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Do managers overreact to salient risks? Evidence from hurricane strikes☆

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ABSTRACT

We study how managers respond to hurricane events when their firms are located in the neighborhood of the disaster area. We find that the sudden shock to the perceived liquidity risk leads managers to increase corporate cash holdings and to express more concerns about hurricane risk in 10-Ks/10-Qs, even though the actual risk remains unchanged. Both effects are temporary. Over time, the perceived risk decreases, and the bias disappears. The distortion between perceived and actual risk is large, and the increase in cash is suboptimal. Overall, managerial reaction to hurricanes is consistent with salience theories of choice.

"It is a common experience that the subjective probability of traffic accidents rises temporarily when one sees a car overturned by the side of the road."
A. Tversky and D. Kahneman (1974)

1. Introduction

How do managers assess risk? Most corporate finance decisions involve risk assessment. For example, the first step in capital budgeting is to estimate future cash flows by judging the likelihood of various scenarios for a wide range of variables (e.g., customer demand, production costs, competition, and regulatory changes). The standard assumption is that managers estimate probabilities using all available information. However, prior research in psychology finds that individuals frequently deviate from this assumption (e.g., Tversky and Kahneman, 1973, 1974). This literature shows that individuals use heuristics, i.e.,

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mental shortcuts, for assessing probabilities. In doing so, they save time and effort, but they also make mistakes because their risk assessment ignores part of the information that is available. This paper asks whether firm managers use heuristics and make predictable risk assessment mistakes that may affect corporate policies.

One such heuristic is to infer the frequency of an event from its availability, i.e., the ease with which concrete occurrences of the event come to mind (Tversky and Kahneman, 1973, 1974). As the quote above suggests, the drawback is that availability may be affected by the salience of the event, which is specific to the local context in which the risk is estimated (Bordalo, Gennaioli, and Shleifer, 2012b, 2013).[1] Contextual factors such as emotional affect, novelty, time proximity, or media coverage increase the salience of an event. Because salient events come to mind more easily, people using the availability heuristic will then overestimate their frequency until the local context changes. If firm managers also use this heuristic, they may overreact to salient risk situations. Specifically, we hypothesize that managers' perceived risk *temporarily* increases even though the real risk does not change.

Testing this hypothesis empirically involves two main difficulties. First, the risk perceived by the manager cannot be directly observed. To address this issue, we focus on how managers estimate the risk of a liquidity shock at the firm level, and we use variation in corporate cash holdings to measure how their perception of this risk changes. Given the evidence that corporate cash holdings are used as a buffer against the risk of a liquidity shortage, variation in cash holdings provides a good indication of changes in perceived liquidity risk.[2] Second, testing this hypothesis also requires the identification of a change in a local context affecting the salience of the risk but not the real risk. We address this problem by using hurricanes as a source of liquidity shocks and by focusing on firms that could have been affected by a hurricane but were not because of chance.

Hurricanes are well suited for our purpose for the following reasons. First, the occurrence of a hurricane contains no information about the probability of a hurricane occurring again in the near future. Estimating the marginal increase in the local probability of hurricane landfall in response to the occurrence of a hurricane over the past two years produces a statistically insignificant coefficient that is negative or equal to zero. This result is consistent with the climate literature, which shows that, in the US mainland, hurricane frequency has been mostly stationary since 1850 (e.g., Elsner and Bossak, 2001; Pielke, Landsea, Mayfield, Laver, and Pasch, 2005). Second, their occurrence is exogenous to firm and manager characteristics. As a result, variations in corporate policies observed after a hurricane cannot easily be attributed to unobserved heterogeneity or reverse causality. Third, hurricanes inflict heavy damage to the affected region. As such, they are salient events, not only for firms located in that area but also for firms located in its neighborhood that could have been affected by a similar liquidity shock. Finally, hurricane events permit a difference-in-differences identification strategy because the salience of the danger decreases with distance from the disaster zone. This feature allows us to estimate the effect of risk saliency on perceived risk by comparing how a treatment group of unaffected firms located in the neighborhood of the disaster zone and a control group of distant firms adjust their cash holdings after a disaster.

We document three main findings. First, managers of unaffected firms respond to a hurricane in their proximity by increasing corporate cash holdings. Cash holdings increase by 1.1 percentage points of total assets relative to firms farther away. This effect represents an average increase in cash of $15 million and accounts for 10% of the within-firm standard deviation of cash holdings. Second, this cash increase is temporary. The amount of cash increases during the first four quarters following the disaster and then reverts to pre-hurricane levels over the year. Third, cash increases the first and second time a firm is located in the neighborhood area but not in subsequent occurrences. All three findings are consistent with the availability heuristic theory. The sudden salience of liquidity risk increases perceived risk and leads managers to increase cash holdings even though the real risk does not change. Over time, as salience decreases, both perceived risk and cash holdings revert to pre-hurricane levels. Finally, when the salience of the event decreases because the same event repeats and becomes less unusual, the overreaction is weaker and the increase in cash tends to disappear.

To further document the risk perception channel, we show that managers of firms located in the neighborhood area are also more likely to explicitly mention hurricane risk in subsequent regulatory filings. This effect occurs exactly at the peak of the increase in cash holdings. At this time, the likelihood that hurricane risk is mentioned is 62% higher than the unconditional probability. This effect is also temporary. Two years after the event, the likelihood that these firms mention hurricane risk reverts to the pre-hurricane level. Finally, firms that mention hurricane risk in their 10-Ks/8-Ks/10-Qs also increase cash holdings more. The observed increase in cash is three times larger for this subset of firms. This latter test allows us to include county-year fixed effects, which eliminates any time-varying heterogeneity across counties, including possible fluctuations in local economic activity.

Measuring the distortion between perceived and actual risk is challenging. Ideally, one should compare the manager-assessed probability of future hurricanes with the actual probability. This is not possible because the perceived probability is not observable. Instead, we com-

[1] Our definition of "salience" follows the definition given in the literature. "Salience refers to the phenomenon that when one's attention is differentially directed to one portion of the environment rather than to others, the information contained in that portion will receive disproportionate weighting in subsequent judgments" (Taylor and Thompson, 1982).

[2] Froot, Scharfstein, and Stein (1993) and Holmstrom and Tirole (1998, 2000) provide a theoretical basis for predicting that cash will be used in imperfect financial markets as an insurance mechanism against the risk of liquidity shock. Empirically, several papers document a positive correlation among various possible sources of cash shortfall in the future and the current amount of cash holdings; these studies thus confirm that precautionary motives are central to accumulating cash reserves (e.g., Kim, Mauer, and Sherman, 1998; Opler, Pinkowitz., Stulz, and Williamson, 1999; Almeida, Campello, and Weisbach, 2004; Bates, Kahle, and Stulz, 2009; Acharya, Davydenko, and Strebulaev, 2012).

pare the magnitude of the increase in cash with the actual amount of possible hurricane-induced losses. When a firm is hit by a hurricane (i.e., is located in the disaster zone), its market value drops by $14 million on average. In response to this possible loss, unaffected firms in the neighborhood area increase cash holdings by nearly the same amount despite that the probability of a major hurricane hitting them is only 6%. This comparison suggests that the magnitude of the mistake is economically meaningful.

In the specific context of our study, increasing cash holdings is also costly and inefficient. First, the average return on cash for our sample of treated firms is lower than the risk-free rate, and interest income on cash is taxable. Second, we find that cash holdings increase via retained earnings. Third, using the methodology of Faulkender and Wang (2006), we show that the market value of cash decreases following the hurricane for neighboring firms. The additional cash leads to a lower increase in market capitalization relative to control firms, suggesting that markets see it as wasteful.

We close with a discussion of possible non-behavioral interpretations of our findings. First, cash holdings might increase if the actual probability of a disaster (or the intensity of hurricanes) increases. However, this explanation implies a permanent increase in cash, which we do not find. Cash holdings could also increase if managers ignore the risk and learn about its probability when the hurricane occurs. However, this explanation cannot easily explain why cash holdings return to the pre-hurricane level and why the reversal occurs after 21 months only. If managers completely ignore the risk before the hurricane, cash holdings after the hurricane cannot return to the pre-hurricane level because this level is suboptimal ex post. Indeed, after the hurricane, managers no longer ignore this risk. If managers know the risk but ignore the probability, the learning explanation predicts that they will revise their estimate upward when a disaster occurs and downward when nothing happens. However, for low-probability events, the magnitude of the revision made when nothing happens is small, so cash should revert downward in the aftermath of the disaster but only after many years without hurricanes, which is not what we find.

Second, cash might increase temporarily if firms located in the neighborhood area are in fact indirectly affected via regional spillovers. However, if so, cash should increase after each hurricane, but we find that it does so only the first and second times a firm is located in the neighborhood area. We also test several possible spillover effects and find that they are unlikely to drive our results. For instance, the hurricane may create new business opportunities for firms in the neighborhood area, which would then make more profits and hold more cash. However, this implies a positive change in operating performance (sales or income), which we do not find. The hurricane might also increase local business uncertainty. Neighboring firms may postpone investment and accumulate cash. However, more uncertainty also implies a significant drop in investment or greater cross-sectional variance in revenues that are not in the data. To further alleviate the concern that regional spillovers are driving our results, we perform two additional tests. First, we focus on all US firms vulnerable to hurricane risk, excluding firms located in the affected region and its neighborhood. Those firms may be far from the disaster zone (e.g., firms located on the East coast when a hurricane hits Louisiana). Second, we focus on US firms exposed to earthquake risk and examine how they react to violent earthquakes that occur outside the US. In both cases, regional spillovers are implausible, and yet, cash holdings increase after the disaster.

Our paper contributes first to the behavioral corporate finance literature (see Baker and Wurgler (2012) for a complete survey). In particular, we contribute to the strand of this literature that studies the effects of managers' behavioral biases. Prior research primarily focuses on hubris, overconfidence, and optimism (e.g., Roll, 1986; Malmendier and Tate, 2005, 2008; Landier and Thesmar, 2009) or reference point thinking (Loughran and Ritter, 2002; Baker, Pan, and Wurgler, 2012; Dougal, Engelberg, Parsons, and Van Wesep, 2015). By contrast, research on managers' heuristics remains scarce. Our paper fills this gap by showing that managers are prone to use the availability heuristic to assess risk, which affects firm value by reducing the value of cash.

Next, our paper contributes to the "boom and leniency" literature. Initially propelled by Minksy (1977) and Kindleberger (1978), this literature conjectures that in good times, agents tend to extrapolate the current state of the world as if it would last forever (e.g., Cheng, Raina and Xiong, 2014; Greenwood and Hanson, 2013, 2015; Greenwood and Shleifer, 2014). Prolonged economic booms then lead to over-optimism and risk neglect, which introduces fragility into the financial system and increases the likelihood of a crash (e.g., Gennaioli, Shleifer, and Vishny, 2012). By showing that managers tend to overweight the probability that recent events will further repeat, our paper provides new evidence supporting the premise of this literature.

