and hypotheses

The data cover the entire history of large-scale aviation disasters—a 58-year period with 14,678 trading days, from January 1950 to December 2007. To test the impact of the disasters on stock returns, we employ the rates of return on the NYSE Composite Index taken from the Center for Research in Security Prices (CRSP). We select the Value-Weighted Index as the main index, and we repeat the main regressions with the Equally Weighted Index and the Dow Jones Transportation Index to test for robustness. To further analyze a possible differential effect corresponding to firm size, stock volatility, and firm industry, we use Fama and French's (1992) 10 value-weighted portfolios constructed by size and also the 10 value-weighted portfolios constructed by industry and by volatility, corresponding with the CRSP definitions.

To test the impact of aviation disasters on market volatility, we employ all available historical data corresponding to the Chicago Board of Options Exchange's VXO and VIX indexes. The available daily data of the VXO and VIX are from 1986 and from 1990, respectively.[10] To test for a possible event effect on U.S. Treasury securities we employ the Federal Reserve Board's Selected Interest Rates series,[11] which cover daily market yields on U.S. Treasury securities for various maturities. Finally, to test for a possible currency effect, we employ the Federal Reserve Board's Foreign Exchange Rates Major Currencies Index. This index is a weighted average of the foreign exchange values of the U.S. dollar against the Broad Index currencies, which include the currencies of a large group of major U.S. trading partners.

The large-scale aviation disasters incorporate 288 aviation disasters with at least 75 casualties worldwide during the studied period. The primary source of aviation disasters data is The Aviation Safety Network of the Flight Safety Foundation database.[12] We use two other sources to validate the exact time and location of each accident.[13] The casualties' cut-off number of 75 has been arbitrarily

[7] As Rothbaum, Hodges, Smith, Lee and Price (2000) note, even people who try to avoid flying cannot escape the issue as "avoidance of flying causes sufferers serious vocational and social consequences" (p. 1020).

[8] See http://www.guidetopsychology.com/fearfly.htm.

[9] Gigerenzer (2004) provides an illuminating example of the wrong perception of risk with regard to the 9/11 disaster. He shows that the number of Americans who lost their lives on the road in an attempt to avoid the risk of flying during the first three months after the 9/11 disaster was higher than the total number of passengers killed on the four fatal flights.

[10] See the Chicago Board of Options Exchange (CBOE) Web site at www.cboe.com.

[11] See the Federal Reserve Board Web site at http://www.federalreserve.gov/.

[12] See http://aviation-safety.net.

[13] This includes EM-DAT: The OFDA/CRED International Disaster Database—ww.emdat.be, Université Catholique de Louvain, Brussels (Belgium) and the SkyNet Server Airline Crash Research Site (www.airdisasters.co.uk). In a few disasters where data are partially missing, we also looked for relevant reports in news and newspaper archives such as the British Broadcasting Corporation (BBC) archive (www.bbc.co.uk) and also in the formal crash investigation reports.

selected to include events whose effect on public sentiment is large enough to be noticed. However, separate robustness tests confirm that the effect is similar for a wide range of other cut-off numbers.

The disasters occurred at any time during the day, all around the world. Therefore, to achieve a standardized and consistent approach, the date and time of each disaster is calculated relative to the date and time in New York City Eastern Daylight Time (EDT), corresponding to the NYSE trading hours. Thus, for example, as the Concorde disaster occurred on July 25, 2000 at 5:00 p.m. Paris time, the date and time of the event are considered to be July 25 at 11:00 a.m. EDT. Similarly, as the Guam Korean Air Boeing 747 disaster occurred on August 6, 1997 at 2:00 a.m. Guam time, which is August 5, 11:00 a.m. EDT, then the date of the event is considered to be August 5. This definition not only uniformly organizes the data,[14] but more importantly is consistent with the relevant time of the NYSE trading hours. Nevertheless, to verify that this definition does not account for the results by mere chance, we conduct robustness tests with several alternative event time definitions.

The actual effects in the case of a disaster may start only when the unexpected news about the event first comes to the public's attention. This may take several hours after the accident occurrence since in many cases, even the authorities are in the dark until after the first few hours. Moreover, since in this study we are more interested in the detailed information, rather than just the news on the event, our hypothesis asserts that the effect starts on the first day after the disaster, hereafter called the *event day*. This definition follows Borenstein and Zimmerman (1988), who find a negative effect on the stock price of the airline company on the day following an aviation disaster. Chance and Ferris (1987) and Bosch, Eckard, and Singal (1998), who focus on U.S. disasters, find a negative effect on the stock price of the airline company on the day following the disaster and also on the same day, provided that the U.S. market was still open when the disaster occurred.

Corresponding with the above-mentioned studies, we also test the hypothesis that the effect begins on the day the disaster occurred, as long as the U.S. market is still open. We separately test this hypothesis in two situations in which the information flows relatively faster: when disasters occur on U.S. soil and only when disasters occurred during the last three decades. Finally, from Fig. 1, we observe that the reversal effect starts two days after the event day. This is probably because the event effect continues, albeit in a weaker form, on the second day. This result conforms to our findings that the event usually receives the main headlines on the next two days after the event has occurred. Therefore, to test the significance of the reversal effect, we look at the first three trading days after each disaster.[15]

To test the null hypothesis and to estimate the impact that various events have on stock returns, we adopt a similar methodology used in previous event studies (see, e.g., Kamstra, Kramer, and Levi, 2003; Brown and Warner, 1980, 1985). Thus, we run the following regression:

$$R_t = \gamma_0 + \sum_{i=1}^{5} \gamma_{1i} R_{t-i} + \sum_{i=1}^{4} \gamma_{2i} D_{it} + \gamma_3 H_t + \gamma_4 T_t + \sum_{i=1}^{3} \gamma_{5i} E_{it} + \varepsilon_t, \tag{1}$$

where R_t is the daily rate of return on the relevant index, γ_0 is the regression intercept, R_{t-i} is the ith previous day rate of return. D_{it}, i=1…4, are dummy variables for the day of the week: Monday, Tuesday, Wednesday, and Thursday, respectively, H_t is a dummy variable for days after non-weekend holidays, T_t is a dummy variable for the first five days of the taxation year, and $E_i\,(i = 1, 2, 3)$ stands for possible effect and reversal effect variables. Although we run similar regressions without the control variables as part of the robustness checks, dealing with daily returns on consecutive days we must control for known anomalies to ensure they do not contaminate the results.

First, we account for any possible serial correlation, as previous studies find a weak tendency for movements in aggregate stock returns to persist. Schwert (1990a), for example, finds a positive autocorrelation at lag 1 for all U.S. indexes including historical pre-CRSP stock indexes. In addition, Schwert (1990b) also finds a significant negative autocorrelation at lag 2 and significant positive autocorrelation at lag 3, 4, 5, 7, and 8 in the Standard & Poor's (S&P) Composite Index. Possible explanations for this phenomenon include non-synchronous trading, market-maker inventory control, transaction costs, and time-varying expected returns. The most accepted explanation is non-synchronous trading, first pointed out by Fisher (1966). Non-synchronous trading takes place when transactions, in particular securities, occur infrequently; hence, these stocks exhibit a delayed price adjustment. In such a case, the end-of-the-day transaction price quotations of the frequently traded securities reflect all available news, whereas the price quotations of the less frequently traded stocks might be outdated and will adjust to the most recent news on the next coming transaction, which does not occur until the following day. Therefore, sampling closing prices may not reflect all available information for the less frequently traded securities (for more on the subject see Scholes and Williams, 1977; Kadlec and Patterson, 1999).[16]

[14] Note that the same database may have several definitions for the event time; sometimes it corresponds to the time at the disaster location, sometimes it corresponds to the time at the departure field, and sometimes to Greenwich Mean Time (GMT). Thus, to be consistent in each case, we translate the time to EDT.

[15] We also test longer periods after the event, since according to Fig. 1, the reversal effect continues several days after the event. However, as the reversal effect is found to be significant only on the third day after the event, for the sake of brevity, we do not report these tests here.

[16] Note, however, that Atchison, Butler, and Simond (1987), Schwert (1990a), Lo and MacKinlay (1990), Kadlec and Patterson (1999), and others show that non-synchronous trading cannot explain all of the observed autocorrelation.

To account for a possible serial correlation, we add to the main regression the previous days' rates of return variables (R_{t-i}). Specifically, we look at as many past returns as is necessary to guarantee that all significant serial correlations have been accounted for. In the most relevant case of the NYSE Composite Value-Weighted Index, only the first two previous days were found to be significant. However, since in some cases we find five previous days to be significant (see, e.g., the case of Equally Weighted Index in Table 10), to be on the safe side we conduct all tests with five previous days' rates of return variables. For the larger autocorrelation corresponding to equally weighted relative to value-weighted portfolios, see Atchison, Butler, and Simond (1987). Nevertheless, in unreported tests we also confirm that the results are robust to either a smaller or a larger number of previous days' rates of return variables.

Second, the disasters' occurrences may not be evenly spread over the week either by coincidence or due to a unique flight schedule over the week. As the so-called "weekend effect" or "Monday effect" is known to exist throughout the entire period, as found by French (1980), Schwert (1990a), and others, this may bias the regression results. Therefore, we add dummy variables for the day of the week (D_{it}, i=1…4) to capture this effect. For recent evidence of this effect, see Cho, Linton, and Whang (2007). Moreover, the same argument holds true with regard to days after non-weekend holidays and to the first days of the year, which are known to have both unusual flight schedules and market returns. For returns on non-weekend holidays, see Kim and Park (1994); for returns on the first five days of the taxation year, see Keim (1983) and Dyl and Maberly (1992). Thus, we also add a dummy variable for days after non-weekend holidays (H_t) and a dummy variable for the first five days of the taxation year (T_t). Nevertheless, in unreported tests we confirm that the aviation disaster event effect is highly robust to the inclusion of each variable separately.

Below, we summarize the hypotheses tested in this study.

1. We first test the joint hypothesis of both the event effect and the reversal effect asserting that there is a below average rate of return (−) on the event days and an above average rate of return (+) on the reversal days immediately afterwards. The joint hypothesis proposes that the frequency of the joint result (−,+) is greater than the frequency corresponding to the null hypothesis.
2. We test the hypotheses that on event days there is an increase in options implied volatility, a decrease in yield on short-term U.S. Treasury securities, and a decrease in the U.S. dollar exchange rate against other currencies. Furthermore, we test whether on event days and a few days afterward, there is also an increase in actual volatility.
   Employing regression (1), we next test the following hypotheses:
3. The event day coefficient, $\gamma_{5,1}$, is negative and significantly different from zero.
4. The reversal day coefficient, $\gamma_{5,3}$, is positive and significantly different from zero.
5. The more difficult the effect is to arbitrage (i.e., where the stocks belong to relatively small firms, the stocks are more volatile, or the firms belong to less stable industries), the larger (in absolute terms) the event day coefficient, $\gamma_{5,1}$, will be.
   Because we focus on the U.S. market in this study, we should expect that the more relevant the disaster is to the U.S. investors, the stronger the effect will be. This hypothesis may also be driven by the link between the disaster's national orientation and the level of media exposure to U.S. investors. Thus, we also examine the following hypotheses:
6. The event day coefficient corresponding to American aviation disasters, $\gamma_{5,1}$, is larger (in absolute terms) than the coefficient corresponding to other disasters.
7. The time elapsed between the occurrence of a disaster and the event effect is shorter when the disaster occurs on U.S. soil.
8. The time period elapsed between the occurrence of a disaster and the event effect has been shorter over the last three decades than in the three decades preceding that.

4. Results

In this section, we present the main results, robustness tests, and sensitivity analyses. However, to evaluate the magnitude of the event effect on the stock market, we first analyze the average direct costs involved in aviation disasters compared to the average recorded market loss.

4.1. *Aviation disaster costs: actual effect versus sentiment effect*

Aviation disasters engender a certain amount of economic loss. Thus, the most natural question is whether the effect found in the current study is simply a result of the actual economic loss induced by the disaster. In the case of aviation disasters, there are direct costs to: (i) the insurer of the airline company; (ii) the airline company; and (iii) the aircraft manufacturer. Despite the difficulty in measuring the direct costs of aviation disaster to the economy, below we discuss these costs with one purpose in mind—to be able to provide a rough upper bound on the total actual economic costs involved.

(i) With regard to the insurance company, in the short run there is an immediate loss related to the expected direct payout claims. Note, however, that in the long run, aviation disasters create demand for the insurance company's services. Therefore, the immediate loss overestimates the long-run loss. Below we conservatively estimate these payout claims and show that they are very small relative to the loss in the stock market, keeping in mind that the immediate payout claims overestimate the true long-run loss.

There is a direct cost of the loss of the aircraft itself, which would range from \$125 to \$300 million, depending on the aircraft type and size (Boeing's 2007 prices for new, large aircrafts). In addition, there is the cost induced from the life lost, which is strictly limited, due to the Warsaw Convention of 1929 and its amendments. Nevertheless, the actual costs may exceed these limits, especially in the case of U.S. non-international flights. Rose (1992) provides a rough estimate of about $500,000 per death (about $800,000 in today's dollar). Thus, the total immediate cost to the insurance industry of a very large aviation disaster with 300 casualties can be roughly estimated at no more than $300 million (for the aircraft) + $240 million (for the deaths)=$540 million.

(ii) With regard to the manufacturer, Rose (1992) shows that in the worst nightmare of an aircraft manufacturer—the case of the 1979 McDonnell Douglas DC-10, where an accident grounded the aircraft indefinitely—the immediate market value loss of the manufacturing company was roughly $100 million, in 1990 dollars. Moreover, in early accidents involving this aircraft type, no negative effect was recorded to the manufacturing company at all. Chalk (1987) finds an insignificant average market value loss of $22 million to the manufacturer after an aviation disaster, which is much smaller when the calculations do not include the above-mentioned 1979 DC-10 disaster. Thus, the economic loss to the manufacturer can be roughly estimated at a maximum of about $200 million in today's dollar, which is a little more than the $100 million in 1990 dollars corresponding to the 1979 DC-10 disaster.