Because saliency is experienced-based, our paper also adds to a number of papers showing that past experiences affect subsequent risk-taking (Malmendier and Nagel, 2011; Greenwood and Nagel, 2009) and corporate policy choices (Malmendier, Tate, and Yan, 2011; Benmelech and Frydman, 2015; Bernile, Bhagwat, and Rau 2017; Dittmar and Duchin, 2016).[3] While existing evidence is informative about the link between past experiences and policy choices across managers, we still know little about the efficiency of this link. Our finding that salient experiences lead managers to make suboptimal decisions improves our understanding of such efficiency effects. It is also more-direct evidence that experience fluctuation matters because this effect is estimated for the same firm and—more importantly—the same manager.

Finally, our paper contributes to the literature on behavioral biases "in the field." Evidence consistent with the availability heuristic have been documented in lab

[3] Another strand of research examines how salience affects investors' attention. This literature shows that investors pay more attention to salient news (Barber and Odean, 2008), which affects stock prices (Ho and Michaely, 1988; Klibanoff, Lamont, and Wizman, 1998; Huberman and Regev, 2001).

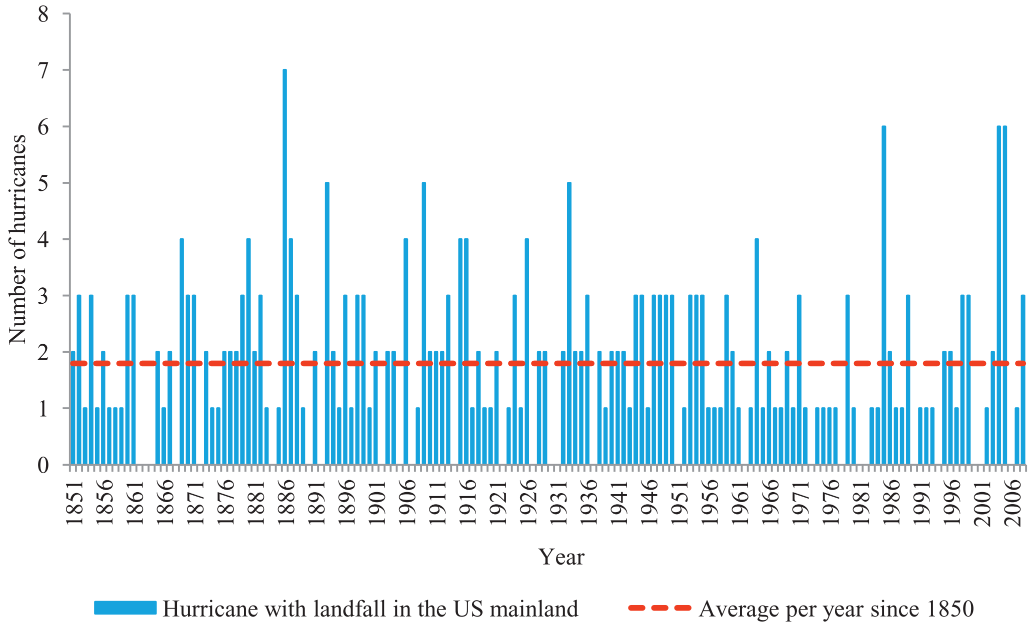

Fig. 1. Annual number of hurricanes with landfall in the US mainland since 1850. This graph presents the total annual number of hurricanes with landfall in the US mainland since 1850. The source of the information is the National Oceanic and Atmospheric Administration (NOAA) Technical Memorandum (Blake, Landsea, and Gibney, 2011).

experiments (Lichtenstein, Slovic, Fischhoff, Layman, and Combs, 1978) or in surveys of insurance retail buyers (Kunreuther, 1978), but not at the level of firm management. A priori, managers may act rationally because they are not uninformed and unsophisticated agents. Market forces should induce managers to behave in a rational manner. Internal procedures, decision committees, and the organizational structure of the firm may also mitigate the effects of top executives' biases. Therefore, whether managers make incorrect financial decisions in the real world because of the availability heuristic remains an open question, and to our knowledge, this paper is the first to empirically show that managers use the availability heuristic and to study its effects.

The paper proceeds as follows. Section 2 summarizes what is known about hurricane risk. Section 3 proposes hypotheses based on the availability heuristic and reviews the related scientific and anecdotal evidence. Section 4 presents our empirical design. Section 5 provides evidence of managers overreacting to salient risks. Section 6 investigates whether this reaction is costly. Section 7 discusses alternative non-behavioral explanations. Section 8 concludes.

2. Hurricane activity on the US mainland

In this section, we summarize what is known about the risk of hurricanes in the US and why it is justified to use such a risk for our experiment. We highlight that hurricane risk can randomly affect an extensive number of firms throughout the US territory, is impossible to predict accurately, and has not changed historically in terms of both volume (frequency) and value (normalized economic cost).

2.1. Event location

Hurricanes can randomly affect a large fraction of the US territory. Coastal regions from Texas to Maine are the main areas at risk. An extensive inland area can also be affected by floods or high winds. In the Spatial Hazard Events and Losses Database for the United States (SHELDUS), 1341 distinct counties (approximately 44% of the total counties in the US) are reported to have been affected at least once by a major hurricane since the 1980s.

2.2. Event frequency

Hurricanes are regular events in the US. Since 1850, an average of two hurricanes have struck the US mainland every year.

Fig. 1 shows no increasing or decreasing trend in this frequency, nor does it suggest the presence of autocorrelation (the Durbin–Watson statistic for the annual series depicted in Fig. 1 is 1.92, which cannot reject the null that hurricane strikes are not serially correlated). This absence of a trend is supported by the climatology literature. Existing studies show that, so far, the distribution of hurricane strikes in the US has been stationary for all hurricanes and major hurricanes at both the country and regional levels (e.g., Elsner and Bossak, 2001; Landsea, 2005; Emanuel, 2005; Pielke, Landsea, Mayfield, Laver, and Pasch, 2005; Landsea, Harper, Hoarau, and Knaff, 2006; Blake, Landsea, and Gibney, 2011).[4] Our own tests (see Section 7) are consistent with this finding. We estimate

[4] See, for instance, Elsner and Bossak (2001, p. 4349): "the distributions of hurricanes during each [time] subinterval are indistinguishable, indicating a stationary record of hurricanes since early industrial times.

an impulse response function to determine how the local probability of hurricane disaster changes over different horizons in response to the occurrence of a hurricane in the region. We find that in the US mainland and over the period of our sample, the occurrence of a hurricane never reveals information about future disaster likelihood.

2.3. Event cost

The total cost of hurricane strikes in terms of economic damages is now larger than it was at the beginning of the past century (Blake, Landsea, and Gibney, 2011). However, after normalizing hurricane-related damage for inflation, coastal population, and wealth, no trend of increasing damage appears in the data (Pielke, 2005; Pielke, Gratz, Landsea, Collins, Saunders, and Musulin, 2008). Pielke, Gratz, Landsea, Collins, Saunders, and Musulin (2008) show that the normalized economic cost of hurricane events in the US has not changed over time, consistent with the absence of trends in hurricane frequency and intensity observed over the last century.[5]

2.4. Event anticipation

Global tropical storm activity partly depends on climatic conditions that are predictable on seasonal time scales. However, the exact time, location, and intensity of future hurricane strikes are “largely determined by weather patterns in place as the hurricane approaches, which are only predictable when the storm is within several days of making landfall.” Therefore, hurricane disasters in the US mainland are uncertain events that are very difficult to anticipate. Such events “can occur whether the season is active or relatively quiet,” and in many instances, they come as a surprise to the local population.[6]

3. The psychological mechanisms for probability evaluation and risk assessment

3.1. Evidence from field surveys and lab experiments

Surveys and lab experiments document systematic risk assessment mistakes, in particular for low-probability events which are "either ignored or over-weighted" (Kahneman and Tversky, 1979). For example, surveys by Kunreuther (1978) show that homeowners in disaster-prone areas usually treat the possibility of earthquake or flood as so unlikely that they ignore their consequences and do not buy insurance. However, when the risk materializes and draws the attention, uninsured homeowners are willing to take insurance for a price that is ten times higher than the normal price.[7] Laboratory studies confirm this finding. Small probabilities are neglected in Slovic, Fischhoff, Lichtenstein, Corrigan, and Combs (1977) but overestimated when the outcome draws the attention in Lichtenstein, Slovic, Fischhoff, Layman, and Combs (1978).

3.2. The availability heuristic

One explanation for this tendency provided by Tversky and Kahneman (1973 , 1974) is that people simplify the task of assessing probabilities by using a heuristic which they call availability. This “availability heuristic” derives from the experience that “frequent events are much easier to recall or imagine than infrequent ones.” Therefore, when judging the probability of an event, most people assess how easy it is to imagine an example of a situation in which this event actually occurred (e.g., one may assess the probability of a car accident by recalling examples of such occurrences among one’s acquaintances). The drawback of this rule is that availability may also be affected by factors that are unrelated to actual frequency. Factors such as the salience of the event, and/or its proximity can affect its availability and generate a discrepancy between perceived and actual risk. When a natural disaster has been recently observed (salience), the availability of a disaster is high and its probability is overestimated. In normal times, however, these infrequent events are less available and their probability is underestimated.

3.3. The effect of salience on choices under risk

Bordalo, Gennaioli, and Shleifer (2012b, 2013) further study the effect of salience on decision making. In their model, decision makers have standard valuation of a lottery’s payoffs, but when evaluating the expected value of the lottery, they replace objective probabilities with “decision weights.” The extent to which these decision weights are distorted depends on the salience of the associated payoffs (i.e., how different the payoff is from the payoffs of the other lotteries). Under these assumptions, decision makers overweight states that draw their attention and neglect the others. In addition, low-probabilities are subject to the greatest distortions because the distortion does not depend on objective probabilities. As a result, unlikely events are overweighted when the associated outcome is salient and underweighted otherwise.[8]

3.4. Implications and hypothesis development

In this paper, we ask whether managers use the availability heuristic and overreact to salient risks (the *availability heuristic* hypothesis). Under this hypothesis, the level of perceived risk by managers is too high when the risk is

Stationarity is found for all hurricanes and major hurricanes as well as for regional activity."

[5] For instance, had the great 1926 Miami hurricane occurred in 2005, it would have been twice as costly as Katrina; thus, “Hurricane Katrina is not outside the range of normalized estimates for past storms.” (Pielke, Gratz, Landsea, Collins, Saunders, and Musulin, 2008, p.38)

[6] Source for quotes is the National Oceanic and Atmospheric Administration (NOAA) website.

[7] Gallagher (2014) also finds that people buy more flood insurance policies in the year following a large regional flood.

[8] Other models based on the mechanism of salience include Bordalo Bordalo, Gennaioli, and Shleifer(2012a, 2013), Gabaix (2014), and Kőszegi and Szeidl (2013). The common assumption is that individuals do not consider all available information before making a decision. Significant judgment errors then occur when the neglected information is relevant.

salient, and too low when it is not. This implies that perceived risk goes up when the salience of the risk increases and down as decision makers' attention is directed toward other salient risks. Temporary changes in perceived risk will then be observed in response to a shock of "salience" even though the real risk does not change. To test this specific prediction, we assume that changes in risk perception can be inferred from variations in corporate cash holdings. Prior research shows that risk management is the main driver of cash holdings policies. When firms have limited access to external financing, cash is used as an insurance mechanism against the risk of a liquidity shock (Froot, Scharfstein, and Stein, 1993; Holstrom and Tirole, 1998 , 2000). In other words, cash holdings offer a buffer against any risk of cash shortage that would prevent firms from financing valuable investment projects.[9] If managers rely on the availability heuristic to assess the risk of an event that would trigger a cash shortage, cash holdings should vary in response to the salience of this event. Under the *availability heuristic* hypothesis, we thus argue that corporate cash holdings will temporarily increase in those situations in which the risk of cash shortage becomes more salient.