(iii) Finally, with regard to the airline company, as the direct costs fall mainly on the insurer, Rose (1992) concludes that apart from a very small and insignificant impact of the above DC-10 disaster,[17] "evidence of market responses to other accidents is weak to non-existent" (p. 90). Nevertheless, Rose (1992) mentions two potential sources of costs to the airline company: a direct cost of increased insurance premiums and an indirect cost due to the reduction in consumer demand and reputation effects. Although Golbe (1986) does not find any association between financial variables, such as profitability, and the airline's accident rate, more recent studies find some evidence of these costs. Mitchell and Maloney (1989) estimate the additional insurance costs for the next five years after a disaster at about $10 million in 1990 dollars.

With regard to the demand, Borenstein and Zimmerman (1988) find a short-term demand reduction only for the specific company involved in the accident, and estimate it at about $100 million for a large-scale disaster with many casualties. On the other hand, in the case of 100 casualties and above, they also find that this reduction was accompanied by a 1% increase in demand for other airline companies. Hence, the total damage to the industry as a whole is much smaller.

Finally, several studies directly estimate the all-inclusive damage to the airline company by looking at the change in the market value of its stock. Borenstein and Zimmerman (1988) find an average decline of 1.35% in the specific airline company's share price on the day following the disaster, corresponding to a $22–$31 million market value loss in 1990 dollars. Bosch, Eckard, and Singal (1998) find an average decline of 1.17% and 0.93% on the day of the event and on the following day, respectively, which is equivalent to a total value loss of <$50 million in today's dollar in the case of a large company. Similar to Borenstein and Zimmerman (1988), they also find some evidence that consumers switch from the involved airline company to the competitors; hence, the damage to the airline company is offset to some extent by the gains of the competitors. Thus, we can estimate the average damage to the airline company at about $50 million, and no more than $200 million in today's dollar in the case of a very large disaster, equivalent to the $100+$10 million in 1988 dollars estimated by Borenstein and Zimmerman (1988).

To sum up, a total of the above maximum costs—$540 million for the insurance companies, $200 million for the aircraft manufacturer, and $200 million for the airline company—implies that the upper bound on the loss to the economy from a very large disaster with many casualties is no more than $1 billion. However, the observed market effect is about 60 times larger than this value. To show this, we multiplied the difference between the event day's mean return and the all-days' mean return (both are presented in Table 1) by the value of the NYSE Composite Index (over $18 trillion in 2006), as this is the average observed market value loss. Thus, we have $(-0.00155 - 0.000479) \times \$18,000\,\text{billion} \cong -\$36.5\,\text{billion}$.[18] Similarly, in the case of American and European disasters, which as we show below is the more relevant case in our study, the market loss is $(-0.00295 - 0.000479) \times \$18,000\,\text{billion} \cong -\$61.7\,\text{billion}$. These numbers are much larger than the direct economic damage conservatively estimated above. Moreover, as we also find a reversal effect, we can safely conclude that the initial market reaction is a transitory one, disappearing after a few days (see Fig. 1).[19] To support this claim, let us next examine the event effect and the reversal effect in greater detail.

4.2. Descriptive statistics and tests for the joint hypothesis

We first examine the data and test for the joint Hypothesis 1 discussed in the previous section. Table 1 presents the descriptive statistics of the event days and some raw results.

For example, the average rate of return on the first day after American and European disasters is −0.00295 compared to an all-days mean rate of return of

[17] In the special case in which the McDonnell Douglas DC-10 disaster resulted in the indefinite grounding of all such aircrafts, there was also additional damage to other companies, especially to two other airline companies with fleets composed mainly of this aircraft. However, even in this dramatic case, the decrease in the share price of these two companies was only about 2%. Moreover, as a possible, yet very rare, decision on indefinitely grounding an aircraft takes time, the effect of such an event may only take place long after the disaster and therefore, it cannot explain even a portion of the immediate effect, let alone the reversal effect.

[18] Actually, the loss is much larger, as other markets (e.g., the Nasdaq) are not included in the loss calculations.

[19] One may also speculate that an aviation disaster might be linked to a terror attack in which additional costs are involved. However, in Section 4.4.2 below we rule out this possibility.

Table 1
Descriptive statistics.
The table reports the data used in this study. The 288 aviation disasters occurred during a period from January 1950 to December 2007. The third column reports the number of observations, the fourth column reports the average rate of return on the relevant days, and the last column reports the *t*-value for a two-sample test. One and two asterisks indicate a significance level of 5% and 1%, respectively. Note that the number of event days and the number of disasters are not the same, as there are four days with two unrelated disasters. Specifically to American and European disasters, there is one day with both European and American disasters, and one day with two unrelated American disasters (we also have one disaster corresponding to both European and American companies).

Data	Day post the event	Number of days	Average daily rate of return, R_t	t-Test for two-sample
NYSE Composite Index (Value Weighted)		14,478	0.000479	
Event days—all disasters (288 disasters)	1st	284	−0.00155	−3.41**
	2nd	284	0.00032	−0.33
	3rd	284	0.00111	1.39
Event days—disaster corresponding to American and European companies only (172 disasters)	1st	170	−0.00295	−4.40**
	2nd	170	0.00020	−0.48
	3rd	170	0.00188	2.26*

0.000479. The last column of the table reports the *t*-values of a two-sample mean test. The null hypothesis is that the mean rate of return on the event days is equal to the mean rate of return on all other days. Corresponding with the event effect hypothesis, the mean rate of return on the first day after aviation disasters is negative, relatively large (in absolute terms), and highly significant (*t*-value of −3.41). The mean rate of return on the third day after aviation disasters is relatively large, positive, and in the case of American and European disasters, it is also significant. Finally, the mean rate of return on the second day is just below the all-days mean rate of return and is insignificant.

To quickly check that these significant results are not driven by only a few extreme observations, Fig. 2 compares the frequency distributions (Fig. 2a) and the cumulative distributions (Fig. 2b) of daily rates of return on the first and third days after aviation disasters.

The most striking result emerging from Fig. 2a is that the frequency distribution of daily rates of return on the first days is almost entirely located to the left of the frequency distribution of daily rates of return on the third days. This result is even more apparent in Fig. 2b, where we compare the two cumulative distributions. Indeed, as is presented in Table 1, the rates of return on the first days are significantly lower than the rates of return on the third days, and this is a general phenomenon, rather than an artifact of a few outlier observations.

To analyze the significance of the event effect and the reversal effect, we first conduct a matched-pair *t*-test on the difference between the mean rate of return on event days, and the mean rate of return on reversal days for disasters involving American and European companies, which reveals a large *t*-value of −4.56. Thus, the null hypothesis asserting that the mean rate of return on the first days (event days) does not differ from the mean rate of return on the third days (reversal days) is rejected at a significance level of $P<4.9\times10^{-6}$.[20] We next test the joint hypothesis asserting that there is a below-average rate of return (−) on the event days and an above-average rate of return (+) on the reversal days. Under the null hypothesis, the occurrence of the joint results $(-,+),(+,-),(-,-)$, and $(+,+)$ is equally likely (i.e., each result should occur with an equal frequency of 25%). Employing the binomial test, we obtain the expected result of $(-,+)$ in 57 out of 170 observations; hence, the null hypothesis is rejected at a significance level of $P<0.007852$.[21]

If returns are positively skewed, the frequency of (+) and (−) are not identical; hence, the frequency of the result of $(-,+)$ is not necessarily 25%. However, even in this case the frequency of $(-,+)$ should be identical to the frequency of $(+,-)$. Thus, we test the null hypothesis asserting that the frequencies of $(-,+)$ and $(+,-)$ are identical. Obtaining the result of $(-,+)$ in 57 out of 83 observations in which rates of return on the event day and the reversal day are either $(-,+)$ or $(+,-)$, the null hypothesis is rejected at a significance level of $P<0.000267$.[22]

So far, we have shown that the actual direct economic loss induced by aviation disasters cannot explain either the observed decline in average stock prices or the observed reversal in stock prices. This evidence is consistent with psychological studies revealing that fear and anxiety lead people to be more pessimistic or more risk-averse at these times, which in turn affects stock prices. Table 1 and Figs. 1 and 2 provide a rough initial estimate of this effect, mainly for American and European disasters. We now turn to the more rigorous statistical analyses.

[20] A non-parametric Wilcoxon test reveals similar result where the null hypothesis is rejected at a significant level of $P<0.0003195$.

[21] The probability of obtaining $(-,+)$ 57 or more times under the null hypothesis is given by

$$P=1-\sum_{X=57}^{170}\binom{170}{X}(0.25)^X(0.75)^{170-X}\cong0.007852$$

.

[22] We repeat the joint hypothesis test in two alternate forms: once when negative rates of return correspond to (−) and positive rates of return correspond to (+), and once when rates of return below the median correspond to (−) and rates of return above the median correspond to (+). The null hypothesis in these tests is rejected at significance levels of $P<0.000267$ and $P<0.001097$, respectively.

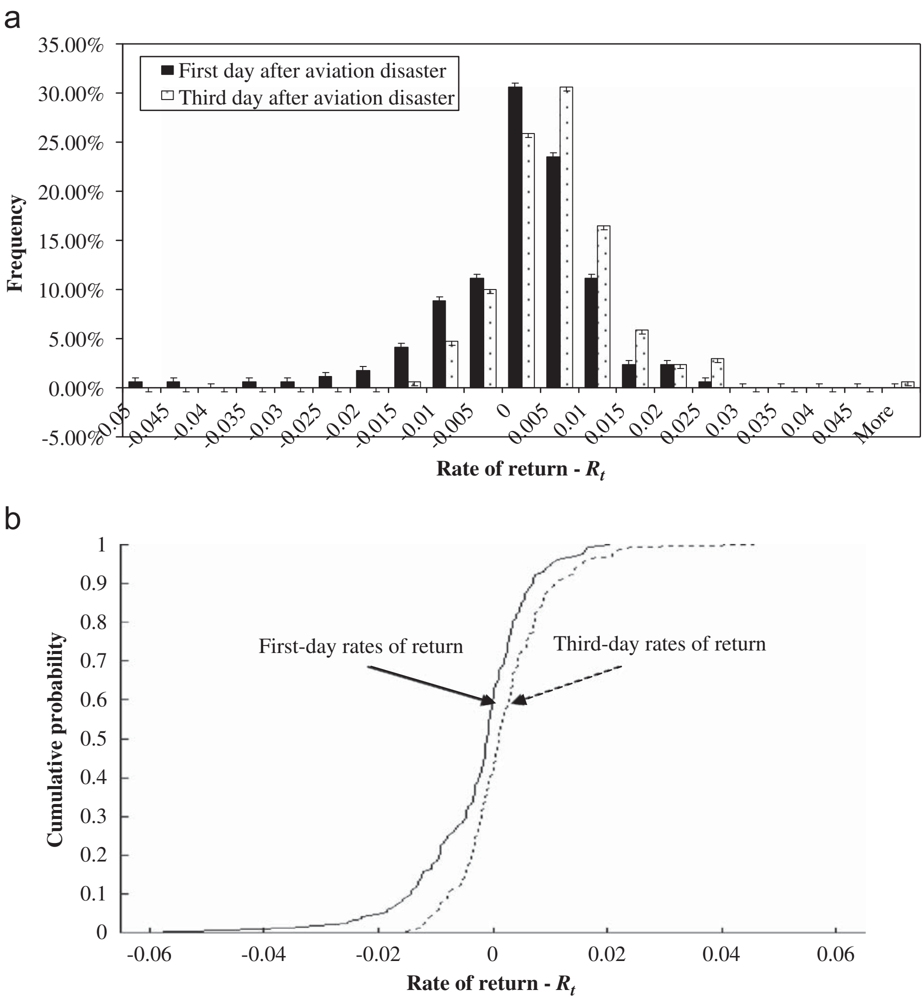

Fig. 2. Frequency distribution and cumulative distribution of daily rates of return: First day versus third day. The figure depicts the frequency of rates of return (Fig. 2a) and the cumulative distribution of rates of return (Fig. 2b) on the first day after aviation disasters versus those on the third day after aviation disasters on the NYSE Composite Value-Weighted Index. The events occurred during a 58-year period from January 1950 to December 2007 and include 170 first days and 170 third days corresponding to aviation disasters of American and European airline companies.

4.3. Regression results: disasters and classification by the nationality of the airline company

In the previous section, we hypothesized that American and European oriented disasters may have a stronger effect on U.S. investors than other aviation disasters. This may be due to the fact that U.S. investors either feel that these disasters are more relevant to them or, more likely, that they are more exposed to the wider media coverage that accompanies American and European disasters. To further test this hypothesis, we divide all aviation disasters into three groups: American, European (subdivided into Western European and Eastern European disasters),[23] and the rest of the world. We classified the disasters according to the nationality of the airline company. This approach guarantees an objective division.[24] Table 2 summarizes the results of the regression model given in Eq. (1) for the above groups.

Table 2 reveals that all-disasters first day coefficient is negative and large in absolute terms (−0.0018), highly significant (t-value of −3.65), and, as expected, it is largest for American disasters (−0.0037 and −4.22, respectively). The coefficient is also relatively large and significant for European disasters (−0.0026 and −2.99, respectively). However, it is close to zero and insignificant for disasters corresponding to the rest-of-the-world group (0.0003 and 0.44, respectively). Note that the large t-values corresponding to American and European disasters are obtained despite the sharp decline in the number of observations corresponding to these groups. Moreover, consistent with the national orientation hypothesis, the first-day coefficient is larger (in absolute terms) for

[23] This subdivision is interesting as we cover the "Cold War" period in this study.