4. Empirical design

4.1. Identification strategy

We use both the occurrence of hurricanes and the proximity of the firm to the disaster area to identify situations in which the risk of liquidity shocks becomes salient. Our motivation for the use of hurricanes relies on the following arguments. First, hurricanes can trigger liquidity shocks because of the heavy damage they inflict.[10] Although firms might buy insurance to cover this risk, direct insurance is unlikely to cover the wide variety of indirect losses that may happen. In addition, the insurance market for natural disasters is imperfect.[11] Most firms prefer to self-insure by accumulating cash reserves instead of directly insuring this liquidity risk.[12] Second, the occurrence of hurricanes is a salient event because hurricanes draw people's attention and leave their marks on observers' minds. Third, this saliency effect is magnified by the proximity of the landfall. The hurricane event will typically receive more attention by local firms because this risk is a real concern for them (they were or could have been hit) and because their managers are more likely to be emotionally affected (their relatives or friends could have been injured). Fourth, the occurrence of a hurricane makes hurricane risk salient but does not imply a change in the risk itself in subsequent years. Over our sample period, the occurrence of a hurricane never predicts future hurricane risk (see Section 7). Finally, hurricanes are exogenous events that can randomly affect a large number of firms. A firm's distance from hurricane landfalls thus offers an ideal natural experiment framework to test for the presence of a causal link between event saliency and managers' risk perception through changes in corporate cash holdings.

4.2. Data

We obtain the names, dates, and county locations of the main hurricane landfalls in the US since the early 1960s from the Spatial Hazard Events and Losses Database for the United States (SHELDUS v12) at the University of South Carolina.[13] In SHELDUS, a county is reported as an affected county whenever the hurricane event and the subsequent rainfalls cause monetary or human losses. To ensure that the event is sufficiently salient, we focus on hurricanes with total direct damages (adjusted for inflation) above five billion dollars. We also restrict the list to hurricanes that occurred after 1985 because there are no financial data available from Compustat Quarterly before that date. This selection procedure leaves us with 15 hurricanes between 1989 and 2008.[14] We obtain detailed information about their characteristics from the tropical storm reports available in the archive section of the National Hurricane Center (NHC) website and from the 2011 NOAA Technical Memorandum by Blake, Landsea, and Gibney (2011). Table 1 presents summary statistics for these 15 hurricanes.

We obtain financial data and information about firm headquarters' locations from Compustat Quarterly.[15] We use headquarters rather than plants or clients' locations to identify the location of the firm because our objective is to study managers' risk perception, which requires knowing where the decision makers are. Ideally, we would also like to know where the facilities are to avoid any misclassification problem. For instance, if a firm's headquarters are in the neighborhood area while its plants are in the disaster

[9] Consistent with this argument, many papers document a positive correlation among various possible sources of cash shortfalls for future and current levels of cash holdings (Kim, Mauer, and Sherman, 1998; Opler, Pinkowitz., Stulz, and Williamson, 1999; Almeida, Campello, and Weisbach, 2004; Bates, Kahle, and Stulz, 2009; Acharya, Davydenko, and Strebulaev, 2012). Surveys of managers also confirm this link. Lins, Servaes and Tufano (2010) find that a majority of managers indicate that they use cash holdings for general insurance purposes.

[10] Cash shortages can arise in many ways, including reinvestment needs caused by the partial destruction of operating assets (headquarters, plants, equipment, etc.), a drop in earnings because of a drop in local demand, or new investment financing needs caused by unexpected growth opportunities (reconstruction opportunities, acquisition of a local competitor, etc.).

[11] Froot (2001) shows that hurricane insurance is in short supply because of the market power enjoyed by the small number of catastrophe reinsurers. As a result, insurance premiums are much higher than the value of expected losses.

[12] Garmaise and Moskowitz (2009) provide evidence that inefficiencies in the hurricane insurance market lead to partial coverage of this risk at the firm level.

[13] We have compared the information provided by SHELDUS with other available sources of information about hurricane landfalls in the US. We find that county locations reported in SHELDUS v12 for the 15 hurricanes used in our study are generally accurate, except for Ike 2008. Data location for Hurricane Ike have been hand-collected from the storm report available in the archive section of the National Hurricane Center website and from the disaster declarations available in the Federal Emergency Management Agency (FEMA) website.

[14] Results are the same when using all named hurricane events or when removing the largest hurricanes (e.g., Katrina).

[15] One concern is that Compustat only reports the current county of firms' headquarters. However, Pirinsky and Wang (2006) show that in the period 1992–1997, less than 3% of firms in Compustat changed their headquarter locations.

Table 1
Major hurricane landfalls in the US mainland over the 1987–2011 period.

This table describes the 15 major hurricanes according to total damages (adjusted for inflation) that occurred in the US mainland over the 1987–2011 period. Fatalities is the estimated total number of direct deaths in the US mainland due to the hurricane. Damages is the estimated value of total direct damages due to tropical storms in the US mainland expressed in billions of dollars. Damages (CPI adjusted) is the estimated value of total damages expressed in billions of dollars adjusted for the Consumer Price Index as of 2010. Category measures the wind intensity according to the Saffir and Simpson Hurricane Wind Scale, which ranges from one (lowest intensity) to five (highest intensity). "TS" indicates Tropical Storm. The primary source of information is SHELDUS. Information about Start date, End date, Landfall date, Damages, and Fatalities comes from the tropical storm reports available in the archive section of the National Hurricane Center website. Information about Category comes from the NOAA Technical Memorandum (Blake, Landsea, and Gibney, 2011).

Name	Year	Start date	End date	Landfall date	Fatalities	Damages	Damages (CPI adjusted)	Category
Hugo	1989	10/09/1989	22/09/1989	22/09/1989	21	7.0	12.3	4
Andrew	1992	16/08/1992	28/08/1992	24/08/1992	26	26.5	41.2	5
Opal	1995	27/09/1995	05/10/1995	04/10/1995	9	5.1	7.4	3
Fran	1996	23/08/1996	08/09/1996	06/09/1996	26	4.2	5.8	3
Floyd	1999	07/09/1999	17/09/1999	14/09/1999	56	6.9	9.0	2
Alison	2001	05/06/2001	17/06/2001	05/06/2001	41	9.0	11.1	TS
Isabel	2003	06/09/2003	19/09/2003	18/09/2003	16	5.4	6.4	2
Charley	2004	09/08/2004	14/08/2004	13/08/2004	10	15.1	17.4	4
Frances	2004	25/08/2004	08/09/2004	05/09/2004	7	9.5	11.0	2
Ivan	2004	02/09/2004	24/09/2004	16/09/2004	25	18.8	21.7	3
Jeanne	2004	13/09/2004	28/09/2004	26/09/2004	4	7.7	8.8	3
Katrina	2005	23/08/2005	30/08/2005	25/08/2005	1500	108.0	120.6	3
Rita	2005	18/09/2005	26/09/2005	24/09/2005	7	12.0	13.4	3
Wilma	2005	15/10/2005	25/10/2005	24/10/2005	5	21.0	23.5	3
Ike	2008	01/09/2008	14/09/2008	13/09/2008	20	29.5	29.9	2

zone, this firm will be misclassified as a neighboring firm. Because we do not have access to plant-level information, we follow Chaney, Sraer, and Thesmar (2012) and assume that, on average, plants are located in the same area as a firm's headquarters. This approximation should not affect our conclusions, for the following reasons. First, if neighboring firms have plants in the disaster area, the most likely scenario is that these plants will be little affected by the hurricane because damages are relatively small in the affected counties closest to where the headquarters are. As we will see, most severe damage occurs hundreds of miles away. Second, cash decreases when a firm is affected by a hurricane (see Fig. 3 and Table 3). Therefore, cash should also decrease for neighboring firms whose plants are in the disaster zone, and including those firms (if any) in our treatment group only biases our finding toward the null. Finally, we show that our results remain robust when focusing on distant firms that are less likely to have plants in the disaster area (see Table 10), thereby further mitigating the above misclassification concern.

Quarterly rather than annual data are used to identify changes in cash holdings in firms near hurricane landfalls with the highest possible precision. We restrict our sample to non-financial and non-utility firms. If the fiscal year-end month is not a calendar quarter-end month (i.e., March, June, September, or December), the firm is removed from the sample. We obtain a firm-quarter panel dataset of 11,948 firms over the 1987–2011 period. In Panel A of Table 2, we present statistics for our main variables. All variables are winsorized at the 1st and 99th percentiles and are defined in Appendix B.

4.3. Assignment to treatment and control groups

We measure the degree of salience of each hurricane event according to the distance between the firm's headquarters and the landfall area. For this purpose, we define three different geographic perimeters that correspond to various distances from the landfall area: the *disaster zone*, the *neighborhood* area, and the *rest of the US mainland*. The *disaster zone* includes all counties affected by the hurricane according to the SHELDUS database. The *neighborhood* area is obtained by matching each affected county with its five closest non-affected counties according to geographical distance. [16] We estimate distances across counties using the average latitude and longitude of all the cities in the county. This matching procedure leaves us with a set of matched counties that constitute our neighborhood area and a set of non-matched counties that form the *rest of the US mainland* area. On average, counties from the neighborhood area are 295 miles from the affected counties, 35 miles from the closest affected county, which is typically little affected by the disaster, and 390 miles from the most affected county in terms of damages. Damages are indeed not uniform across affected counties. In SHELDUS, the definition of "affected county" is broad: a county enters the database when monetary or human losses are strictly positive. As a result, many counties in the disaster zone are little affected by the hurricane. In the affected counties adjacent to the neighborhood area, damage per inhabitant is equal to $57 (median $2), i.e., 0.4% (median 0.06%) of the amount observed for the most affected county. Fig. 2 presents the results of this identification procedure on a map for Hurricane Katrina.

[16] We find that, on average, a county has approximately five adjacent counties. Our results remain the same when we use three, four, six, or seven rather than five nearest non-affected counties. We identify the *N*th-nearest neighbors by matching with replacement each affected county with the nearest non-affected counties not already identified as *N*-1th-nearest neighbors.

Table 2
Descriptive statistics.

This table reports firm-level summary statistics. The sample contains 11,948 US firms from Compustat Quarterly over the 1987–2011 period. Panel A reports statistics of the main firm-level variables. Panel B presents average values of the variables for treated and control firms one quarter before the hurricane strike. Treated and control firms are defined according to their headquarter locations. The last column shows the *t*-statistics from a two-sample test for equality of means across treated and control firms. All variables are winsorized at the 1st and 99th percentiles. The variables are defined in Appendix B. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A

	N	Mean	SD	P25	Median	P75
Age	411,490	10.0	7.8	3.8	8.0	14.5
Assets	411,490	1,156	3,716	19	95	510
Cash	411,490	18.0%	22.4%	2.0%	7.8%	26.0%
Debt	409,801	29.8%	34.8%	3.8%	21.8%	41.9%
Dividend	210,680	11.0%	20.7%	0.0%	0.0%	14.4%
Operating margin	397,098	−54.8%	246.6%	−9.1%	4.5%	11.5%
Market-to-book	359,449	2.8	6.7	1.0	1.9	3.5
Investment	384,494	16.3%	65.3%	2.1%	5.1%	11.7%
Net working capital	408,312	49.8%	229.3%	23.2%	63.9%	108.5%
Repurchases	209,049	25.7%	88.8%	0.0%	0.0%	0.4%
Sales growth	371,703	23.8%	73.6%	−6.2%	8.2%	28.2%

Panel B

Firm headquarter location: Group assignment:	Disaster zone Excluded	Neighborhood Treatment	Rest of US Control	*t*-statistic
Age	11.1	11.3	10.3	2.19**
Assets	1316	1308	1135	1.15
Cash	14.5%	18.1%	18.7%	−0.41
Debt	33.0%	30.0%	29.0%	0.96
Dividend	8.4%	8.9%	10.4%	−1.95*
Operating margin	−62.2%	−59.4%	−55.3%	−0.55
Market-to-book	2.90	3.08	2.85	1.34
Investment	21.0%	18.0%	17.0%	0.69
Net working capital	33.1%	42.3%	48.1%	−0.94
Repurchases	28.7%	23.8%	23.6%	0.09
Sales growth	28.8%	23.7%	24.5%	−0.45
N	2,941	3,102	40,087	
N distinct firms	1,959	2,201	9,801	

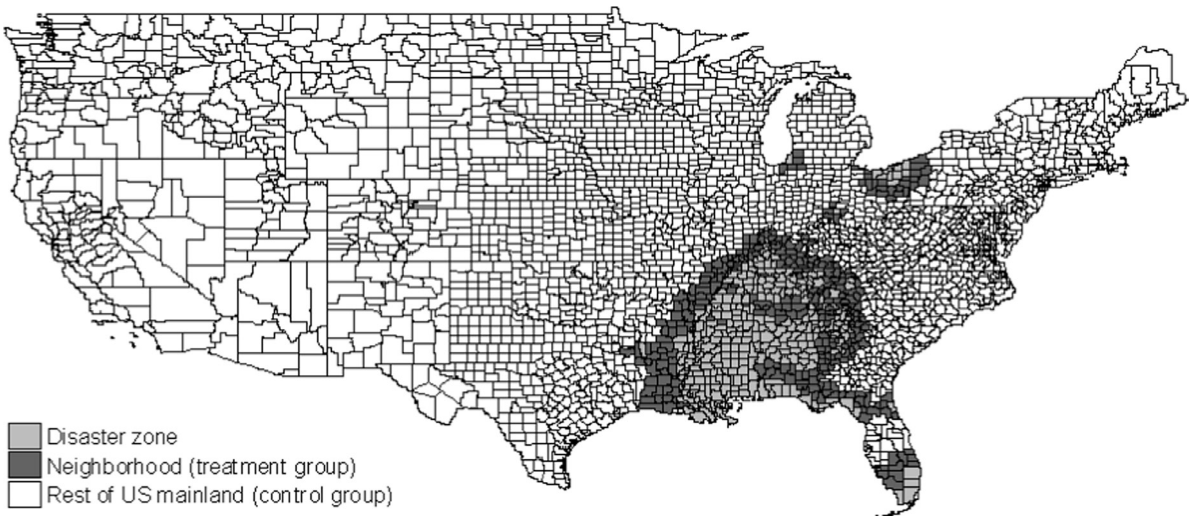

Fig. 2. Identification of neighbors: illustration for Hurricane Katrina (2005). This map presents the result of the matching procedure performed to identify the degree of proximity of each county to the area affected by Hurricane Katrina in 2005. Each county inside the disaster area is matched with replacement with the five nearest counties outside the disaster area according to geographical distance. The geographical distance is computed using the average latitude and longitude of all urban communities in the county. Firms located in the Neighborhood (dark grey counties on the map) are assigned to the treatment group. Firms located in the rest of the US mainland (white counties on the map) are assigned to the control group. Firms located in the disaster zone (light grey counties on the map) are not considered in the analysis.

Firms located in the *neighborhood* area (represented by the dark grey zone on the map) are assigned to the treatment group because the hurricane landfall should be a salient event for the managers of such firms. Given their proximity to the disaster zone, the hurricane is indeed a near-miss event, meaning they could have been affected by the hurricane but were not, by chance. For that reason, we expect the event to draw firm managers' attention. Firms located in the *rest of the US mainland* (the blank zone on the map) are assigned to the control group.[17] Given their distance from the landfall area, the hurricane should not be a salient event for the managers of these firms. Some of these managers may even completely ignore the event if they are located in an area in which the risk of a hurricane strike is of no concern. Firms located in the *disaster zone* (the light grey zone on the map) are separated in our analysis because of the direct effects of the hurricane on their cash levels. For these firms, the disaster is also a potential source of direct cash outflow (e.g., replacement costs of destroyed operating assets) or cash inflow (e.g., receipt of the proceeds of insurance claims). The variation in cash surrounding the hurricane event is thus more likely to reflect the direct effects of the disaster rather than the change in risk perceived by the managers. In practice, we do not remove these firms from our sample. Instead, we control to ensure that the variation in cash holdings we observe when these firms are hit by the hurricane does not influence our results. Panel B of Table 2 presents summary statistics for each group of firms.

The statistics are mean values computed one quarter before a hurricane's occurrence. The last column shows the *t*-statistic from a two-sample test for equality of means across treated and control firms. Treatment firms and control firms are similar along various dimensions, including the amount of cash holdings.[18]

4.4. Methodology

We examine the effect of the hurricane saliency on managers' risk perception through changes in the levels of corporate cash holdings using a difference-in-differences estimation. The basic regression we estimate is

$$Cash_{iyqc} = \alpha_{iq} + \delta_{yq} + \gamma X_{iyqc} + \beta Neighbor_{yqc} + \varepsilon_{iyqc},$$

where i indexes firm, y indexes year, q indexes calendar quarter (1 to 4), c indexes county location, $Cash_{iyqc}$ is the amount of cash as a percentage of total assets at the end of quarter q of year y, α_{iq} are firm-quarter fixed effects (hereafter "firm-season fixed effects"), δ_{yq} are time (i.e., year-quarter) fixed effects, X_{iyqc} are control variables, $Neighbor_{yqc}$ is a dummy variable that equals one if the county location of the firm is in the neighborhood of an area hit by a hurricane over the last 12 months and zero if not, and ε_{iyqc} is the error term we cluster at the county level to account for potential serial correlations.

We use firm-season fixed effects (i.e., four-quarter fixed effects for each firm) because hurricane activity is seasonal. Doing so allows us to control for time-invariant differences among firms *and* across seasons by firm.[19] Time (year-quarter) fixed effects control for differences between time periods. The other variables, X_{iyqc}, systematically include a dummy variable $Disaster\_zone_{yqc}$ to capture the effect of the hurricane when the firm is in the disaster zone. This $Disaster\_zone_{yqc}$ variable enables the comparison of firms in the neighborhood area with firms farther away (the rest of the US mainland) by isolating the changes in cash holdings observed when firms are located in the disaster zone from the rest of our estimation. Our estimate of the effect of hurricane landfall proximity is β, which is our main coefficient of interest. It measures the change in the level of cash holdings after a hurricane event for firms in the neighborhood of the disaster area relative to a control group of more-distant firms.

5. Do managers overreact to salient risks?

5.1. Main results

We examine the effect of the event saliency on the risk perceived by firm managers through differences in corporate cash holdings after a hurricane landfall.

Table 3 reports the effects of being in the neighborhood of a disaster area after a hurricane. Column 1 shows that, on average, neighboring firms increase their cash holdings (as % of total assets) by approximately one percentage point during the four quarters following the hurricane event. This effect represents an average increase in cash holdings of $11 million and accounts for 8% of the within-firm standard deviation. Consistent with the *availability heuristic* hypothesis, managers respond to the sudden salience of danger by increasing their firm cash holdings, although there is no indication that the risk is greater now than it was previously.

We investigate the dynamic of this increase in cash in Column 2. We study the difference in the level of cash holdings between treated and control firms at different points in time before and after hurricane landfall. We do so by replacing the *Neighbor* variable with a set of dummy variables, *Neighbor_q(i)*, that captures the effect of the event saliency at the end of every quarter surrounding the hurricane. The regression coefficient estimated for each dummy variable measures the difference-in-differences in the level of cash holdings i (-i) quarters after (before) the

[17] We have experimented alternative definitions of the control group and find similar results whether control firms are firms located in zero-risk areas only, or distant firms facing the same risk of disaster.

[18] We have examined the relation between the average level of cash holdings across firms and hurricane probability. After controlling for known determinants of cash holdings, we find that firms at risk do not usually hold more cash than the other firms as long as the probability of disaster remains low (i.e. below 10%-15%). This comparison across firms is not evidence of a causal relationship and can reflect other relevant differences. In addition, there might be some fixed costs to adjusting cash reserves, which could explain why firms with low exposure do not hold more cash. Nevertheless, the absence of association between the level of cash holdings and hurricane risk (as long as the risk is low) is consistent with our hypothesis, which predicts that non-salient risks are neglected.

[19] Using firm fixed effects rather than firm-season fixed effects leads to the same results. We follow the procedure proposed by Guimarães and Portugal (2010) to fit models with high-dimensional fixed effects.

Table 3
Hurricane proximity and corporate cash holdings.

This table presents difference-in-differences estimates of the effects of the proximity of a firm to a hurricane strike on the level of corporate cash holdings. *Cash* is the total amount of cash and cash equivalents scaled by the total assets of the firm at the end of the quarter. *Neighbor* is a dummy variable equal to one if the county of the firm headquarters is in the neighborhood of an area hit by a hurricane over the past 12 months. *Disaster zone* is a dummy variable equal to one if the county of the firm headquarters is in an area hit by a hurricane over the past 12 months. *Neighbor_q+i* (*Disaster zone_q+i*) is a dummy equal to one if the county of the firm headquarters at quarter $q+i$ is in the neighborhood of an area (is in an area) hit by a hurricane during quarter $q0$. Standard errors are corrected for clustering of the observations at the county level. *t*-stats are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable: Cash / Assets (in percentage points)				
OLS	[1]		[2]	
	coef.	*t*-stat	coef.	*t*-stat
Neighbor	0.84***	(3.71)		
Disaster zone	−0.29	(−1.33)		
Neighbor_q-4			0.37	(1.32)
Neighbor_q-3			0.01	(0.04)
Neighbor_q-2			0.31	(1.12)
Neighbor_q-1			0.4	(1.25)
Neighbor_q0			0.68**	(2.08)
Neighbor_q+1			0.75**	(2.42)
Neighbor_q+2			1.16***	(4.22)
Neighbor_q+3			1.06***	(3.94)
Neighbor_q+4			0.59**	(1.99)
Neighbor_q+5			0.70**	(2.49)
Neighbor_q+6			0.42*	(1.75)
Neighbor_q+7			0.34	(1.19)
Neighbor_q+8			0.29	(1.03)
Disaster Zone_q-4			−0.2	(−0.76)
Disaster Zone_q-3			0.04	(0.16)
Disaster Zone_q-2			−0.15	(−0.63)
Disaster Zone_q-1			0.04	(0.15)
Disaster Zone_q0			−0.31	(−1.04)
Disaster Zone_q+1			−0.21	(−0.87)
Disaster Zone_q+2			−0.34	(−1.26)
Disaster Zone_q+3			−0.56**	(−2.30)
Disaster Zone_q+4			−0.4	(−1.55)
Disaster Zone_q+5			−0.27	(−1.00)
Disaster Zone_q+6			−0.07	(−0.22)
Disaster Zone_q+7			−0.21	(−0.63)
Disaster Zone_q+8			−0.2	(−0.70)
Firm-season fixed effects	Yes		Yes	
Time fixed effects	Yes		Yes	
N	411,490		411,490	

disaster. We undertake the same procedure for the *Disaster_zone* variable. This approach allows us to identify when the effect starts and how long it lasts.