[24] In the few disasters in which two aircrafts from different nations are involved, we considered the disaster a two-nationality disaster.

Table 2
Aviation disasters by national orientation.
The table reports the results of the following regression:

$$R_t = \gamma_0 + \sum_{i=1}^{5} \gamma_{1i} R_{t-i} + \sum_{i=1}^{4} \gamma_{2i} D_{it} + \gamma_3 H_t + \gamma_4 T_t + \sum_{i=1}^{3} \gamma_{5i} E_{it} + \varepsilon_t,$$

where R_t is the daily rate of return on the NYSE Composite Index, γ_0 is the regression intercept, R_{t-i} is the daily rate of return on the $t-i$ day, D_{it}, i=1…4, are dummy variables for the day of the week, H_t is a dummy variable for days after a non-weekend holiday, T_t is a dummy variable for the first five days of the taxation year, and E_i, i=1,2,3 stands for the event effect days. The events include 284 event days (288 aviation disasters) over a period of 14,678 trading days, from January 1950 to December 2007. The number of days and the number of disasters are not the same, as there are two days each with two rest-of-the-world disasters, one day with both Western European and American disasters, and one day with two unrelated American disasters. One disaster involves both Western European and American companies. The first line of each event reports the regression coefficients, while the second line reports the corresponding t-values (in brackets). One and two asterisks indicate a significance level of 5% and 1%, respectively (a one-tail test in the case of the first and third days).

	Aviation disasters	γ_0	R_{t-1}	R_{t-2}	R_{t-3}	R_{t-4}	R_{t-5}	Non-weekend holidays	Mon.	Tues.	Wed.	Thurs.	First 5 days of the tax year	Post aviation disaster			R^2
														1st day	2nd day	3rd day	F
1.	All aviation disasters	0.0009	0.1269	−0.0402	0.0048	−0.0026	0.0004	0.0016	−0.0016	−0.0003	0.0001	−0.0005	0.0008	−0.0018	0.0000	0.0005	0.023
	(288 disasters, 284 days)	(5.90**)	(15.38**)	(−4.83**)	(0.57)	(−0.31)	(0.05)	(2.69**)	(−7.31**)	(−1.63)	(0.35)	(−2.38*)	(1.25)	(−3.65**)	(0.04)	(0.97)	25.199
2.	American companies	0.0009	0.1272	−0.0406	0.0048	−0.0027	0.0008	0.0016	−0.0016	−0.0003	0.0001	−0.0005	0.0008	−0.0037	0.0000	0.0006	0.024
	(88 disasters, 87 days)	(5.88**)	(15.41**)	(−4.88**)	(0.58)	(−0.33)	(0.10)	(2.66**)	(−7.40**)	(−1.64)	(0.37)	(−2.36*)	(1.19)	(−4.22**)	(0.02)	(0.69)	25.503
3.	European companies	0.0009	0.1267	−0.0399	0.0047	−0.0029	0.0007	0.0016	−0.0016	−0.0004	0.0001	−0.0005	0.0008	−0.0026	0.0001	0.0019	0.023
	(85 disasters, 85 days)	(5.81**)	(15.35**)	(−4.80**)	(0.56)	(−0.35)	(0.08)	(2.67**)	(−7.43**)	(−1.69)	(0.35)	(−2.35*)	(1.21)	(−2.99**)	(0.13)	(2.14*)	25.150
3a	Western European companies (37 disasters, 37 days)	0.0009	0.1268	−0.0401	0.0046	−0.0030	0.0007	0.0016	−0.0016	−0.0004	0.0001	−0.0005	0.0008	−0.0035	0.0005	0.0019	0.023
		(5.80**)	(15.36**)	(−4.82**)	(0.55)	(−0.36)	(0.08)	(2.69**)	(−7.46**)	(−1.67)	(0.40)	(−2.36*)	(1.18)	(−2.65**)	(0.40)	(1.42)	24.840
3b	Eastern European companies	0.0009	0.1268	−0.0404	0.0050	−0.0028	0.0007	0.0016	−0.0016	−0.0004	0.0001	−0.0005	0.0008	−0.0019	−0.0002	0.0018	0.023
	(48 disasters, 48 days)	(5.83**)	(15.36**)	(−4.86**)	(0.60)	(−0.34)	(0.09)	(2.64**)	(−7.53**)	(−1.71)	(0.35)	(−2.38*)	(1.21)	(−1.62)	(−0.17)	(1.56)	24.540
4.	Rest-of-the-world's companies (116 disasters, 114 days)	0.0009	0.1269	−0.0407	0.0050	−0.0029	0.0008	0.0016	−0.0016	−0.0004	0.0001	−0.0005	0.0008	0.0003	−0.0001	−0.0007	0.023
		(5.84**)	(15.37**)	(−4.89**)	(0.60)	(−0.35)	(0.10)	(2.65**)	(−7.58**)	(−1.70)	(0.42)	(−2.37*)	(1.18)	(0.44)	(−0.07)	(−0.94)	24.245
5. (2.+3.)	Base Model (BM) – American and European companies (172 disasters, 170 days)	0.0009	0.1270	−0.0397	0.0044	−0.0026	0.0007	0.0016	−0.0016	−0.0003	0.0001	−0.0005	0.0008	−0.0032	0.0001	0.0012	0.024
		(5.87**)	(15.39**)	(−4.78**)	(0.53)	(−0.31)	(0.08)	(2.68**)	(−7.28**)	(−1.64)	(0.33)	(−2.33*)	(1.20)	(−5.03**)	(0.11)	(1.95*)	26.283
1a	All aviation disasters only if classified as accidents (265 disasters, 261 days)	0.0009	0.1269	−0.0403	0.0049	−0.0025	0.0004	0.0016	−0.0016	−0.0003	0.0001	−0.0005	0.0008	−0.0018	0.0000	0.0005	0.023
		(5.89**)	(15.38**)	(−4.84**)	(0.58)	(−0.31)	(0.05)	(2.68**)	(−7.33**)	(−1.64)	(0.35)	(−2.38*)	(1.24)	(−3.48**)	(0.09)	(0.91)	25.105
5a	BM aviation disasters only if classified as accidents (163 disasters, 161 days)	0.0009	0.1270	−0.0399	0.0045	−0.0025	0.0006	0.0016	−0.0016	−0.0003	0.0001	−0.0005	0.0008	−0.0029	0.0001	0.0014	0.024
		(5.85**)	(15.39**)	(−4.80**)	(0.54)	(−0.30)	(0.07)	(2.68**)	(−7.32**)	(−1.64)	(0.33)	(−2.34*)	(1.20)	(−4.52**)	(0.12)	(2.13*)	25.992

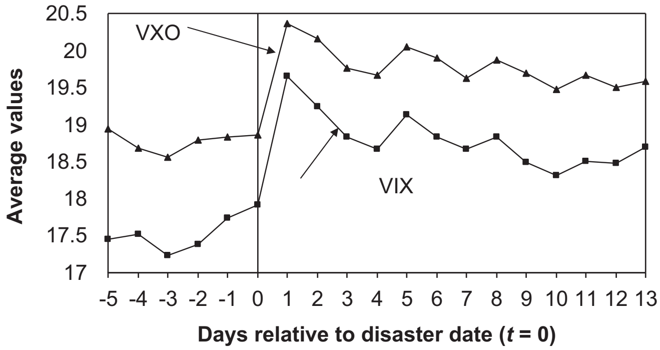

Fig. 3. Fear Index around the disaster date. The figure depicts the average value of the VIX and VXO indexes around the event date (t=0). The VIX index covers the period of 1990–2007, which includes 39 American and European aviation disasters. The VXO index covers the period of 1986–2007, which includes 57 American and European aviation disasters.

Western European disasters (−0.0035 and −2.65, respectively) than for Eastern European disasters (−0.0019 and −1.62, respectively). All coefficients corresponding to the second day after the disasters are close to zero and insignificant.

As can be seen from Table 2, less significant results are obtained for the third-day coefficients. While the coefficients corresponding to all disasters and American disasters are small (0.0005 and 0.006, respectively) and insignificant, the coefficient corresponding to European disasters is relatively large and significant (0.0019 with a t-value of 2.14). Similar to the first-day coefficient, the third-day coefficient is small, negative (−0.0007), and insignificant for disasters corresponding to the rest-of-the-world group. However, it is important to note that our results do not rule out the existence of an effect for disasters in the rest-of-the-world group, but rather suggest that we could not observe it. This may be, for example, due to a greater variation in the period of time elapsing between these disasters and their proliferation within the U.S. media. Thus, a more subtle analysis is required in this case.

The results corresponding to the control variables (i.e., serial correlation, the weekend effect, etc.) are similar to previous empirical studies, and therefore, we only briefly report them in the rest of the study. Thus, for example, the serial correlation coefficient at lag 1, attributed to non-synchronous trading, is positive and highly significant and the coefficient at lag 2 is negative and also significant. Similarly, the Monday coefficient is negative and highly significant (for similar results see Schwert, 1990a, 1990b).

To sum up, Table 2 reveals that the event effect is found only in disasters of American and European airline companies. The first-day effect is negative and highly significant, whereas the third-day reversal effect is positive but in most cases insignificant. The reason for obtaining a relatively weak reversal effect may be due to a reversal effect that actually lasts longer than one day. This claim is supported by the results of Fig. 1, where the reversal effect seems to persist for several days after the event. Nevertheless, when we refine the analysis (see Table 7) the reversal effect becomes significant in most important cases. As we observe a strong and significant event effect only with American and European disasters, for the remainder of the paper we will focus on American and European disasters, and refer to the regression that corresponds to this case as the "Base Model" (BM). Test 5 in Table 2 reports the regression results for the BM. The first-day coefficient is very large in absolute terms (−0.0032) and highly significant (a t-value of −5.03), and the third-day coefficient is also large and significant (0.0012 with a t-value of 1.95). We next refine the analysis of the BM and analyze it in greater detail.

4.4. Other effects of aviation disasters

We have seen in the previous subsection that stock prices, on average, decline following aviation disasters. In this subsection we analyze other effects that may be related to aviation disasters and to the observed event effect on rates of return.

4.4.1. Event effect on implied volatility: VXO and VIX

Following Baker and Wurgler (2007), we use implied volatility as a proxy for investors' sentiment. Therefore, we next test whether aviation disasters affect the implied volatility. To test for a possible effect we employ two alternate measures of the Fear Index (see Whaley, 2000): the VIX and the VXO. These serve as estimators of the one-month-ahead implied volatility.[25] Fig. 3 presents the average increase in volatility on the event day.

While Fig. 3 reveals a strong event effect, with regard to the reversal effect we do not observe a return to the prevailing average value before the event. This result conforms to previous findings showing that market

[25] The Fear Index was launched in 1993 by the Chicago Board of Options Exchange (CBOE). The main difference between the VIX and VXO indexes is that the VXO relies on average implied volatilities of options written on the S&P100 Index, as measured by the Black-Scholes (1973) option pricing model, whereas the VIX relies on the average price of the options themselves written on the broader S&P500 Index. In addition, data are available for the VXO beginning in 1986 (which includes the stock market crash in 1987), while the VIX coverage starts in 1990. Carr and Wu (2006) analyze the differences between these two indexes, and show that the VIX definition allows for a more accurate view of investors' expectations regarding future market volatility. As the data of the VXO are available for a longer period, we report the main findings for both indexes.

volatility is persistent (see, e.g., Schwert, 1987; French, Schwert, and Stambaugh, 1987). To test the significance of the average increase in volatility shown in Fig. 3, we employ a matched-pair t-test on the VIX and VXO values on the day before the event day and the values on the event day. We find the effect to be significant with t-values of t=2.07 ($P<0.023$) and t=2.55 ($P<0.007$) for the VIX and VXO, respectively.[26] Note that these significant results were obtained even though the period corresponding to the Fear Index is much shorter than the period covered in this study; only 39 disasters corresponding to the VIX and 53 disasters corresponding to the VXO are relevant.

4.4.2. Event effect on actual volatility

We suggest that the increase in the Fear Index reported above is due to a mood effect induced by aviation disasters. However, the increase in the Fear Index may also be due to an increase in actual market volatility, which may occur either coincidentally with aviation disasters or more reasonably, due to the fact that some aviation disasters are involved with sociopolitical incidents (e.g., terror attacks and military assaults). Such aviation disasters may have substantial economic implications far beyond the accidents themselves. Thus, if an aviation disaster is involved with a crisis, it may also affect actual volatility, as several studies show that volatility increases after macroeconomic crises and stock market crashes. Schwert (1989), for example, analyzes a very long time period and finds that the monthly stock volatility was higher during economic recessions and in periods of major banking crises (see also Schwert, 1990b).

We examine a possible event effect on actual volatility in two ways. First, we compare the actual volatility before the disasters to that after the disasters, where actual volatility is measured over various alternate horizons of one week, two weeks, or one month. We repeat this test in several forms in which the event days and the reversal days are included or excluded from the volatility calculations and for various periods (e.g., for the entire period and only for the period for which the VIX is covered). In all tests the average actual volatilities before and after the disasters are almost identical and the small difference is not even with the same sign for the various tests. Indeed, matched-pair t-tests reveal insignificant t-values, all below one.

Second, in the regression analysis we exclude all aviation disasters which may have economic implications beyond the disasters themselves. To do so, we use the Flight Safety Foundation classification system which classifies aviation disasters as accident, hijacking, incident (e.g., terror bomb, military attack, etc.), criminal occurrence, or other occurrence. Out of the 288 aviation disasters, 23 events are classified as hijacking, incident, or criminal occurrence; nine of them are aviation disasters of American or European companies.