Column 2 of Table 3 shows that no statistically significant change in cash holdings appears before the hurricane event for firms located in the neighborhood area. The amount of cash begins to increase following the occurrence of the hurricane.[20] This effect increases during the subsequent four quarters, and the increases in cash holdings reach their maximum during $q+2$ and $q+3$. The coefficients for the *Neighbor_q+2* and *Neighbor_q+3* variables show that, on average, firms located in the neighborhood area respond to the salience of the disaster by increasing their cash levels by 1.16% and 1.06% of their total assets (approximately $15 million or 10% of the within-firm standard deviation of *cash*) at the end of the second and third quarters after the hurricane, respectively. The level of cash holdings then begins to decrease, and the effect progressively vanishes over the next three quarters. The coefficient for the *Neighbor_q+8* variable shows that the average difference in cash holdings between firms in the neighborhood area and control firms is indistinguishable from zero two years after the hurricane landfall.

This drop in the amount of cash holdings is consistent with our behavioral interpretation. As time goes by, other pressing needs take center stage, the salience of the event decreases, and the perceived probability of risk retreats to its initial value. Managers then reduce corporate cash holdings.

We plot the result of this analysis in Fig. 3, in which we also display the evolution of the difference in corporate cash holdings between firms located in the disaster zone and the control firms. While firms in the neighborhood area experience a temporary increase in cash holdings, firms hit by the hurricane display a symmetric decrease. This "reversed mirror" trend is notable for two reasons. First, it confirms that the occurrence of a hurricane can trigger a liquidity shock, as firms hit by a hurricane experience a drop of 0.6 percentage points in cash holdings (significant at the 5% level). Second, it suggests that managers' response to hurricane proximity is disproportionate to the real risk. Indeed, the graph demonstrates that the additional amount of cash accrued in the balance sheet (+1.2% of total assets), presumably to insure against the risk of cash shortage after a hurricane strike, exceeds the actual loss of cash (−0.6% of total assets) firms experience when this risk materializes. This finding suggests that the mistake regarding the real risk incurred is economically meaningful. [21]

Assessing the exact magnitude of this mistake is challenging. Ideally, we would like to compare the probability of future hurricane strikes perceived by the manager with the real probability. Because the perceived probability is unobservable, we cannot perform this comparison. However, we can compare the increase in cash holdings by $15 million to the expected losses, i.e., the average incurred losses when a firm is affected by a hurricane weighted by the probability of the event. In an efficient market, the change in market value of an affected firm at the time of landfall can be interpreted as the total economic cost of the disaster. We find that this cost is, on average, $14 million, or 1.03% of the total assets of the firm (see Section 7). Next, we estimate the true probability of being affected by

[20] The positive and statistically significant effect for *Neighbor_q0* does not contradict our interpretation. Indeed, $q0$ is the first balance sheet published after the event and therefore shows the change in cash that occurs in reaction to the hurricane.

[21] This finding is also useful for determining whether managers overreact to the salience of hurricane risk or if, alternatively, they properly take hurricane risk into account only when a disaster occurs and neglect this risk in normal times. Indeed, the magnitude of the increase in cash compared to the magnitude of the loss of cash when the disaster occurs suggests that managers overshoot and increase cash holdings too much, which is more consistent with an overreaction-based explanation.

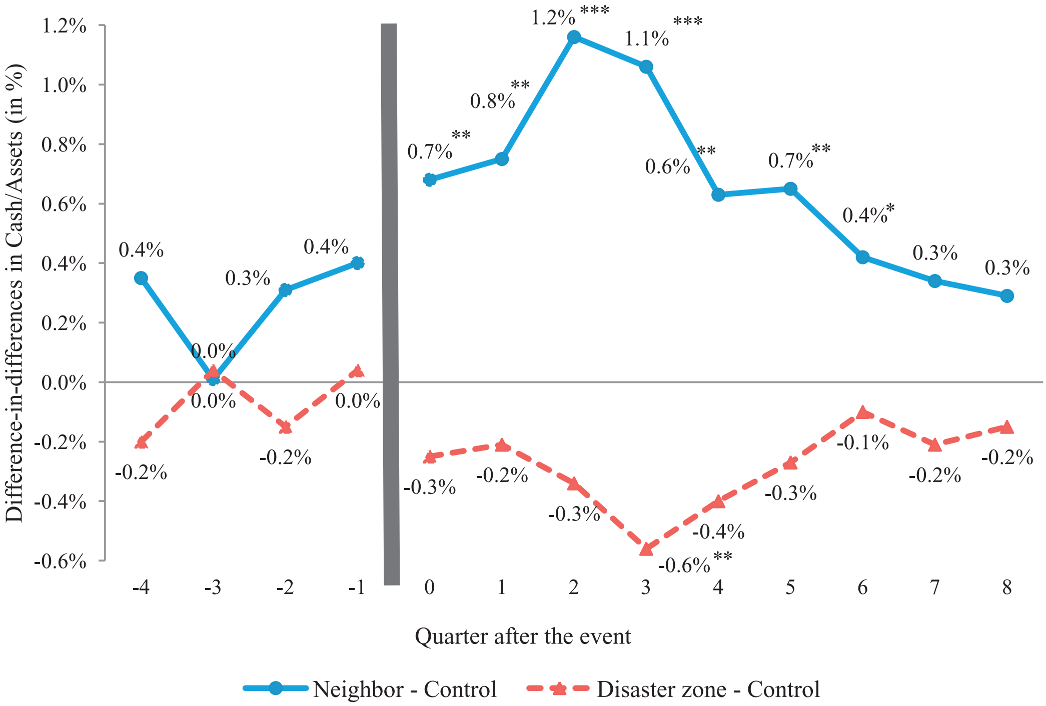

Fig. 3. Hurricane proximity and corporate cash holdings. This graph presents difference-in-differences in the level of corporate cash holdings at different quarters surrounding the hurricane event (quarter *q*0). The solid line plots the difference-in-differences in the level of corporate cash holdings for firms located in the neighborhood area. The dashed line plots the difference-in-differences in the level of corporate cash holdings for firms located in the disaster zone. All difference-in-differences estimates use firms in the Rest of the US Mainland zone as the control group. The graph plots the regression coefficients from Column 2 of Table 3. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The sample contains 11,948 US firms from Compustat Quarterly over the 1987–2011 period.

a hurricane for firms located in the neighborhood area and find that this probability is approximately 6% using hurricanes with damages above five billion dollars, and 9% using all named hurricane events from SHELDUS. Therefore, the real amount of expected losses for firms located in the neighborhood area is only $0.8 to $1.3 million. Under standard insurance utility theory, this means that a manager who learns of the existence of hurricanes and wishes to insure against this risk should pay a maximum premium of approximately one million dollars. If he prefers that the firm self-insure, he may increase cash holdings by a similar amount. Instead, we find that cash increases by $15 million, which corresponds to the maximum insurance premium this manager should pay if the risk were certain. This comparison assumes that losses for firms in the disaster zone and for neighbor firms are similar. This may not be the case. In particular, we may underestimate the amount of incurred losses for neighbor firms. However, even if the cost for firms located in the neighborhood area were twice as large, the amount of the increase in cash would still be greater than the expected loss. Therefore, what this comparison suggests is that the magnitude of the distortion between perceived and actual risk is large.

We have studied whether this reaction varies with firm size and why. Both small and medium-size firms increase cash holdings by an amount similar to the amount of possible losses. For large firms, the reaction is weaker. We find that large firms increase less cash holdings because they are less credit constrained, are less exposed to local markets, and have more collective decision making procedures (measured by the number of occurrences of the word “committee” in 10-Ks/Qs).

5.2. Repetitive hurricane proximity and variation in managers’ responses

Under the *availability heuristic* hypothesis, managers’ responses to the proximity of a hurricane should be lower when the salience of the event decreases. Because “salient” means “whatever is odd, different, or unusual” (Kahneman, 2011), we test whether the increase in cash holdings documented above disappears when the same event is repeated and becomes less unusual. To this end, we create a variable *Occurrence* equal to the number of occurrences a firm has been located in the neighborhood of the disaster area. We also create three dummy variables, denoted *First time, Second time*, and *Third time (and more)* to identify when the county location of a firm’s headquarters has never been located in the neighborhood area, when it has been located once in this area, and when it has been located in this area in multiple instances, respectively.[22] We then estimate the effect of the hurricane proximity conditioned on the number of past occurrences of the same event by interacting all three dummy variables with *Neighbor* as well as with the

[22] A total of 1,377 firms are located multiple times in the neighborhood of an area affected by a hurricane.

firm and time fixed effects. This is achieved by introducing three interaction terms in our baseline specification as well as occurrence-firm fixed effects and occurrence-time fixed effects. The occurrence-firm fixed effects control for differences in cash holdings policies that are independent of the hurricane event.[23] The occurrence-time fixed effects ensure that firms used as a control group are distant firms with the same experience in terms of hurricane proximity.[24] Because we compare firms at different points of their life cycle, we also control for age. We do so by augmenting the specification with age fixed effects (also interacted with *Occurrence*) and by including an interaction term between *Neighbor* and *Age*. Table 4 reports the estimation results.

Column 1 shows that managers significantly increase cash holdings when they are located in the neighborhood area for the first time, i.e., when the event is new and unusual. The second time, managers still respond the same way, but the magnitude of the effect is 10% lower than the increase in cash observed for the first occurrence of the event. When this event repeats, the effect disappears. The coefficient on the interaction between *Neighbor* and *Third time (and more)* is close to zero and is statistically insignificant. Column 2 investigates the robustness of this result when we remove firms that are located in the neighborhood area only once over the sample period. All coefficients remain of the same magnitude, suggesting that our result is not driven by firms for which the proximity of hurricane landfall is exceptional.

Overall, the results of Table 4 are consistent with our availability heuristic hypothesis. When risks are less salient because of the repetition of the same event, the overreaction decreases.[25] These results are also important because they mitigate the concern that our main finding is driven by possible regional spillover effects between the disaster area and the neighborhood area. As further discussed in Section 7, corporate cash holdings may increase temporarily in the neighborhood area because of possible connections between the neighboring firms and the local economy shocked by the disaster. However, this explanation implies that a temporary increase in cash should be consistently observed after each hurricane, which is not what we find.

Table 4
Repetitive hurricane proximity and corporate cash holdings.

This table presents difference-in-differences estimates of the effects of the proximity of a firm to a hurricane strike on the level of corporate cash holdings conditional on the number of past occurrences of a similar situation. *Cash* is the total amount of cash and cash equivalents scaled by the total assets of the firm at the end of the quarter. *Neighbor* is a dummy variable equal to one if the county of the firm headquarters is in the neighborhood of an area hit by a hurricane over the past 12 months. *First time, Second time*, and *Third time (or more)* are dummy variables equal to one if the county of the firm is located in the neighborhood area for the first, second, and third time (or more), respectively. All specifications include *Occurrence* fixed effects, where *Occurrence* is an indicator variable equal to zero if the county location of the firm has never been in the neighborhood area, to one if it has been in this area only once, and two if it has been in the neighborhood area in multiple instances. All other variables are defined in Appendix B. In Column 2, the test is performed on a subsample excluding firms located only once in the neighborhood of an area hit by a hurricane over the sample period. Baseline effects are omitted from the regression when absorbed by (or fully interacted with) the fixed effects. Standard errors are corrected for clustering of the observations at the county level. *t*-stats are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable: Cash / Assets (in percentage points)		
OLS	[1]	[2]
Neighbor × First time	2.11***	2.09*
	(2.57)	(1.94)
Neighbor × Second time	1.88**	1.79
	(2.27)	(1.43)
Neighbor × Third time (and more)	0.04	0.02
	(0.04)	(0.01)
Neighbor × Age	−0.58*	−0.46
	(−1.76)	(−1.06)
Disaster zone	−0.27	−0.01
	(−1.23)	(−0.03)
Occurrence-firm fixed effects	Yes	Yes
Occurrence-time fixed effects	Yes	Yes
Occurrence-age fixed effects	Yes	Yes
Subsample		Yes
N	411,490	336,061
Neighbor × First time − Neighbor × Third time (and more)	2.07	2.07
F-test	6.82***	5.02**

5.3. The risk perception channel

A natural extension of our analysis is to investigate whether the proximity of a firm to a hurricane strike leads managers to express more concerns about hurricane risk. To do so, we perform a textual analysis of all 10-Ks, 10-Qs, and 8-Ks filed by the firms in our sample to detect when hurricane risk is mentioned as a risk factor. We search for expressions such as “hurricane risk”, “hurricane threat”, or “susceptible to hurricanes”, indicating that managers express concerns about the likelihood of this event. Because hurricane risk is often mentioned with a list of other risk factors, we also search for expressions like “such as hurricanes” or “, hurricanes,” (between commas).[26] We find that the risk of hurricane is explicitly mentioned in 3,767 documents filed by 805 distinct firms over the 1997–2011

[23] Results are similar when interacting *Occurrence* with firm-season fixed effects instead of firm fixed effects.

[24] For instance, when we estimate the effect of being in the neighborhood area for the second time, interacting *Occurrence* with time fixed effects allows us to tailor the control group such that control firms are distant firms located in counties that have the same hurricane history (i.e., exactly one treatment in the past) but are not in the neighborhood area a second time.

[25] One limitation of this analysis is that it is silent about how more experienced firms perceive hurricane risk in the absence of hurricane strike. Specifically, our finding that more experienced firms “overreact” less to hurricane proximity does not allow us to determine whether these firms are also less subject to risk neglect in normal times.

[26] The list of exact expressions we search is as follows: “hurricane(s) risk(s)”, “risk(s) of hurricane(s)”, “hurricane(s) threat(s)”, “threat(s) of hurricane(s)”, “threat(s) from hurricane(s)”, “possibility of hurricane(s)”, “hurricane(s) occurrence(s)”, “hurricane(s) likelihood”, “hurricane(s) probability”, “probability of hurricane(s)”, “likelihood of hurricane(s)”, “susceptible to hurricanes”, “prone to hurricanes”, “such as hurricanes”, “, hurricanes (,.))”, “and hurricanes (,.))”, “or hurricanes (,.))”.

Table 5
Hurricane proximity and concerns about hurricane risk.
This table presents difference-in-differences estimates of the effect of the proximity of a hurricane strike on the likelihood that hurricane risk is mentioned in regulatory filings. *Hurricane risk* is a dummy variable equal to one if the risk of hurricane is mentioned at least once in the contents of 10-K/10-Q/8-K filings. *Neighbor* is a dummy variable equal to one if the county of the firm headquarters is in the neighborhood of an area hit by a hurricane over the past 12 months. *Disaster zone* is a dummy variable equal to one if the county of the firm headquarters is in an area hit by a hurricane over the past 12 months. *Neighbor_q+i* (*Disaster zone_q+i*) is a dummy equal to one if the county of the firm headquarters at quarter $q+i$ is in the neighborhood of an area (is in an area) hit by a hurricane during quarter $q0$. All regression coefficients are multiplied by 100 for readability purposes. Standard errors are corrected for clustering of the observations at the county level. t-stats are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable: Hurricane risk				
	[1]		[2]	
Linear probability model	coef.	t-stat	coef.	t-stat
Neighbor	0.46***	(2.94)		
Disaster zone	0.41*	(1.85)		
Neighbor_q-4			−0.03	(−0.14)
Neighbor_q-3			−0.28	(−1.53)
Neighbor_q-2			0.12	(0.49)
Neighbor_q-1			0.26	(1.62)
Neighbor_q0			0.1	(0.61)
Neighbor_q+1			0.35*	(1.65)
Neighbor_q+2			0.81***	(2.78)
Neighbor_q+3			0.53**	(2.16)
Neighbor_q+4			0.05	(0.23)
Neighbor_q+5			0.11	(0.43)
Neighbor_q+6			0.25	(0.70)
Neighbor_q+7			0.14	(0.54)
Neighbor_q+8			−0.21	(−0.92)
Disaster zone_q-4			0.05	(0.20)
Disaster zone_q-3			−0.02	(−0.07)
Disaster zone_q-2			0.24	(0.53)
Disaster zone_q-1			−0.62	(−1.60)
Disaster zone_q0			0.14	(0.62)
Disaster zone_q+1			0.57*	(1.66)
Disaster zone_q+2			1.47**	(1.99)
Disaster zone_q+3			−0.18	(−0.57)
Disaster zone_q+4			0.45	(1.59)
Disaster zone_q+5			0.27	(0.81)
Disaster zone_q+6			1.36**	(2.53)
Disaster zone_q+7			−0.19	(−0.63)
Disaster zone_q+8			0.54	(1.56)
Firm-season fixed effects	Yes		Yes	
Time fixed effects	Yes		Yes	
N	248,092		248,092	

period.[27] We then test whether the proximity of a landfall affects the probability that hurricane risk is discussed by the manager. We use the same specification as in Table 3, where the dependent variable is now a dummy variable (denoted *Hurricane risk*) equal to one if hurricane risk is mentioned and zero if not. The estimation results are reported in Table 5.

Column 1 shows that when firms are located in the neighborhood of the disaster zone, the likelihood that managers mention the risk of hurricanes increases by 0.5 percentage points, i.e., by 38% relative to the unconditional mean of 1.3% for our sample of treated firms. Column 2 shows that the dynamic of this effect is similar to that observed for cash holdings. Nothing happens before the hurricane, and the likelihood that hurricane risk is mentioned increases after the occurrence of the disaster. The peak of the increase occurs again at $q+2$. At this time, the likelihood that hurricane risk is mentioned is 62% higher than the unconditional probability. The documented effect is also temporary. Two years after the disaster, the probability that hurricane risk is mentioned in regulatory filings is the same as before the event. Firms located in the disaster zone also express more concerns about hurricane risk. The coefficients on *Disaster_zone_q+1* and *Disaster_zone_q+2* are both positive, economically large, and statistically significant.

To better compare the dynamic of this effect with the dynamic of the increase in cash holdings, we plot the results of this analysis in Fig. 4, in which we also display the evolution of the difference in corporate cash holdings between neighboring firms and control firms. Fig. 4 shows that both dynamics are similar. In particular, both cash holdings and the likelihood that hurricane risk is mentioned strongly increase in quarters $q+2$ and $q+3$. Because we do not observe cash holdings every month but only at the end of every quarter, identifying when the peak of the increase in cash exactly occurs is difficult. On average, $q+2$ corresponds to the end of the month of April following the year of the hurricane landfall and $q+3$ to the end of July. Such a timing implies that the response to hurricane proximity peaks somewhere between the month of May and the month of July during the calendar year following the occurrence of the shock, which is approximately when the following annual hurricane season begins and becomes active (the North Atlantic hurricane season typically starts in early June). This coincidence suggests that managers may increase cash holdings in expectation of the next hurricane season.

Finally, to further cement the risk perception channel behind the increase in cash, we test whether managers who express more concerns about hurricane risk also increase corporate cash holdings more. We perform this test using a triple-difference approach. That is, we estimate how cash holdings marginally increase for neighboring firms mentioning hurricane risk relative to the other neighboring firms. This is achieved by interacting *Hurricane risk* with *Neighbor* in our baseline specification.[28] Table 6 reports the results.

Column 1 shows that the increase in cash holdings is three times greater when firms mention the risk of hurricane. Column 2 shows that this result is robust to the inclusion of county-time fixed effects. The county-time fixed effects control for changes in local economic conditions by comparing only firms located in the same county at the same time, i.e., firms facing the same type of local supply and demand shocks. Because firms that mention hurricane risk may be smaller firms, younger firms, or firms

[27] The coverage by EDGAR of 10-K/8-K/10-Q filings under electronic format is too sparse before 1997.

[28] To estimate a triple-difference effect, the variable *Hurricane risk* also needs to be interacted with the firm fixed effects and the time fixed effects. Results are similar when interacting with firm-season fixed effects instead of firm fixed effects.

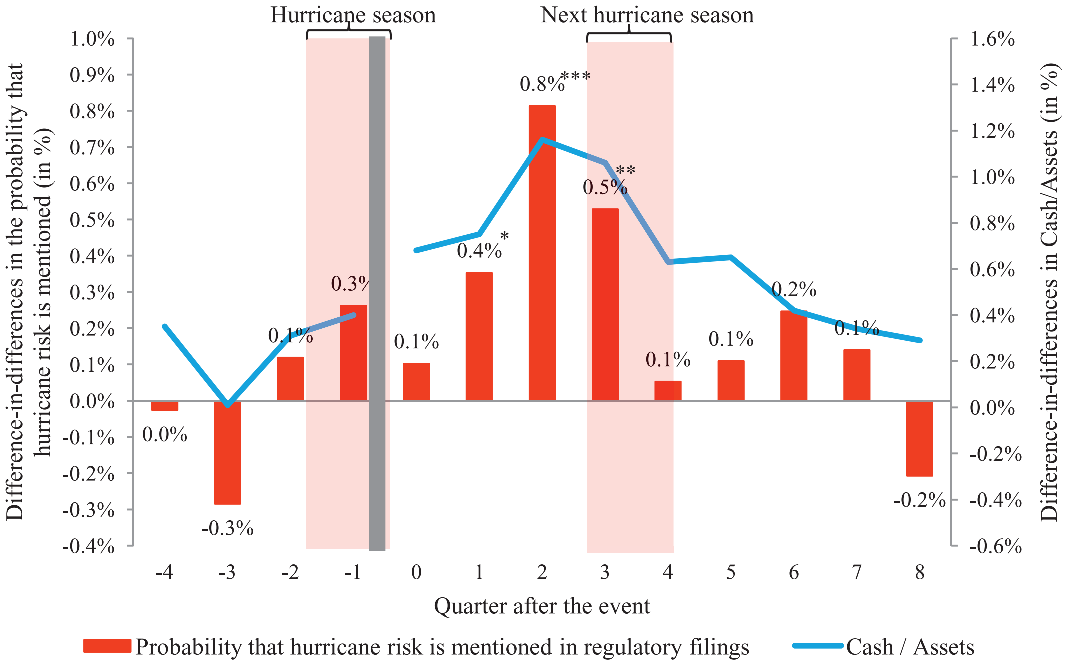

Fig. 4. Hurricane proximity and the likelihood that hurricane risk is mentioned in regulatory filings. This graph compares the effects of the hurricane's proximity on the probability that hurricane risk is explicitly mentioned as a risk factor in regulatory filings with the effects of the hurricane proximity on the level of corporate cash holdings at different quarters surrounding the hurricane event (quarter *q*0). The vertical bars plot the difference-in-differences estimates in the probability that hurricane risk is mentioned in regulatory filings for firms located in the neighborhood area, expressed in percentage points (left-hand-side axis). The line plots the difference-in-differences in the level of corporate cash holdings for firms located in the neighborhood area, expressed in percentage points of total assets (right-hand-side axis). All difference-in-differences estimates use firms in the Rest of the US Mainland zone as the control group. The graph plots the regression coefficients from Column 2 of Table 3 and from Column 2 of Table 5. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The sample contains 11,948 US firms from Compustat Quarterly over the 1987–2011 period.