The last two tests in Table 2 (Tests 1a and 5a) report the results of Test 1 (all disasters) when we exclude those 23 disasters, and Test 5 (BM) when we exclude those nine disasters, respectively. Comparing Tests 1 and 1a reveals that the event day coefficient is unchanged where the t-value only slightly decreases (in absolute terms) from -3.65 to -3.48 and the reversal day coefficient is also very similar and insignificant. The event day coefficient in Test 5a decreases (in absolute terms) from -0.0032 in Test 5 to -0.0029 in Test 5a, where the t-value changes from -5.03 to -4.52, respectively. In contrast, the reversal day coefficient increases from 0.0012 to 0.0014 and the corresponding t-value increases from 1.95 to 2.13. Thus, the changes due to the elimination of aviation disasters which may have sociopolitical implications are minimal. Moreover, these changes are mainly attributed to one unique event: the 9/11 disaster (we elaborate on this event in Section 4.5). Thus, besides the 9/11 event, we do not find a substantially different event effect when eliminating from the analysis the aviation disasters that are involved with sociopolitical implications.

To sum up, the above analysis supports the hypothesis that mood and anxiety, rather than actual economic or sociopolitical factors, affect the Fear Index.

4.4.3. Event effect and firms' risk

In their study of how investor sentiment affects the cross-section of stock returns, Baker and Wurgler (2006) find that investor sentiment has a greater effect on securities with valuations that are highly subjective and difficult to arbitrage (see also Wurgler and Zhuravskaya, 2002). Motivated by their study, below we test the aviation disaster effect on various groups of stocks (e.g., small versus large stocks). Table 3 reports the regression results; each dependent variable is the daily rate of return on a portfolio constructed from stocks that are divided into deciles with respect to stocks' volatility: Decile 1 includes the most volatile stocks and Decile 10 includes the least volatile stocks.

As can be seen, our results are robust and the event effect is intact for all deciles. All event coefficients are negative and highly significant. Moreover, the event day coefficients corresponding to riskier stock portfolios (e.g., the coefficient corresponding to Decile 1 of -0.0032) are larger (in absolute terms) than the coefficients corresponding to less risky stock portfolios (e.g., the coefficient corresponding to Decile 10 of -0.0011). Fig. 4a graphically presents the event day coefficient for each portfolio employed in Table 3. The figure also shows the event day coefficient when running the same regressions as those in Table 3 without the disasters of 9/11 and August 31, 1998 (to which we devote special attention later).

[26] In Section 4.6 we discuss and analyze the possibility that news for nearby disasters on land arrives much faster than in the case of faraway disasters. For the period corresponding to the VIX and VXO, only one disaster might be relevant: the American Airlines Flight 587 disaster which crashed in a New York City neighborhood on November 12, 2001 at 9:00 EDT was probably known to many U.S. investors on the same day when the market was still open. Thus, defining the event day in this case as the disaster date, the results are substantially strengthened. The event day t-values corresponding to this case are t=2.51 ($P<0.008$) and t=2.95 ($P<0.002$), respectively. The matched-pair t-values of the event day and the third-day reversal are t=1.87 ($P<0.035$) and t=1.69 ($P<0.049$), respectively.

Table 3
Aviation disasters: Ten portfolios classified by stock volatility.
The table reports the results of the following regression:

$$R_t = \gamma_0 + \sum_{i=1}^{5} \gamma_{1i} R_{t-i} + \sum_{i=1}^{4} \gamma_{2i} D_{it} + \gamma_3 H_t + \gamma_4 T_t + \sum_{i=1}^{3} \gamma_{5i} E_{it} + \varepsilon_t,$$

where R_t is the daily rate of return on value-weighted portfolios constructed by volatility, γ_0 is the regression intercept, R_{t-i} is the daily rate of return on the $t-i$ day, D_{it}, i=1…4, are dummy variables for the day of the week, H_t is a dummy variable for days after a non-weekend holiday, T_t is a dummy variable for the first five days of the taxation year, and E_i, i=1,2,3 stands for the event effect days. The observed period includes 14,678 trading days and 170 event days corresponding to American and European disasters (called in this study the Base Model) from January 1950 to December 2007. The first line of each test reports the regression coefficients, while the second line reports the corresponding t-values (in brackets). One and two asterisks indicate a significance level of 5% and 1%, respectively (a one-tail test in the case of the first and third days).

	Case	γ_0	R_{t-1}	R_{t-2}	R_{t-3}	R_{t-4}	R_{t-5}	Non-weekend holidays	Mon.	Tues.	Wed.	Thurs.	First 5 days of the tax year	Post aviation disaster			R^2
														1st day	2nd day	3rd day	F
1.	Decile 1	0.0036	0.2449	−0.0026	0.0723	0.0604	0.0503	0.0040	−0.0065	−0.0038	−0.0020	−0.0024	0.0127	−0.0032	0.0000	0.0002	0.154
	(highest volatility)	(18.86**)	(29.64**)	(−0.31)	(8.65**)	(7.22**)	(6.22**)	(5.27**)	(−23.80**)	(−13.93**)	(−7.30**)	(−8.98**)	(15.05**)	(−4.06**)	(0.03)	(0.30)	190.579
2.	Decile 2	0.0023	0.2380	−0.0230	0.0568	0.0423	0.0272	0.0029	−0.0049	−0.0023	−0.0010	−0.0015	0.0067	−0.0038	−0.0005	0.0009	0.102
		(12.62**)	(28.85**)	(−2.72**)	(6.76**)	(5.03**)	(3.32**)	(4.02**)	(−18.93**)	(−8.79**)	(−3.75**)	(−5.96**)	(8.57**)	(−5.11**)	(−0.68)	(1.25)	119.487
3.	Decile 3	0.0019	0.2361	−0.0311	0.0536	0.0346	0.0284	0.0022	−0.0040	−0.0018	−0.0006	−0.0013	0.0050	−0.0033	−0.0002	0.0007	0.089
		(11.21**)	(28.64**)	(−3.68**)	(6.36**)	(4.11**)	(3.47**)	(3.27**)	(−16.54**)	(−7.67**)	(−2.71**)	(−5.35**)	(6.80**)	(−4.68**)	(−0.27)	(1.02)	102.586
4.	Decile 4	0.0016	0.2508	−0.0410	0.0549	0.0303	0.0232	0.0021	−0.0033	−0.0014	−0.0004	−0.0009	0.0041	−0.0031	−0.0001	0.0006	0.091
		(10.32**)	(30.41**)	(−4.83**)	(6.49**)	(3.58**)	(2.83**)	(3.41**)	(−15.11**)	(−6.32**)	(−2.01*)	(−4.33**)	(6.19**)	(−4.84**)	(−0.10)	(0.94)	104.514
5.	Decile 5	0.0013	0.2594	−0.0419	0.0574	0.0290	0.0238	0.0016	−0.0027	−0.0010	−0.0003	−0.0008	0.0030	−0.0031	−0.0004	0.0009	0.091
		(9.60**)	(31.46**)	(−4.92**)	(6.77**)	(3.42**)	(2.90**)	(2.95**)	(−13.50**)	(−5.16**)	(−1.36)	(−4.01**)	(5.00**)	(−5.22**)	(−0.77)	(1.54)	104.273
6.	Decile 6	0.0012	0.2645	−0.0492	0.0562	0.0287	0.0210	0.0016	−0.0024	−0.0009	−0.0003	−0.0008	0.0023	−0.0026	0.0000	0.0009	0.089
		(9.59**)	(32.07**)	(−5.78**)	(6.61**)	(3.37**)	(2.56*)	(3.19**)	(−12.99**)	(−4.85**)	(−1.72)	(−4.17**)	(4.10**)	(−4.80**)	(−0.05)	(1.69*)	102.374
7.	Decile 7	0.0010	0.2702	−0.0423	0.0529	0.0200	0.0245	0.0015	−0.0019	−0.0006	−0.0001	−0.0006	0.0021	−0.0023	−0.0002	0.0010	0.089
		(8.46**)	(32.77**)	(−4.95**)	(6.22**)	(2.34*)	(2.98**)	(3.18**)	(−11.02**)	(−3.70**)	(−0.76)	(−3.40**)	(4.08**)	(−4.72**)	(−0.43)	(2.01*)	102.011
8.	Decile 8	0.0009	0.2847	−0.0510	0.0536	0.0154	0.0250	0.0012	−0.0017	−0.0005	−0.0002	−0.0005	0.0016	−0.0021	−0.0003	0.0008	0.094
		(8.86**)	(34.51**)	(−5.95**)	(6.26**)	(1.80)	(3.04**)	(2.87**)	(−10.97**)	(−3.63**)	(−1.02)	(−3.53**)	(3.52**)	(−4.75**)	(−0.72)	(1.85*)	108.486
9.	Decile 9	0.0008	0.3166	−0.0683	0.0633	0.0138	0.0269	0.0011	−0.0014	−0.0003	−0.0002	−0.0004	0.0016	−0.0017	0.0000	0.0007	0.111
		(8.79**)	(38.39**)	(−7.90**)	(7.33**)	(1.59)	(3.27**)	(3.25**)	(−10.94**)	(−2.70**)	(−1.37)	(−3.39**)	(4.17**)	(−4.60**)	(−0.07)	(1.76*)	131.042
10.	Decile 10	0.0006	0.3738	−0.0752	0.0708	0.0082	0.0351	0.0008	−0.0010	−0.0002	−0.0002	−0.0004	0.0015	−0.0011	−0.0002	0.0004	0.149
	(lowest volatility)	(9.39**)	(45.32**)	(−8.55**)	(8.06**)	(0.93)	(4.27**)	(2.97**)	(−11.01**)	(−2.46)	(−1.84)	(−4.23)	(5.36**)	(−4.18**)	(−0.91)	(1.49)	182.802

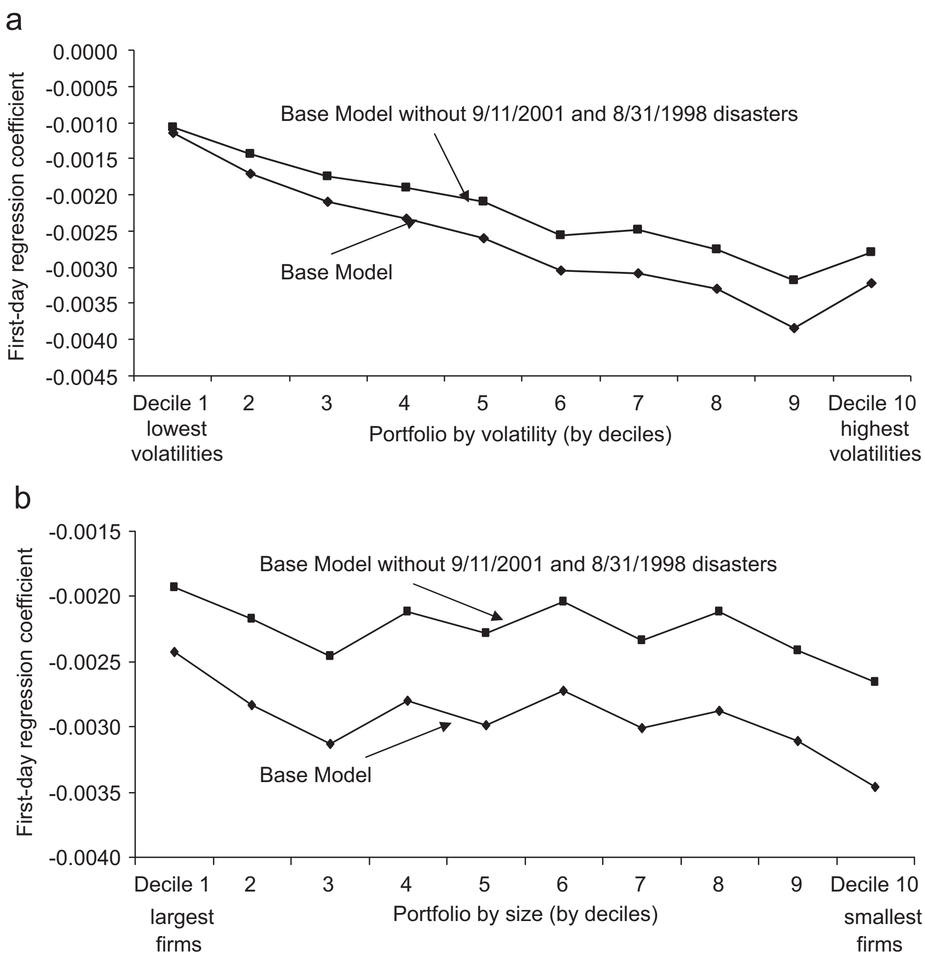

Fig. 4. First-day event effect and firm characteristics. The figure depicts the first-day event effect coefficient for 10 portfolios constructed by volatility (a) and for 10 portfolios constructed by firm size (b). The portfolios are taken from the CRSP. The Base Model events occurred during a 58-year period from January 1950 to December 2007 and incorporate 170 first days and 170 third days corresponding to aviation disasters of American and European airline companies. The upper graph in each figure is similar to the Base Model except for the exclusion of the 9/11/2001 and the 8/31/1998 disasters which were accompanied by major economic events.

4.4.4. Event effect and firm size

By the same logic mentioned for the relation between the magnitude of the event effect and stock volatility we also expect a greater event effect, on average, for small stocks relative to large stocks. Table 4 reports the regression results; each dependent variable is the daily rate of return on a portfolio constructed from stocks belonging to one decile, where deciles are arranged by firm size.

As in the previous case, the results are robust and the effect is intact for all deciles. However, there is no clear monotonic size effect. Fig. 4b depicts the event day coefficient for each decile employed in Table 4 and the coefficients for the same regressions when running the regression without the disasters of 9/11 and August 31, 1998.