Table 6

Concerns about hurricane risk and corporate cash holdings after hurricane events.

This table presents triple difference estimates of the effect of the proximity of a hurricane strike on the level of corporate cash holdings when managers express concerns about the risk of hurricane in regulatory filings. *Cash* is the total amount of cash and cash equivalents scaled by the total assets of the firm at the end of the quarter (in percentage points). *Sales growth* is the growth of sales relative to the same quarter of the previous year (in percentage points). *Hurricane risk* is a dummy equal to one if the risk of hurricane is mentioned at least once in the contents of 10-K/10-Q/8-K filings. *Neighbor* is a dummy variable equal to one if the county of the firm headquarters is in the neighborhood of an area hit by a hurricane over the past 12 months. Control variables (interacted with *Hurricane risk*) systematically include *Disaster zone*. In Column 3, control variables also include *Size*, *Age*, and *Market-to-book* (interacted with *Hurricane risk* and *Neighbor*). Baseline effects are omitted from the regression when absorbed by (or fully interacted with) the fixed effects. Standard errors are corrected for clustering of the observations at the county level. *t*-stats are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Cash / Assets (in percentage points)			Sales growth
OLS	[1]	[2]	[3]	[4]
Neighbor × Hurricane risk	1.92*	2.89**	3.10**	−4.71
	(1.65)	(2.13)	(2.09)	(−0.99)
Neighbor	0.74***			1.22
	(3.32)			(0.82)
Hurricane risk × firm fixed effects	Yes	Yes	Yes	Yes
Hurricane risk × time fixed effects	Yes	Yes	Yes	Yes
Controls (interacted)	Yes	Yes	Yes	Yes
County-time fixed effects		Yes	Yes	
N	248,092	248,092	226,571	227,421

with different sets of investment opportunities, we control for size, age, and market-to-book, respectively, in Column 3. The magnitude of the coefficient remains the same. Finally, neighboring firms mentioning hurricane risk may have economic connections with the disaster zone that other neighboring firms do not have. For instance, the disaster may create new business opportunities for these firms, which would explain why they hold more cash. Column 4 reports the result of a placebo test, where the dependent variable is the growth of sales, that rules out this possibility. The test shows that after the hurricane, neighboring firms mentioning hurricane risk do not generate more revenues than the other firms in the same county.

5.4. Robustness and validity check

In this section, we comment on a number of further robustness tests that, for the sake of exposition, are reported in Appendix A.

In Panel A of Table A1, we investigate whether the increase in corporate cash holdings documented above is robust to alternative specifications. First, we use SIC3-time fixed effects to remove trends by industry. Doing so does not alter our estimation (Column 1). The effect also remains when controlling for local economic trends by adding location-state-time fixed effects (Column 2) or when using CEO fixed effects to control for CEO characteristics despite the loss of 80% of our observations after merging our sample with Execucomp (Column 3). Likewise, the inclusion of the usual firm-specific control variables used by the cash literature does not change our finding (Column 4).[29] Finally, we run a placebo test in which we randomly change the dates of hurricanes to ensure that our results are driven by hurricane landfalls only (Column 5).

In Panel B of Table A1, we check that our results on cash over total assets are not driven by a decrease in total assets. The table shows that whatever the specification, the total assets of neighbor firms are never affected by the hurricane proximity.

Finally, we also combine our difference-in-differences approach with a matching approach to further control for possible heterogeneity between treated and control firms. We match on SIC3 industry, size, age, market-to-book, financial leverage, working capital requirements, investment, and dividends.[30] Overall, this analysis leads to the same conclusion as that obtained with the simple difference-in-differences approach: firms located in the neighborhood area temporarily increase their level of cash holdings after the hurricane.

6. Are managers' reactions costly?

Because the liquidity risk remains unchanged, increasing cash holdings may be suboptimal in terms of resource allocation. In this section, we examine whether this reaction is costly for shareholders. First, we note that holding unnecessary extra cash is costly. Second, we analyze the counterparts to this cash increase. Third, we study whether this reaction negatively impacts firm value by reducing the value of cash.

6.1. The direct costs of holding extra cash

As noted by Servaes and Tufano (2006), the cost of holding extra cash is twofold. First, cash return may be lower than the risk-free rate if liquid assets are partly held in non-interest-bearing accounts. Over our sample period, the cash return for neighboring firms is 0.4%, while the average nominal T-bill rate is 4.1%. Hence, increasing cash by \$11 million over a year generates a cost of carry.[31] Second, the interest income on cash is taxable, which generates a loss of tax shield. Therefore, increasing cash, even temporarily, is a costly decision.

6.2. Source of cash

The cash increase observed after the hurricane landfall may come from a variety of sources: an increase in revenues (*Sales growth* variable) and operating profits (*Operating margin* variable), a drop in net working capital requirements (*NWC* variable), a drop in investments (*Investment* variable), a decrease in repurchases (*Repurchases* variable), a reduction of dividends (*Dividend* variable), or an increase in new financing (debt or equity) (*New_financing* variable). Because total assets include the amount of cash holdings, we do not normalize these items by total assets; instead, we use the amount of sales (unless the literature suggests another more-relevant normalization method). Next, we replicate our difference-in-differences analysis and apply our basic specification to each item separately.

In Panel A Table 7, we examine whether hurricanes affect operating activity. Column 1 shows that the occurrence of a hurricane has no effect on revenues for neighboring firms. Column 2 confirms that neighboring firms' operations are truly unaffected. Unlike firms in the disaster zone, they suffer no statistically significant decrease in operating margin.

In the rest of Panel A, we find no evidence that the proximity of the hurricane modifies either the investment activity (Columns 3 and 4) or the financing activity (Column 7). *All* coefficients have the expected sign and go in the direction of an increase in cash, but none is statistically significant. We also find no evidence that neighboring firms reduce the amount of repurchases after the hurricane (Column 5). The sign of the coefficient is negative, but again, it is not statistically significant. However, we find some evidence suggesting that the proximity of the disaster may alter payout policies. Column 6 indicates that firms in the neighborhood area tend to pay lower dividends after the hurricane (the coefficient on *Neighbor* is negative and significant at the 5% level), but the effect is small. On average, the payout ratio decreases by 0.5 percentage points. Therefore, this effect alone cannot explain the increase in cash holdings. One plausible explanation is that managers marginally adjust all sources of cash inflow. This would explain why all other coefficients have the right sign but turn out insignificant.

In Panel B, we use a linear probability model to assess whether hurricane landfalls affect the likelihood of dividend payment, stock repurchases, and new financing issues. In Column 1, we find that the likelihood of dividend payment is lower in the case of hurricane proximity. Similarly, Column 2 indicates a decrease in the probability of a

[29] In line with previous results from the cash literature, we find that small firms with high market-to-book tend to hold more cash. Note that most of these control variables are themselves affected by the hurricane proximity. Therefore, including them in the regression creates an "over-controlling" problem. For this reason, we do not include them in our baseline specification.

[30] See Web Appendix for the results of this analysis as well as a detailed description of our matching procedure.

[31] The aggregate cost for the 3,102 neighboring firms is \$1.3 billion ($3{,}102 \times 11 \times (4.1\%-0.4\%)$).

Table 7
Source of change in cash due to hurricane landfall proximity.
This table presents difference-in-differences estimates of the effect of the proximity of a hurricane strike on various outcome variables that affect the level of corporate cash holdings. *Neighbor* is a dummy variable equal to one if the county of the firm headquarters is in the neighborhood of an area hit by a hurricane over the past 12 months. *Disaster zone* is a dummy variable equal to one if the county of the firm headquarters is in the area hit by a hurricane over the past 12 months. All other variables are defined in Appendix B. In Panel A, all dependent variables are expressed in percentage points. In Panel B, all dependent variables are dummy variables equal to one if the examined outcome is different from zero, and all regression coefficients are multiplied by 100 for readability purposes. Standard errors are corrected for clustering of the observations at the county level. *t*-stats are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A

Dependent variable OLS	Sales growth (%) [1]	Operating margin (%) [2]	NWC (% Sales) [3]	Investment (% PPE) [4]	Dividend (% Earnings) [5]	Repurchase (% Earnings) [6]	New financing (% Mark. cap.) [7]
Neighbor	1.42	−2.9	−1.64	−0.38	−0.54**	−0.24	0.29
	(1.00)	(−1.25)	(−0.79)	(−0.39)	(−1.99)	(−0.16)	(1.18)
Disaster zone	−2.35**	−6.30**	−2.58	0.61	−0.61**	0.1	−0.71**
	(−1.96)	(−1.99)	(−0.75)	(0.65)	(−2.29)	(0.06)	(−2.34)
Firm-season fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	371,703	397,098	408,312	384,494	210,680	209,049	352,257

Panel B

Dependent variable: Linear probability model	Dividend dummy [1]	Repurchases dummy [2]	New financing dummy [3]
Neighbor	−0.66*	−1.17**	0.58
	(−1.67)	(−2.31)	(1.26)
Disaster zone	0.34	0.03	0.39
	(0.62)	(0.05)	(0.81)
Firm-season fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
N	386,532	357,831	389,921

stock repurchase. However, we find no change in the probability of new security issues in Column 3.

Overall, these results suggest that, when located in the neighborhood area, managers increase earnings retention and marginally adjust all other sources of cash inflow.

6.3. Value of cash

We finally investigate whether this change in cash holdings is an efficient decision or a source of value destruction for shareholders. If it is efficient, the increase in cash holdings should translate into a similar increase in value for firm shareholders. If, by contrast, cash would have been better employed otherwise, the additional cash should be discounted and will not result in a similar increase in terms of market capitalization.