As in the previous case corresponding to portfolios constructed by volatility, here we also observe a difference in the magnitude of the effect, but this time the difference exists mainly in the two extreme deciles, Decile 1 and Decile 10. The coefficient tends to increase (in absolute terms) as size decreases from −0.0024 for the largest firms (Decile 1) to −0.0035 for the smallest firms (Decile 10). A comparison of Fig. 4a and b reveals a consistent result, albeit not at the same magnitude: the event effect is larger for more volatile firms and for small firms than for large and less volatile firms.

Finally, it is worth mentioning that the serial correlation coefficients for 3, 4, and 5 lags corresponding to the largest stocks are positive and significant. These results are in line with those of Schwert (1990b), who finds significant serial correlations for these variables when employing the Standard & Poor's Composite Index, which includes stocks of large companies only.

4.4.5. Event effect on various industries

To further test the relation between the event effect and the characteristics of the affected stocks, Table 5 reports the regression results corresponding to portfolios classified by industry.

Table 4
Aviation disasters: Ten portfolios classified by size.

The table reports the results of the following regression:

$$R_t = \gamma_0 + \sum_{i=1}^{5} \gamma_{1i} R_{t-i} + \sum_{i=1}^{4} \gamma_{2i} D_{it} + \gamma_3 H_t + \gamma_4 T_t + \sum_{i=1}^{3} \gamma_{5i} E_{it} + \varepsilon_t,$$

where R_t is the daily rate of return on value-weighted portfolios constructed by size, γ_0 is the regression intercept, R_{t-i} is the daily rate of return on the $t-i$ day, D_{it}, i=1…4, are dummy variables for the day of the week, H_t is a dummy variable for days after a non-weekend holiday, T_t is a dummy variable for the first five days of the taxation year, and E_i, i=1,2,3 stands for the event effect days. The observed period includes 14,678 trading days and 170 event days corresponding to American and European disasters (called in this study the Base Model) from January 1950 to December 2007. The first line of each test reports the regression coefficients, while the second line reports the corresponding t-values (in brackets). One and two asterisks indicate a significance level of 5% and 1%, respectively (a one-tail test in the case of the first and third days).

	Case	γ_0	R_{t-1}	R_{t-2}	R_{t-3}	R_{t-4}	R_{t-5}	Non-weekend holidays	Mon.	Tues.	Wed.	Thurs.	First 5 days of the tax year	Post aviation disaster			R^2
														1st day	2nd day	3rd day	F
1.	Decile 1 (largest firms)	0.0019	0.3446	−0.0315	0.0784	0.0545	0.0275	0.0008	−0.0039	−0.0020	−0.0010	−0.0013	0.0034	−0.0024	−0.0004	0.0006	0.171
		(12.66**)	(36.51**)	(−3.17**)	(7.92**)	(5.50**)	(2.93**)	(1.33)	(−18.75**)	(−9.65**)	(−4.98**)	(−6.11**)	(5.41**)	(−4.27**)	(−0.72)	(1.04)	165.321
2.	Decile 2	0.0015	0.2291	−0.0034	0.0536	0.0416	0.0158	0.0011	−0.0032	−0.0015	−0.0005	−0.0009	0.0027	−0.0028	−0.0006	0.0009	0.080
		(8.07**)	(24.25**)	(−0.35)	(5.56**)	(4.31**)	(1.68)	(1.48)	(−12.12**)	(−5.79**)	(−1.76)	(−3.34**)	(3.44**)	(−3.98**)	(−0.83)	(1.32)	69.579
3.	Decile 3	0.0013	0.2115	−0.0082	0.0469	0.0367	0.0112	0.0012	−0.0027	−0.0012	−0.0002	−0.0008	0.0019	−0.0031	−0.0004	0.0011	0.065
		(7.08**)	(22.39**)	(−0.85)	(4.87**)	(3.81**)	(1.19)	(1.57)	(−10.19**)	(−4.72**)	(−0.80)	(−2.93**)	(2.39*)	(−4.30**)	(−0.57)	(1.46)	55.308
4.	Decile 4	0.0011	0.2041	−0.0157	0.0501	0.0300	0.0041	0.0013	−0.0025	−0.0009	0.0000	−0.0006	0.0012	−0.0028	−0.0004	0.0008	0.058
		(6.10**)	(21.60**)	(−1.62)	(5.21**)	(3.12**)	(0.44)	(1.67)	(−9.32**)	(−3.40**)	(−0.08)	(−2.29**)	(1.41)	(−3.81**)	(−0.54)	(1.15)	48.953
5.	Decile 5	0.0011	0.1983	−0.0249	0.0466	0.0253	−0.0049	0.0014	−0.0023	−0.0009	−0.0001	−0.0005	0.0011	−0.0030	−0.0005	0.0011	0.052
		(6.01**)	(20.99**)	(−2.59**)	(4.85**)	(2.63**)	(−0.52)	(1.87)	(−8.44**)	(−3.38**)	(−0.28)	(−2.01*)	(1.37)	(−4.06**)	(−0.63)	(1.46)	43.872
6.	Decile 6	0.0010	0.2189	−0.0361	0.0464	0.0240	0.0046	0.0010	−0.0021	−0.0008	0.0001	−0.0005	0.0006	−0.0027	−0.0003	0.0010	0.059
		(5.56**)	(23.17**)	(−3.73**)	(4.81**)	(2.48*)	(0.48)	(1.36)	(−8.23**)	(−3.06**)	(0.29)	(−1.81)	(0.79)	(−3.87**)	(−0.49)	(1.46)	50.416
7.	Decile 7	0.0010	0.2153	−0.0334	0.0272	0.0257	0.0011	0.0011	−0.0021	−0.0006	0.0001	−0.0004	0.0004	−0.0030	−0.0005	0.0009	0.057
		(5.52**)	(22.79**)	(−3.46**)	(2.82**)	(2.66**)	(0.12)	(1.54)	(−8.15**)	(−2.54*)	(0.39)	(−1.72)	(0.54)	(−4.24**)	(−0.77)	(1.23)	47.858
8.	Decile 8	0.0009	0.1885	−0.0348	0.0231	0.0158	−0.0009	0.0012	−0.0018	−0.0006	0.0001	−0.0005	0.0007	−0.0029	−0.0004	0.0012	0.043
		(5.02**)	(19.95**)	(−3.62**)	(2.41*)	(1.64)	(−0.10)	(1.64)	(−6.84**)	(−2.25*)	(0.42)	(−1.80)	(0.88)	(−3.95**)	(−0.61)	(1.59)	35.942
9.	Decile 9	0.0008	0.1543	−0.0361	0.0128	0.0063	−0.0025	0.0010	−0.0015	−0.0005	0.0001	−0.0004	0.0009	−0.0031	−0.0005	0.0013	0.030
		(4.50**)	(16.33**)	(−3.78**)	(1.34)	(0.66)	(−0.27)	(1.38)	(−5.58**)	(−1.77)	(0.52)	(−1.45)	(1.11)	(−4.28**)	(−0.65)	(1.83*)	24.806
10.	Decile 10 (smallest firms)	0.0005	0.0554	−0.0324	−0.0184	−0.0169	−0.0065	0.0012	−0.0006	0.0002	0.0004	−0.0003	0.0009	−0.0035	−0.0002	0.0014	0.009
		(2.41*)	(5.86**)	(−3.43**)	(−1.94)	(−1.78)	(−0.68)	(1.50)	(−2.07*)	(0.54)	(1.40)	(−0.98)	(1.06)	(−4.35**)	(−0.20)	(1.74*)	6.925

Table 5
Aviation disasters: Ten portfolios classified by industry.

The table reports the results of the following regression:

$$R_t = \gamma_0 + \sum_{i=1}^{5} \gamma_{1i} R_{t-i} + \sum_{i=1}^{4} \gamma_{2i} D_{it} + \gamma_3 H_t + \gamma_4 T_t + \sum_{i=1}^{3} \gamma_{5i} E_{it} + \varepsilon_t,$$

where R_t is the daily rate of return on value-weighted portfolios constructed by industry, γ_0 is the regression intercept, R_{t-i} is the daily rate of return on the $t-i$ day, D_{it}, i=1…4, are dummy variables for the day of the week, H_t is a dummy variable for days after a non-weekend holiday, T_t is a dummy variable for the first five days of the taxation year, and E_i, i=1,2,3 stands for the event effect days. The observed period includes 14,678 trading days and 170 event days corresponding to American and European disasters (called in this study the Base Model) from January 1950 to December 2007. The first line of each test reports the regression coefficients, while the second line reports the corresponding t-values (in brackets). One and two asterisks indicate a significance level of 5% and 1%, respectively (a one-tail test in the case of the first and third days).

	Case	γ_0	R_{t-1}	R_{t-2}	R_{t-3}	R_{t-4}	R_{t-5}	Non-weekend holidays	Mon.	Tues.	Wed.	Thurs.	First 5 days of the tax year	Post aviation disaster			R^2
														1st day	2nd day	3rd day	F
1.	NoDur	0.0006	0.1381	−0.0099	−0.0037	0.0128	0.0039	0.0003	−0.0009	−0.0001	0.0003	−0.0002	0.0000	−0.0024	0.0002	0.0011	0.023
		(3.53**)	(14.60**)	(−1.03)	(−0.39)	(1.34)	(0.41)	(0.45)	(−3.64**)	(−0.26)	(1.43)	(−0.99)	(0.05)	(−3.45**)	(0.26)	(1.55)	18.647
2.	Durbl	0.0003	0.0779	−0.0094	0.0107	0.0055	0.0031	0.0022	−0.0002	0.0000	0.0006	−0.0002	0.0036	−0.0036	0.0000	0.0015	0.010
		(1.08)	(8.24**)	(−0.99)	(1.13)	(0.58)	(0.33)	(2.24*)	(−0.55)	(0.08)	(1.74)	(−0.48)	(3.34**)	(−3.77**)	(−0.04)	(1.57)	8.171
3.	Manuf	0.0007	0.1514	−0.0384	0.0205	0.0064	0.0008	0.0009	−0.0011	−0.0002	0.0002	−0.0004	0.0011	−0.0033	−0.0003	0.0014	0.028
		(3.57**)	(16.02**)	(−4.02**)	(2.15*)	(0.67)	(0.08)	(1.18)	(−4.02**)	(−0.66)	(0.66)	(−1.42)	(1.25)	(−4.26**)	(−0.36)	(1.79*)	22.726
4.	Energy	0.0013	0.0969	−0.0446	−0.0102	−0.0252	−0.0053	0.0013	−0.0019	−0.0007	−0.0001	−0.0009	0.0002	−0.0024	−0.0005	0.0005	0.016
		(5.17**)	(10.25**)	(−4.70**)	(−1.07)	(−2.65**)	(−0.56)	(1.34)	(−5.37**)	(−1.94)	(−0.38)	(−2.58**)	(0.23)	(−2.54**)	(−0.52)	(0.56)	12.713
5.	HiTec	0.0003	0.0729	−0.0345	−0.0017	0.0084	−0.0059	0.0018	−0.0005	0.0001	0.0009	0.0000	0.0019	−0.0050	0.0000	0.0020	0.010
		(1.15)	(7.71**)	(−3.64**)	(−0.17)	(0.89)	(−0.62)	(1.47)	(−1.16)	(0.34)	(2.06*)	(−0.03)	(1.45)	(−4.25**)	(−0.00)	(1.72*)	7.941
6.	Telcm	0.0009	0.0422	−0.0162	−0.0346	−0.0185	−0.0011	0.0012	−0.0013	−0.0004	−0.0001	−0.0006	0.0041	−0.0025	−0.0003	0.0006	0.009
		(3.94**)	(4.47**)	(−1.72)	(−3.66**)	(−1.96*)	(−0.12)	(1.39)	(−4.07**)	(−1.27)	(−0.45)	(−1.92)	(4.33**)	(−2.90**)	(−0.35)	(0.71)	6.923
7.	Shops	0.0008	0.1626	−0.0277	0.0100	0.0151	−0.0063	0.0009	−0.0015	−0.0004	0.0003	−0.0004	0.0003	−0.0026	0.0003	0.0014	0.031
		(3.60**)	(17.20**)	(−2.89**)	(1.05)	(1.57)	(−0.67)	(1.10)	(−4.89**)	(−1.23)	(1.00)	(−1.18)	(0.31)	(−3.17**)	(0.30)	(1.63)	25.457
8.	Hlth	0.0005	0.1575	−0.0391	−0.0333	0.0035	−0.0001	0.0012	−0.0010	0.0002	0.0007	−0.0002	−0.0010	−0.0032	−0.0003	0.0009	0.031
		(2.39*)	(16.67**)	(−4.09**)	(−3.48**)	(0.37)	(−0.01)	(1.33)	(−3.08**)	(0.69)	(2.23*)	(−0.50)	(−1.03)	(−3.67**)	(−0.38)	(1.01)	25.200
9.	Utils	0.0007	0.1621	0.0031	0.0343	−0.0260	0.0229	0.0010	−0.0008	−0.0005	−0.0002	−0.0005	0.0010	−0.0017	−0.0004	0.0006	0.031
		(4.72**)	(17.15**)	(0.33)	(3.59**)	(−2.72**)	(2.43*)	(1.69)	(−3.61**)	(−2.50*)	(−0.71)	(−2.51*)	(1.46)	(−2.84**)	(−0.73)	(0.98)	25.875
10.	Other	0.0010	0.1745	−0.0199	0.0265	0.0037	−0.0005	0.0012	−0.0018	−0.0005	0.0000	−0.0006	0.0008	−0.0038	−0.0003	0.0015	0.038
		(4.80**)	(18.47**)	(−2.08*)	(2.77**)	(0.39)	(−0.05)	(1.50)	(−6.52**)	(−1.75)	(0.06)	(−2.11*)	(0.92)	(−4.88**)	(−0.39)	(1.90*)	31.703

Table 6
Rates of return on the best and worst trading days.
The table reports the ten highest rates of return (R_t) and the ten lowest rates of return on the NYSE Composite Index (either equally weighted or value-weighted) during the studied period, from January 1950 to December 2007. **Bold** return stands for the relevant index for which this is an extreme rate of return. The fourth column provides the common explanation for the market collapse. The fifth column reports if these days coincided with an event day corresponding to all 288 aviation disasters covered in this study, and the last two columns report whether this day is in favor of rejecting the null hypothesis.

Date	Negative R_t (equally weighted/value-weighted)	Positive R_t (equally weighted/value-weighted)	Possible explanation	Event day?	Increases the possibility to reject the null hypothesis of:	
					The event effect first day	The reversal third day
29-Jul-02		**4.26%**/**5.23%**		No		
24-Jul-02		2.60%/**5.31%**		No		
17-Sep-01	−**4.68%**/−4.78%		9/11/2001 Terror attack	Yes	Yes*	
14-Apr-00	−3.56%/−**5.26%**		Dot Com Bubble	No		
16-Mar-00		3.25%/**4.81%**		No		
08-Sep-98		2.88%/**4.59%**		Yes		Yes
31-Aug-98	−**4.47%**/−**6.15%**		Russia's financial crisis	Yes	Yes*	
27-Oct-97	−**4.98%**/−**6.39%**		Economic crisis in Asia	No		
13-Oct-89	−4.07%/−**5.72%**		Junk bond market crash	No		
08-Jan-88	−4.10%/−**6.00%**			No		
30-Oct-87		**5.60**%/3.45% 4.23%/**4.49**% **9.82**%/**8.79**%	Potential causes include program trading, overvaluation, illiquidity, and market psychology	No		
29-Oct-87				No		
26-Oct-87	−**8.74%**/−**8.10%**			No		
21-Oct-87				No		
20-Oct-87	−**4. 70%**/2.63%			No		
19-Oct-87	−**15.0%**/−**18.4%**			No		
27-Mar-80	−**4.39%**/−1.15%		Silver Thursday crash	No		
01-Nov-78		**4.80%**/4.21%		No		
02-Jan-75		**4.85%**/2.60%		No		
09-Oct-74		2.86%/**4.95%**		No		
03-Jan-74		**4.47%**/2.36%		No		
16-Aug-71		**4.71%**/3.61%		No		
27-May-70		**6.00%**/**5.20%**		No		
31-May-62		**4.80%**/2.75%		No		
29-May-62		2.01%/**4.95%**		No		
28-May-62	−**6.11%**/−**6.95%**			No		
23-Oct-57		**4.36%**/**4.48%**		No		
26-Sep-55	−**6.32%**/−**6.52%**		U.S. President D. Eisenhower suffers coronary thrombosis	No		
26-Jun-50	−**5.30%**/−**5.25%**		The Korean War	No		

* All tests were repeated without these two disasters to guarantee that they do not account for the results.

Once again, all event effect coefficients are negative and highly significant. Moreover, we observe some evidence for the industry effect. Specifically, the coefficient corresponding to the HiTec industry is the largest in absolute terms (−0.0050) whereas the coefficient corresponding to Utilities is the smallest in absolute terms (−0.0017). The same phenomenon exists in the case of the third-day reversal coefficient.

To verify that these differences are significant we first employ the Chow Test (see Chow, 1960). Comparing each two regressions, the null hypothesis asserting that each two regressions are identical is rejected in 29 out of 36 possible pairs at a 5% significance level. However, as the differences in the regressions may be due to other variables rather than the event variables, we also test for a difference in the event effect coefficients only (see Gujarati, 1970). The null hypothesis asserting that the first-day coefficients are identical is rejected at a 5% significance level for the coefficients of the following pairs of regressions: HiTec and Non-durable, HiTec and Energy, HiTec and Telecom, HiTec and Utilities, and Other[27] and Utilities. Thus, the differences are significant for the portfolios at the two extremes, with a significantly larger effect on HiTec and Other industries relative to less volatile industries.

4.4.6. *Event effect on U.S. treasury securities and the U.S. dollar*

So far, we advocate that bad mood and anxiety induced by aviation disasters affect people's investment decisions. As explained above, this indicates that investors in their normal

[27] The other industry portfolio includes companies from the following industries: mines, construction, building materials, transportation, hotels, business services, entertainment, and finance.

daily trading activity are probably inclined to invest in safe assets. To test whether there is also a flight to safety by shifting investments from risky assets to less risky assets, we also test the effect of aviation disasters on two other financial assets that are commonly considered to be safe-haven assets: U.S. Treasury securities and the U.S. dollar.

We test whether there is an event effect in the prices of U.S. Treasury securities (and a corresponding effect in their yields) and in the value of the U.S. dollar against the other main currencies. If there is a flight to safety, we expect to find an increase in Treasury securities prices and a corresponding decrease in their yields as well as an increase in the U.S. dollar exchange rate relative to other currencies. With regard to yield on U.S. Treasury securities we find on the event day an average decrease in yield on all relatively short-term Treasury securities and an increase in yield on relatively long-term Treasury securities. We find an average decrease in yield on Treasury securities at 1-month, 3-month, 6-month, 1-year, and 2-year maturities and an average increase in yield on Treasury securities at 3-, 5-, 7-, and 10-year maturities. However, in all cases the event effect is insignificant. Specifically, a matched-pair t-test for the event day's yield and the previous day's yield reveals t-values of <1 in all cases. Thus, we conclude that there is no significant event effect corresponding to U.S. Treasury securities.

Next, we test whether there is an effect in the exchange rate of the U.S. dollar against the currencies of the major trading partners of the U.S., as reflected in the Federal Reserve Major Index. Although the index on average decreases by 0.04 from 100.59 to 100.55 (i.e., the U.S. dollar strengthens), there is no clear pattern in the index on event days. Indeed, a matched-pair t-test for exchange rate on the event day and on the previous day reveals a t-value of -0.91; hence, there is no significant event effect in the U.S. dollar.

To sum up, although we find an insignificant effect on both the U.S. Treasury securities and the U.S. dollar exchange rate, the direction of the average change on the event days conforms to the event effect hypothesis: on the event day, on average, the U.S. dollar strengthens and the yield on short-term Treasury securities decreases in contrast to the increase in yield on the riskier long-term Treasury securities. One can imagine two possible explanations, which are not mutually exclusive, for these results. First, it is possible that there is indeed a flight to safety on the event days. However, as there are many relatively safe assets (e.g., the U.S. dollar, short-term T-bills, bank deposits, etc.) the event effect is diluted and therefore, testing the effect on each safe asset reveals a change in the predicted direction, yet it is insignificant. Alternatively, it is possible that there is no flight to safety in the classical sense, i.e., liquidation of risky assets and a shift toward safer assets. Instead, on the days after aviation disasters, investors tend to hold the cash intended for buying risky assets, thus postponing planned investments in risky assets for a few more days.

4.5. Impact of possible spurious correlations and outliers

A legitimate question emerging from the previous results is whether a few extreme observations, induced by real economic reasons (rather than by psychological reasons) account for the results. This may be especially true, as it is well-known that some disasters (e.g., 9/11) were related to events that had major economic effects. Although Tests 1a and 5a in Table 2 provide a first indication that the effect is not driven only by disasters which are classified as hijacking, incident, or criminal occurrence, we have also taken the following steps in an attempt to examine whether the effect found is spurious:

1. First, the results could be driven by well-known effects such as the weekend effect, serial correlation, etc. To ensure against such a possibility, we run the regressions three times: with all control variables, without control variables, and without serial correlation control variables.
2. It is possible that on the event day after a given disaster, a major negative economic event also occurs; hence, the negative rates of return recorded are induced by this major economic event rather than by the disaster. Table 6 summarizes the 10 most extreme positive and the 10 most extreme negative daily rates of return during the studied period.[28]
   Table 6 reveals that two extreme negative event days increase the probability of rejecting the null hypothesis. The two event days are the first trading day after the 9/11 disaster, and August 31, 1998, which was the worst day of Russia's 1998 financial crisis. On both days, we observe a sharp decline in stock prices driven by economic factors. Therefore, we run regression (1) without these two unique disasters.
3. As the results could be affected by several days with extreme negative or extreme positive returns (presented in Table 6), even if no clear economic event occurred, we also run a quantile regression (QR). First introduced by Koenker and Bassett (1978), QR is not as sensitive to extreme observations as the classical Ordinary Least Squares (OLS) regression. For more details on QR, see Portnoy and Koenker (1997) and Koenker and Hallock (2001). Thus, instead of estimating the conditional mean by the OLS method we employ the QR method to estimate the conditional median.[29]
4. Finally, to take into account a possible conditional heteroskedasticity, we also assume a time-varying volatility and employ a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) (1,1) model (see Engle, 1982; and Bollerslev, 1986).[30]

[28] Schwert (1990b) reports the 25 smallest and the 25 largest daily rates of returns for the period of 1885 to 1988. For the relevant period, the numbers appearing in Table 6 are not identical to those reported in Schwert's table as different market indexes are employed: Standard & Poor's Composite Index versus the NYSE Composite Index.

[29] To control for a possible bias from a few extreme days we also run the OLS regression with a dummy variable for the ten event days with the most extreme negative rates of return and with a dummy variable for the ten days with the most extreme negative rates of return given in Table 6. As the results are very similar to the results corresponding to the QR and as the QR is a preferred method (because it is not exposed to the arbitrary selection of the number of extreme days), we report only the results corresponding to the QR for brevity.

[30] Specifically, we use the residuals of the model specified in Eq. (1) to model the volatility of the error term as a GARCH (1,1) process: $\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$, where σ_t^2 is the return volatility on day t. We

Table 7 reports the results of the tests discussed above.

Comparing Tests 1, 2, and 3 in Table 7 reveals that the event effect is negative and highly significant with or without all the control variables (compare Tests 1 and 2) and without the serial correlation control variables (Test 3). Moreover, the results are intact when employing QR (Test 4) and a GARCH model (Test 5). The first-day coefficient corresponding to the QR is large in absolute terms (−0.0017) and highly significant (t-value of −3.30) and the third-day coefficient is positive, yet insignificant. Similarly, the first-day coefficient corresponding to the GARCH model is relatively large in absolute terms (−0.0030) and significant (t-value of −4.74). The third-day coefficient is also positive, yet again insignificant.

As the 9/11 and the August 31, 1998 aviation disasters are accompanied by major economic events (see Table 6), in the second part of Table 7 we report the same regressions as in the first part, only this time these two disasters are eliminated from the event days. Obviously, the elimination of these two observations somewhat weakens the results. However, Table 7 reveals that the first-day effect is robust for these two disasters, and the coefficient is still very large in absolute terms and highly significant in all tests. Moreover, when we eliminate these two disasters, the third-day reversal coefficient somewhat strengthens. This result may be explained by the fact that the 9/11 disaster indeed had major economic implications and therefore, its negative effect continued for many days after the event. As a result, it negatively biased the third-day reversal mean rate of return.

To sum up, we have primary evidence that the event effect is not spurious; it remains intact when eliminating disaster days accompanied by dramatic, unrelated economic events, and this result is intact with and without the control variables and when employing the QR and GARCH models.

4.6. Analysis of the speed of information inflow

In this subsection we analyze the sensitivity of the results to the definition of the event day, when we consider the date and the exact time and location the disaster occurred. As previously explained, in the analysis so far, the event day is defined as the first day after the disaster occurs, which is measured relative to the U.S. market trading hours (EDT). This definition is not necessarily the best fit for all disasters. The reason for this is that the actual effect timing also depends on the speed at which the information is delivered to U.S. investors. As a result, there may be different definitions for the event timing depending on the disaster's characteristics. For example, if a disaster occurs on U.S. soil at 9:00 a.m. when the stock market is open, it is reasonable to assume that the negative effect begins the same day, rather than the next day. Similarly, it is reasonable to assume that with the development of the communication media (e.g., CNN worldwide broadcasting and the Internet medium), information about the disaster, as well as disturbing pictures from it, arrived faster to the U.S. public over the last three decades, relative to the earlier years covered in this study. Therefore, below we investigate the timing of this information inflow and provide additional tests that address this issue.

Table 8 reports the regression results under different definitions of the event day. Corresponding to the previous results, in all the tests the 9/11 and the August 31, 1998 disasters are eliminated; hence, these days are considered as non-event days, which is a conservative approach.

Test 1 of Table 8 reports the previous result of the BM, where the event days are determined according to EDT time, at the time the event occurs. The second test reported in Table 8 assumes that the date of the event is the date corresponding to the disaster location. As expected, the results of both the event effect and the reversal effect in this case are weaker because what is more important to the U.S. market is the EDT time of the disaster (compare Tests 1 and 2). Nevertheless, even in this case, the first-day coefficient is large in absolute terms (−0.0020) and significant with a t-value of −3.20. In the next test, the event day is assumed to be the day of the disaster (rather than the next day), corresponding to EDT time, as long as the U.S. market was still open when the disaster occurred. The first-day coefficient sharply decreases to −0.0015 with a t-value of −2.36, while the third-day coefficient becomes insignificant. Notably, the second-day coefficient becomes relatively large (−0.0012) with a t-value of −1.90. Thus, the effect in this case partially shifts to the second day. These results support the sentiment effect hypothesis. This is because although news of the disaster was publicly available on the day of the disaster itself and the market was still open, there is only partial evidence of the effect on this day. Only on the day following the disaster, when the media is regularly flooded with information on casualties accompanied by dramatic pictures, do we observe the full market negative effect.

As what probably affects investors' anxiety is not only the news but rather the images seen on TV, it is crucial to define the event day as the day when the dramatic scenes appear on TV. Thus, one may argue that at present the development of the communication media expedites the arrival of the dramatic information to the public; hence, this factor should be taken into account in determining the event day.

To analyze the speed of information inflow, we repeat the previous test, only this time we split the 58-year period into two periods: 1950–1984 and 1985–2007. For the later period, the event day is assumed to be the date of the event, as long as the U.S. market was still open. Otherwise, the event day is assumed to be the first day after the disaster occurred. Corresponding with the hypothesis that electronic media currently expedites the

(*footnote continued*)
then normalize the index returns according to $R_t^N = a + bR_t/(\hat{\sigma}_t)$, where $\hat{\sigma}_t^2$ is the estimated volatility of the GARCH process, and a and b are selected so that the mean and variance of the normalized returns are identical to those of the raw returns. This normalization allows us to compare not only the t-values, but also the coefficients with those of the constant-volatility model. The normalized returns R_t^N are then used in a second pass over the model specification (1).

Table 7
Aviation disasters: outlier sensitivity.
The table reports the results of the following regression:

$$R_t = \gamma_0 + \sum_{i=1}^{5} \gamma_{1i} R_{t-i} + \sum_{i=1}^{4} \gamma_{2i} D_{it} + \gamma_3 H_t + \gamma_4 T_t + \sum_{i=1}^{3} \gamma_{5i} E_{it} + \varepsilon_t,$$

where R_t is the daily rate of return on the NYSE Composite Index, γ_0 is the regression intercept, R_{t-i} is the daily rate of return on the $t-i$ day, D_{it}, i=1…4, are dummy variables for the day of the week, H_t is a dummy variable for days after a non-weekend holiday, T_t is a dummy variable for the first five days of the taxation year, and E_i, i=1,2,3 stands for the event effect days. The observed period includes 14,678 trading days and 170 event days corresponding to American and European disasters (called in this study the Base Model) from January 1950 to December 2007. The first line of each test reports the regression coefficients, while the second line reports the corresponding t-values (in brackets). One and two asterisks indicate a significance level of 5% and 1%, respectively (a one-tail test in the case of the first and third days).

	Case	γ_0	R_{t-1}	R_{t-2}	R_{t-3}	R_{t-4}	R_{t-5}	Non-weekend holidays	Mon.	Tues.	Wed.	Thurs.	First 5 days of the tax year	Post aviation disaster			R^2
														1st day	2nd day	3rd day	F
								Base Model									
1.	Base Model (BM)	0.0009	0.1270	−0.0397	0.0044	−0.0026	0.0007	0.0016	−0.0016	−0.0003	0.0001	−0.0005	0.0008	−0.0032	0.0001	0.0012	0.024
		(5.87**)	(15.39**)	(−4.78**)	(0.53)	(−0.31)	(0.08)	(2.68**)	(−7.28**)	(−1.64)	(0.33)	(−2.33*)	(1.20)	(−5.03**)	(0.11)	(1.95*)	26.283
2.	BM without control variables	0.0005												−0.0035	−0.0003	0.0014	0.002
		(7.33**)												(−5.49**)	(−0.44)	(2.27*)	11.783
3.	BM without serial correlation control variables	0.0009						0.0018	−0.0015	−0.0005	0.0001	−0.0004	0.0009	−0.0032	−0.0003	0.0013	0.008
		(6.06**)						(3.05**)	(−6.96**)	(−2.19*)	(0.51)	(−1.96)	(1.30)	(−4.98**)	(−0.53)	(2.07)	13.432
4.	Quantile Regression ($\tau = 0.5$)	0.0011	0.1157	−0.0512	0.0100	0.0111	−0.0015	0.0013	−0.0013	−0.0007	−0.0001	−0.0005	0.0003	−0.0017	0.0002	0.0005	
		(8.76**)	(10.48**)	(−4.53**)	(0.94)	(1.01)	(−0.13)	(2.69**)	(−6.71**)	(−3.80**)	(−0.47)	(−2.98**)	(0.32)	(−3.30**)	(0.34)	(0.86)	
5.	BM with GARCH adjustment	0.0010	0.1078	−0.0203	0.0083	0.0041	−0.0014	0.0012	−0.0018	−0.0006	0.0000	−0.0005	0.0005	−0.0030	−0.0003	0.0008	0.020
		(6.73**)	(13.03**)	(−2.44*)	(0.99)	(0.50)	(−0.17)	(2.03*)	(−8.44**)	(−2.96**)	(−0.01)	(−2.35*)	(0.78)	(−4.74**)	(−0.48)	(1.33)	21.849
								Base Model without 9/11/2001 and 8/31/1998									
1a	BM	0.0009	0.1269	−0.0397	0.0046	−0.0028	0.0007	0.0016	−0.0016	−0.0003	0.0001	−0.0005	0.0008	−0.0025	−0.0002	0.0014	0.024
		(5.85**)	(15.38**)	(−4.77**)	(0.55)	(−0.33)	(0.08)	(2.66**)	(−7.35**)	(−1.64)	(0.32)	(−2.35*)	(1.21)	(−4.03**)	(−0.25)	(2.22*)	25.708
2a	BM without control variables	0.0005												−0.0029	−0.0004	0.0016	0.002
		(7.23**)												(−4.49**)	(−0.67)	(2.46**)	8.847
3a	BM without serial correlation control variables	0.0009						0.0018	−0.0015	−0.0005	0.0001	−0.0004	0.0009	−0.0025	−0.0005	0.0014	0.008
		(6.04**)						(3.04**)	(−7.03**)	(−2.20*)	(0.50)	(−1.98*)	(1.30)	(−3.99**)	(−0.77)	(2.27)	12.575
4a	Quantile Regression ($\tau = 0.5$)	0.0011	0.1157	−0.0514	0.0099	0.0109	−0.0027	0.0013	−0.0013	−0.0007	−0.0001	−0.0005	0.0003	−0.0017	0.0002	0.0006	
		(8.78**)	(10.50**)	(−4.55**)	(0.93)	(1.00)	(−0.24)	(2.66**)	(−6.74**)	(−3.83**)	(−0.50)	(−3.01**)	(0.32)	(−3.20**)	(0.34)	(0.94)	
5a	BM with GARCH adjustment	0.0010	0.1113	−0.0208	0.0084	0.0040	−0.0016	0.0012	−0.0018	−0.0006	0.0000	−0.0005	0.0006	−0.0027	−0.0004	0.0009	0.021
		(6.71**)	(13.46**)	(−2.49*)	(1.01)	(0.49)	(−0.20)	(2.05*)	(−8.50**)	(−2.94**)	(−0.01)	(−2.39*)	(0.86)	(−4.24**)	(−0.56)	(1.45)	22.386

Table 8
Aviation disasters: Speed of information inflow analysis.

The table reports the results of the following regression:

$$R_t = \gamma_0 + \sum_{i=1}^{5} \gamma_{1i} R_{t-i} + \sum_{i=1}^{4} \gamma_{2i} D_{it} + \gamma_3 H_t + \gamma_4 T_t + \sum_{i=1}^{3} \gamma_{5i} E_{it} + \varepsilon_t,$$

where R_t is the daily rate of return on the NYSE Composite Index, γ_0 is the regression intercept, R_{t-i} is the daily rate of return on the $t-i$ day, D_{it}, i=1…4, are dummy variables for the day of the week, H_t is a dummy variable for days after a non-weekend holiday, T_t is a dummy variable for the first five days of the taxation year, and E_i, i=1,2,3 stands for the event effect days. The observed period includes 14,678 trading days and 170 event days corresponding to American and European disasters (called in this study the Base Model) from January 1950 to December 2007. The first line of each test reports the regression coefficients, while the second line reports the corresponding t-values (in brackets). One and two asterisks indicate a significance level of 5% and 1%, respectively (a one-tail test in the case of the first and third days).

	Case	γ_0	R_{t-1}	R_{t-2}	R_{t-3}	R_{t-4}	R_{t-5}	Non-weekend holidays	Mon.	Tues.	Wed.	Thurs.	First 5 days of the tax year	Same/post aviation disaster: 1st day	2nd day	3rd day	R^2 / F
	Various event effect day definitions (without 9/11 and 8/31/1998 outliers)																
1.	Base Model	0.0009	0.1269	−0.0397	0.0046	−0.0028	0.0007	0.0016	−0.0016	−0.0003	0.0001	−0.0005	0.0008	−0.0025	−0.0002	0.0014	0.024
		(5.85**)	(15.38**)	(−4.77**)	(0.55)	(−0.33)	(0.08)	(2.66**)	(−7.35**)	(−1.64)	(0.32)	(−2.35*)	(1.21)	(−4.03**)	(−0.25)	(2.22*)	25.708
2.	BM—Event date is defined as the date at the disaster site (instead of NYC time)	0.0009	0.1268	−0.0400	0.0047	−0.0028	0.0007	0.0016	−0.0016	−0.0004	0.0001	−0.0005	0.0008	−0.0020	−0.0001	0.0012	0.023
		(5.87**)	(15.37**)	(−4.80**)	(0.57)	(−0.34)	(0.08)	(2.64**)	(−7.41**)	(−1.67)	(0.28)	(−2.39*)	(1.20)	(−3.20**)	(−0.16)	(1.92*)	25.179
3.	BM—Event day is the same as the date of the event if the U.S. market was still open (otherwise it is the next day)	0.0009	0.1268	−0.0403	0.0050	−0.0027	0.0005	0.0016	−0.0016	−0.0003	0.0001	−0.0005	0.0008	−0.0015	−0.0012	0.0005	0.023
		(5.94**)	(15.36**)	(−4.85**)	(0.61)	(−0.33)	(0.06)	(2.66**)	(−7.44**)	(−1.60)	(0.34)	(−2.39*)	(1.19)	(−2.36**)	(−1.90*)	(0.86)	24.892
3a	BM—Event day is the same as the date of the event if the U.S. market was still open—only for later period: 1985−2007 (otherwise it is the next day)	0.0009	0.1270	−0.0398	0.0047	−0.0028	0.0005	0.0016	−0.0016	−0.0003	0.0001	−0.0005	0.0008	−0.0023	−0.0006	0.0014	0.024
		(5.87**)	(15.39**)	(−4.79**)	(0.56)	(−0.33)	(0.06)	(2.66**)	(−7.35**)	(−1.61)	(0.32)	(−2.35*)	(1.19)	(−3.69**)	(−1.00)	(2.14*)	25.571
3b	BM—Event day is the same as the date of the event if the U.S. market was still open—only for disasters on U.S. soil (otherwise it is the next day)	0.0009	0.1269	−0.0398	0.0047	−0.0027	0.0006	0.0016	−0.0016	−0.0004	0.0001	−0.0005	0.0008	−0.0026	−0.0001	0.0012	0.024
		(5.88**)	(15.38**)	(−4.79**)	(0.57)	(−0.33)	(0.07)	(2.67**)	(−7.35**)	(−1.67)	(0.31)	(−2.36*)	(1.20)	(−4.15**)	(−0.09)	(1.90*)	25.673

arrival of information, both the event effect and the reversal effect in this case are much stronger than in the previous case (compare Tests 3 and 3a). The first-day coefficient increases in absolute terms to −0.0023 with a *t*-value of −3.69, while the third-day coefficient increases to 0.0014 with a *t*-value of 2.14.

Finally, one may suspect that the news and the detailed media coverage seen in nearby disasters on land arrive much faster than in the case of faraway disasters, many of which occurred at sea or in sparsely populated areas. For example, as previously mentioned, the detailed news and reports on the American Airlines Flight 587 disaster that crashed in a New York City neighborhood on November 12, 2001 at 9:00 EDT, probably reached many U.S. investors when the market was still open that same day. To take this factor into account in determining the event day, we repeat the regression analysis, but this time it is assumed that the event day is the date of the event only for disasters that occurred on U.S. soil, as long as the U.S. market was still open. Corresponding with the closer distance event hypothesis, the coefficient of the first day in this case is the largest (−0.0026), with a *t*-value of −4.15 (see the last test in Table 8).

To sum up, Table 8 presents that the aviation disasters' effect is robust in relation to various definitions of the event day, depending on the assumed speed at which the information reaches U.S. investors. In addition, the results reveal that a relatively long time period—one trading day on average—passes from the time of the event and the observed event effect. A refinement of the event day definition somewhat changes the results, but a very similar picture emerges under all definitions presented in Table 8. Generally, our results support the sentiment effect hypothesis, as it seems that it is not the event, but rather the media coverage that induces the effect in the stock market. In other words, the collective shock and trauma of the disaster (see Barton, 1998) has a stronger effect than the event itself.

4.7. Additional robustness checks

In this study we find an effect that can be explained by psychological factors but not by economic factors. One should be cautious and check for as many factors as possible that could account for a possible spurious correlation.

First, we have defined a large-scale aviation disaster as an accident with at least 75 casualties. To test that the event effect is robust to this definition we repeat regression (1) when the minimal number of casualties varies from 75 to 185. We find that the first-day event coefficient is significant in all tests up to a minimal number of 175 casualties, and the third-day reversal effect is significant up to a minimal number of 145 casualties. The largest first-day coefficient in absolute terms (−0.0041) is obtained for disasters with at least 165 casualties, while the largest third-day coefficient (0.0033) is obtained for disasters with at least 115 casualties. Thus, we conclude that the arbitrary selection of a threshold level of 75 casualties does not account for the results and even stronger results are obtained for other selections.

Second, Table 9 reports the results of regression (1), either with (upper part) or without (lower part) the 9/11 and the August 31, 1998 disasters, when rates of return are calculated either over the NYSE Composite Equally Weighted Index (Tests 2 and 2a) or the Dow Jones Transportation Index (Tests 3 and 3a).

Note that in all tests the first-day coefficient is highly significant and the third-day coefficient is positive and relatively large, though its significance depends on the employed index. The important result of Table 9 is that without the 9/11 disaster, the first-day coefficient corresponding to the Dow Jones Transportation Index (−0.0027) is of the same size order as the coefficient corresponding to the NYSE Composite Index (−0.0025), and with a smaller *t*-value (in absolute terms) of −3.20 in comparison to −4.03. This result confirms the sentiment effect hypothesis because if the effect were driven mainly by economic factors, we would expect a much larger effect in the case of the transportation companies, presumably because people tend to fly less after a disaster. However, there is no evidence of a significantly stronger effect in the transportation industry. Indeed, when we also add the 9/11 disaster, the coefficient corresponding to the Dow Jones Transportation Index is substantially larger (in absolute terms) than that corresponding to the NYSE Composite Index (−0.0038 versus −0.0032) probably because after this event the market anticipated that people would indeed avoid flying as much as they could.

Finally, in Appendix A we compare the effect of aviation disasters with the effect of other transport disasters as well as industrial and miscellaneous disasters. We find some evidence of an event effect corresponding to transport disasters. The effect is substantially weaker than the event effect corresponding to aviation disasters and no significant event effect is found for industrial and miscellaneous disasters. One possible explanation for this result can be related to the relatively larger risk perception of aviation risk (see Slovic, 1987).

5. Concluding remarks

In this study, we find that aviation disasters are followed by negative rates of return in the stock market accompanied by a reversal effect two days later. As the transitory decline in the stock market is more than 60 times larger than the direct economic loss, we look for an explanation of this discrepancy in the realm of behavioral economics. Indeed, psychological studies show that exposure to media coverage of aviation disasters can provoke bad mood, anxiety and fear which may induce people to be more pessimistic, not to take risks, or both. Therefore, the hypothesis of this study is that with the increased anxiety following aviation disasters there is a short-term reduction in the demand for risky assets, which in turn affects stock prices. When anxiety subsides, or when sophisticated investors exploit the effect, a reversal in the stock market takes place.

Table 9
Aviation disasters: Additional robustness checks.

The table reports the results of the following regression:

$$R_t = \gamma_0 + \sum_i \gamma_{1i} R_{t-i} + \sum_{i=1}^{4} \gamma_{2i} D_{it} + \gamma_3 H_t + \gamma_4 T_t + \sum_{i=1}^{3} \gamma_{5i} E_{it} + \varepsilon_t,$$

where R_t is the relevant stock index rate of return on day t, γ_0 is the regression intercept, R_{t-i} is the daily rate of return on the $t-i$ day, H_t is a dummy variable for days after a non-weekend holiday, D_{it}, i=1…4, are dummy variables for the day of the week, T_t is a dummy variable for the first five days of the taxation year, and E_{it}, i=1,2,3 stands for the event effect days. The observed period includes 14,678 trading days and 170 event days corresponding to American and European disasters (called in this study the Base Model) from January 1950 to December 2007. The first line of each test reports the regression coefficients, while the second line reports the corresponding t-values (in brackets). One and two asterisks indicate a significance level of 5% and 1%, respectively (a one-tail test in the case of the first and third days). In the Base Model (Tests 1 and 1a) we employ the NYSE Composite Value-Weighted Index.

	Case	γ_0	R_{t-1}	R_{t-2}	R_{t-3}	R_{t-4}	R_{t-5}	Non-weekend holidays	Mon.	Tues.	Wed.	Thurs.	First 5 days of the tax year	Post aviation disaster			R^2
														1st day	2nd day	3rd day	F
	Base Model																
1.	Base Model (BM)	0.0009	0.1270	−0.0397	0.0044	−0.0026	0.0007	0.0016	−0.0016	−0.0003	0.0001	−0.0005	0.0008	−0.0032	0.0001	0.0012	0.024
		(5.87**)	(15.39**)	(−4.78**)	(0.53)	(−0.31)	(0.08)	(2.68**)	(−7.28**)	(−1.64)	(0.33)	(−2.33*)	(1.20)	(−5.03**)	(0.11)	(1.95*)	26.283
2.	BM on NYSE Composite Equally Weighted Index	0.0013	0.2526	−0.0497	0.0520	0.0218	0.0224	0.0018	−0.0026	−0.0009	−0.0003	−0.0008	0.0033	−0.0028	−0.0001	0.0008	0.086
		(9.91**)	(30.64**)	(−5.85**)	(6.13**)	(2.57*)	(2.73**)	(3.51**)	(−13.90**)	(−5.09**)	(−1.72)	(−4.32**)	(5.78**)	(−5.12**)	(−0.12)	(1.40)	98.773
3.	BM on Dow Jones Transportation Index	0.0006	0.1445	−0.0245	0.0269	0.0030	0.0142	0.0024	−0.0020	−0.0004	0.0005	−0.0004	0.0033	−0.0038	0.0001	0.0013	0.031
		(3.01**)	(17.10**)	(−2.87**)	(3.16**)	(0.35)	(1.69)	(2.94**)	(−6.81**)	(−1.28)	(1.64)	(−1.20)	(3.64**)	(−4.51**)	(0.13)	(1.51)	32.262
	Base Model without 9/11/2001 and 8/31/1998																
1a	BM without 9/11 and 8/31/1998 outliers	0.0009	0.1269	−0.0397	0.0046	−0.0028	0.0007	0.0016	−0.0016	−0.0003	0.0001	−0.0005	0.0008	−0.0025	−0.0002	0.0014	0.024
		(5.85**)	(15.38**)	(−4.77**)	(0.55)	(−0.33)	(0.08)	(2.66**)	(−7.35**)	(−1.64)	(0.32)	(−2.35*)	(1.21)	(−4.03**)	(−0.25)	(2.22*)	25.708
2a	BM on NYSE Composite Equally Weighted Index	0.0013	0.2525	−0.0496	0.0521	0.0217	0.0224	0.0018	−0.0026	−0.0009	−0.0003	−0.0008	0.0033	−0.0023	−0.0003	0.0009	0.086
		(9.90**)	(30.63**)	(−5.84**)	(6.15**)	(2.56*)	(2.74**)	(3.50**)	(−13.96**)	(−5.08**)	(−1.73)	(−4.34**)	(5.77**)	(−4.20**)	(−0.49)	(1.65*)	98.181
3a	BM on Dow Jones Transportation Index	0.0006	0.1445	−0.0244	0.0271	0.0029	0.0143	0.0024	−0.0020	−0.0004	0.0005	−0.0004	0.0033	−0.0027	0.0001	0.0016	0.031
		(2.96**)	(17.10**)	(−2.86**)	(3.18**)	(0.34)	(1.69)	(2.93**)	(−6.89**)	(−1.29)	(1.63)	(−1.22)	(3.64**)	(−3.20**)	(0.10)	(1.83*)	31.598

Table A1
Comparison to other disasters: A regression corresponding to all disasters.

The table reports the results of the following regression:

$$R_t = \gamma_0 + \gamma_1 H_t + \sum_{i=1}^{4} \gamma_{2i} D_{it} + \gamma_3 T_t + \sum_{i=1}^{9} \gamma_{4i} E_{it} + \varepsilon_t,$$

where R_t is the rate of return on the relevant index on day t, γ_0 is the regression intercept, D_{it}, i=1..4, are dummy variables for the day of the week, H_t is a dummy variable for days after a non-weekend holiday, T_t is a dummy variable for the first five days of the taxation year, and E_i stands for the possible event effect days. The events occurred during a period of 14,678 trading days, from January 1950 to December 2007, and incorporate 284 aviation disaster event days, 270 transportation disaster (rail, boat, and road accident) event days, and 173 general disaster (mainly fire, explosion, gas leak, and dam and building collapse) event days. The first line of each event reports the regression coefficients, while the second line reports the corresponding t-values (in brackets). One and two asterisks indicate a significance level of 5% and 1%, respectively (a one-tail test in the case of the first and third days).

Index	γ_0	Non-weekend holidays	Mon.	Tues.	Wed.	Thurs.	First 5 days of the tax year	Post aviation disasters			Post transport disasters			Post industrial and miscellaneous disasters			R^2
								1st day	2nd day	3rd day	1st day	2nd day	3rd day	1st day	2nd day	3rd day	F
The NYSE Composite Index (Value-Weighted)	0.0009 (6.13**)	0.0018 (3.06**)	−0.0015 (−6.95**)	−0.0004 (−2.09*)	0.0001 (0.54)	−0.0004 (−2.01*)	0.0009 (1.38)	−0.0018 (−3.60**)	−0.0002 (−0.42)	0.0005 (1.07)	−0.0008 (−1.55)	−0.0002 (−0.39)	0.0001 (0.11)	0.0009 (1.40)	−0.0011 (−1.76)	0.0002 (0.37)	0.008 7.575
The NYSE Composite Index (Equally Weighted)	0.0015 (11.02**)	0.0023 (4.31**)	−0.0024 (−12.54**)	−0.0013 (−6.78**)	−0.0003 (−1.62)	−0.0007 (−3.61**)	0.0045 (7.80**)	−0.0015 (−3.49**)	−0.0004 (−0.88)	0.0002 (0.54)	−0.0008 (−1.71*)	0.0000 (0.04)	−0.0004 (−0.93)	0.0013 (2.34*)	−0.0006 (−1.15)	0.0002 (0.42)	0.022 22.049
The Dow Jones Transportation Index	0.0007 (3.36**)	0.0027 (3.26**)	−0.0020 (−6.60**)	−0.0005 (−1.81)	0.0005 (1.79)	−0.0003 (−0.89)	0.0039 (4.22**)	−0.0019 (−2.80**)	−0.0004 (−0.60)	0.0001 (0.14)	−0.0015 (−2.22*)	−0.0007 (−1.01)	0.0001 (0.12)	0.0016 (1.91)	−0.0013 (−1.56)	0.0002 (0.28)	0.010 9.431

We find that the effect is largest for disasters corresponding to American airline companies, smaller but still highly significant for disasters corresponding to European airline companies, and completely disappears for disasters corresponding to the rest of the world's airline companies. In addition, consistent with the prediction of Baker and Wurgler (2006) that market sentiment has a larger effect on stocks with valuations that are highly subjective and difficult to arbitrage, we find the effect to be larger for small firms, firms with more volatile stocks, and firms belonging to less stable industries.

While it is possible that anxiety induces an increase in the degree of risk aversion, we find that on the event day the implied volatility, as reflected in the VIX and VXO, significantly increases, which may imply that aviation disasters also affect the perceived volatility. The hypothesis that fear and anxiety, rather than real economic factors, affect people's decisions after aviation disasters is supported by the fact that we find no evidence for a change in actual volatility after aviation disasters.

Is there also a flight to safety on event days? Here the results are less clear-cut. Although on event days, on average, the yields on short-term Treasury securities decrease and the U.S. dollar strengthens against other currencies, these two changes are insignificant. It is possible that selling risky assets and investing in various relatively safe assets dilutes this phenomenon; the price of each safe asset changes in the predicted direction, but as there are a variety of relatively safe assets, the change corresponding to each asset is insignificant.

The event effect is significant under various definitions of the event day. However, the empirical evidence shows that the effect is more related to the arrival of detailed and disturbing information to the public attention, than to the arrival of the first news on the event itself. Moreover, the effect corresponding to disasters that occur on U.S. soil begins earlier than the effect corresponding to disasters that occur far away. Similarly, over the last three decades, the effect begins earlier than in the three decades preceding that, probably due to the development of the communication media.

An interesting area for future research is to study whether the market is efficient, namely whether one can obtain abnormal returns by executing an investment strategy based on the findings of this paper. Another possible avenue along this line is to examine the change in the price of options due to the increase in the perceived volatility, and whether a profitable position can be established in the option market when transaction costs are incorporated.

Appendix A

In this Appendix, we compare the aviation disasters' event effect with the effects corresponding to other transport disasters and to industrial and miscellaneous disasters. These disasters share similar characteristics with aviation disasters in terms of economic damage and number of casualties (i.e., disasters with 75 casualties or more); however, they lack some psychological fundamentals related to aviation disasters. The null hypothesis in this case is that the event effect corresponding to these disasters is of the same size as in aviation disasters. The alternative hypothesis is that aviation disasters induce a stronger psychological effect on people; hence, the effect that corresponds to aviation disasters is stronger. The transport disasters' data consist of 270 event days with accidents on land (mainly railroad accidents) and in water (mainly ferries and boats).[31] The general disasters' data consist of 173 industrial and miscellaneous disaster event days. Industrial disasters are mainly mining, oil, and gas facility explosions; miscellaneous disasters are mainly fires and dam and building collapses. Many of these disasters involved hundreds and even thousands of casualties, such as the India Bhopal Industrial Accident where a gas leak killed 2,500 people. For brevity's sake, we report in Table A1 only the results of the main tests, which include all disasters worldwide (i.e., in the case of aviation disasters we include all 288 disasters). The main result is that, other than the first-day coefficient corresponding to aviation disasters, only the first-day coefficient in the case of transport disasters is significantly negative, yet it is smaller in absolute terms and less significant than the coefficient corresponding to aviation disasters. Moreover, unlike the aviation disasters' coefficient, in the transport disasters' coefficient there is a significant increase when employing the Dow Jones Transportation Index. This may imply that in this case the event effect is more company and industry oriented.

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[31] The data on transport, industrial, and miscellaneous disasters are taken from EM-DAT: The OFDA/CRED International Disaster Database—www.emdat.be, Université Catholique de Louvain, Brussels (Belgium). Notably, the number of disasters in the early days is quite small. This could be due to fewer events, as mass transportation has increased dramatically over the last few decades. It could also imply that our sample does not cover all transport disaster events during those years.

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