In our tests, we follow the literature on the value of cash (e.g., Faulkender and Wang, 2006; Dittmar and Mahrt-Smith, 2007; Denis and Sibilkov, 2010). First, we estimate the value of a marginal dollar of cash (denoted *Change in cash*) over the whole sample using the specification of Faulkender and Wang (2006).[32] Next, we examine how this value changes for neighboring firms relative to control firms by interacting *Change in cash* with *Neighbor*. We also interact the firm and time fixed effects with all explanatory variables to control for both heterogeneity across firms and trends in the value of a marginal dollar of cash.

Column 1 of Table 8 shows that when cash holdings increase by one dollar, market value increases by 72 cents. Column 2 shows that this increase in market value is lower when cash holdings increase because of the proximity of a hurricane strike. The interaction term between *Neighbor* and *Change in cash* indicates that when both neighboring firms and control firms increase cash holdings after a hurricane by one dollar, the increase in market value is lower for firms located in the neighborhood area during the year following the disaster, and this loss of market value relative to control firms is 29 cents.[33] This 40% discount for each extra dollar in cash suggests that shareholders view this extra cash as wasteful, thereby confirming that managers' decision to increase cash holdings is suboptimal.

Overall, these results show that the decision to temporarily hoard cash after hurricanes negatively impacts firm value by reducing the value of cash.

7. Are there any other alternative explanations?

In this section, we discuss alternative explanations to our results, namely, the possibility of "regional spillover," "change in risk," and/or "risk learning." We first examine and test the implications of each alternative interpretation.

[32] We apply one notable adjustment to their specification: we do not use the market adjusted return as a dependent variable. Instead, we use the raw stock return and add time fixed effects as suggested by Gormley and Matsa (2014).

[33] On average, firms in the neighborhood area increase corporate cash holdings by \$11 million, so the loss of market value for their shareholders is \$3.2 million (11 × 0.29).

Table 8
Change in the value of cash after hurricane landfall.

This table presents difference-in-differences estimates of the effect of the proximity of a hurricane on the marginal value of corporate cash holdings. The dependent variable is the change in equity market value over the quarter scaled by equity market value at the beginning of the quarter. *Change in cash* is the change in corporate cash holdings over the quarter scaled by equity market value at the beginning of the quarter. *Neighbor* is a dummy variable equal to one if the county of the firm headquarters is in the neighborhood of an area hit by a hurricane over the past 12 months. *Disaster zone* is a dummy variable equal to one if the county of the firm headquarters is in the area hit by a hurricane over the past 12 months. Column 1 estimates the marginal value of cash over the whole sample using the specification of Faulkender and Wang (2006). Controls include *Change in earnings, Change in interest, Change in dividends, Change in net assets, Change in R&D, Market leverage, New financing*, and *Lagged cash*. As in Faulkender and Wang (2006), all variables are trimmed at the 1% level in each tail. Column 2 estimates how the marginal value of cash changes for firms in the neighborhood area after the hurricane event relative to a control group of more-distant firms. In Column 2, all explanatory variables are interacted with *Neighbor, Disaster zone*, and the firm and time fixed effects. Baseline effects are omitted from the regression when absorbed by (or fully interacted with) the fixed effects. Standard errors are corrected for clustering of the observations at the county level. *t*-stats are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable: Change in market value				
OLS	[1]		[2]	
	Coef.	*t*-stat	Coef.	*t*-stat
Change in cash	0.72***	(34.41)		
Change in cash x Neighbor			−0.29**	(−2.09)
Change in cash x Disaster zone			−0.15	(−1.21)
Controls	Yes			
Time fixed effects	Yes			
Controls (interacted)			Yes	
Time fixed effects (interacted)			Yes	
Firm fixed effects (interacted)			Yes	
N	293,225		293,225	

Next, we perform another experiment based on earthquake risk whose design further alleviates the concern that such alternative explanations are driving our findings.

7.1. The possibility of “regional spillover”

First, cash might increase temporarily because of regional spillovers. Firms in the neighborhood area could be indirectly affected by the hurricane. Such indirect effects may explain why the amount of cash holdings temporarily increases. However, this explanation implies that a neighboring firm’s cash holdings should increase after every occurrence of a hurricane event, which is not what we find in Table 4. Moreover, this explanation assumes that neighboring firms are much more exposed than control firms to the damaged economy because of their location. In reality, however, this exposure is relatively low because damages are small in the affected counties closest to where neighboring firms are. Much of the damage occurs in a few counties that are hundreds of miles away. This context somewhat mitigates the concern that cash increases because of regional spillover effects. To further alleviate this concern, we review the main possible spillover effects and test whether they affect our results.

7.1.1. Higher business and/or investment opportunities

A first spillover effect might arise if the hurricane creates new business or investment opportunities for firms in the neighborhood area. In this case, neighboring firms may temporarily hold more cash because they make more profits or because they plan to invest in the disaster zone.[34] Under this interpretation, firms located in the neighborhood area should perform better and invest more after the disaster. However, none of our findings in Table 7 are consistent with such predictions. We find no evidence that the proximity of the hurricane positively impacts either growth in terms of revenue or operating income. In addition, we do not find that neighboring firms invest more after the hurricane. We have further investigated how the hurricane affects the growth of sales for neighboring firms at every quarter surrounding the disaster. Fig. 5 illustrates the main outcome of this analysis. [35]

The graph shows that growth in revenues for neighboring firms does not increase significantly relative to the control group after the hurricane. Therefore, and unlike firms in the disaster zone, firms in the neighborhood area are, on average, truly unaffected. The study of the market reaction to the hurricane landfall also supports this conclusion.

The results of this event study are reported in Table 9. For each group of firms (disaster area, neighborhood area, rest of US mainland), we estimate the average cumulated abnormal return of the stock price over the hurricane event period.[36] Unsurprisingly, we find a negative abnormal return for firms in the disaster zone. However, we find no reaction for neighboring firms, which suggests that investors perceive that there are no benefits (new business and/or investment opportunities) from the proximity of the disaster.

7.1.2. Higher business uncertainty

Another concern is that the hurricane increases local business uncertainty. In this case, managers may decide to stop or postpone their investment projects. Neighboring firms would then temporarily hold more cash. However, this explanation implies that firms in the neighborhood area significantly reduce their investments, which is not what we find in Table 7. We have also tested whether the proximity of the disaster had an impact on revenue or stock return volatility. We find that the variance in sales growth within firms does not increase after the hurricane for neighboring firms. The variance of sales growth across firms in the same neighboring county is also unaffected, i.e., revenue volatility by county does not increase. Finally,

[34] For instance, a firm operating in the building materials industry and located in the neighborhood area may face a significant increase in demand caused by new housing and reconstruction needs in the disaster zone. This firm may then temporarily have more revenues and hold more cash. Alternatively, this firm might take advantage of the difficulties faced by local competitors to invest in the disaster zone. In this case, such a firm could accumulate cash temporarily to seize new investment opportunities and would ultimately generate higher revenues.

[35] The graph plots the coefficients of a regression similar to the regression in Table 3 Column 2, where the dependent variable is the growth of sales relative to the same quarter of the previous year (see Web Appendix).

[36] See Web Appendix for a detailed description of our event study methodology.

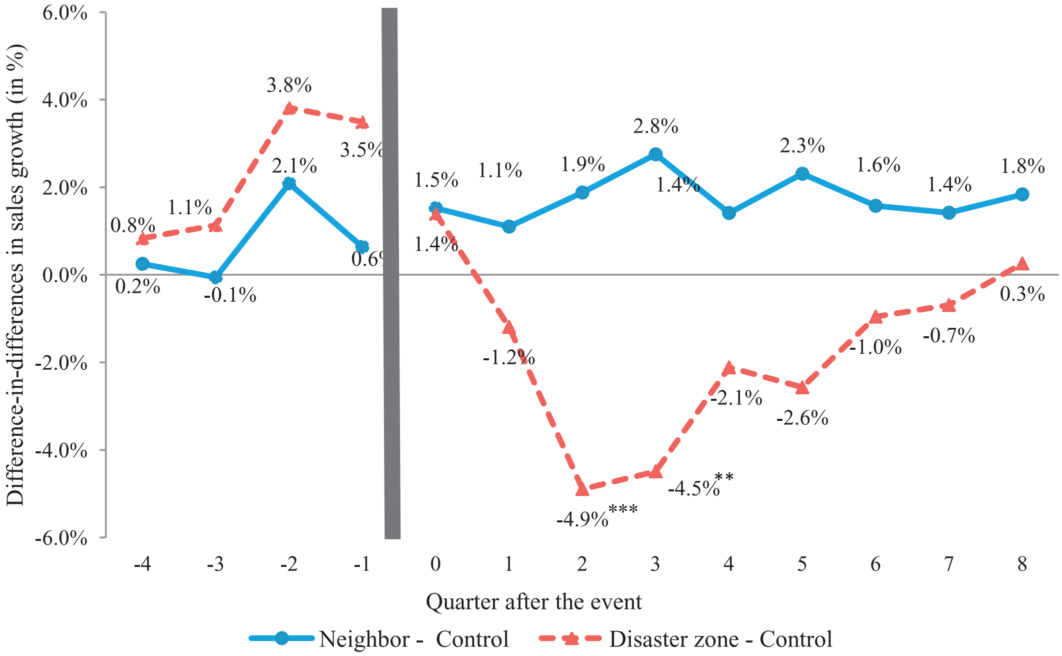

Fig. 5. Hurricane proximity and sales growth. This graph presents difference-in-differences in sales growth at different quarters surrounding the hurricane event (quarter $q0$). The growth in sales is the growth in total revenues relative to the same quarter of the previous year. The solid line plots the difference-in-differences in sales growth for firms located in the neighborhood area. The dashed line plots the difference-in-differences in sales growth for firms located in the disaster zone. All difference-in-differences estimates use firms in the Rest of the US Mainland zone as the control group. The graph plots the regression coefficients from Table B reported in Web Appendix. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The sample contains 11,948 US firms from Compustat Quarterly over the 1987–2011 period.

Table 9
Market reaction at hurricane landfall.

This table presents the average cumulative abnormal stock return (ACAR) over the hurricane landfall period (hereafter, the "event window") depending on the proximity of the firm's headquarters to the disaster area. For each hurricane, firms are assigned to the Disaster zone group, the Neighbor group, or the Control group depending on the location of their headquarters. The event windows start one day before the beginning of the hurricane strike and end one day after the end of the hurricane strike. For each group of firms, ACAR and z-statistics are estimated using equally weighted portfolios of firms with similar event windows. See Web Appendix for the details of the abnormal return estimation. The economic gain is the implicit average change in market value corresponding to the ACAR expressed as a percentage of total assets. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Group	N (firms)	N (portfolios)	ACAR (%)	Z	Economic gain (% of assets)
Neighbor	2583	15	−0.04	(−0.16)	−0.10
Disaster zone	1991	74	−0.82**	(−2.23)	−1.03
Control (Rest of US)	30,350	15	−0.08	(−0.56)	−0.11

we observe no increase in stock return volatility, suggesting that investors do not perceive higher uncertainty after the hurricane.

7.1.3. Higher financing constraints

Other regional spillover effects include the possibility that the hurricane hurts the lending capacity of banks. If bank customers withdraw their deposits after the hurricane, banks located in the disaster zone and/or the neighborhood area may no longer be able to finance the local economy. Neighboring firms might anticipate that banks will be constrained after the shock and may decide to hold more cash as a precaution. Under this explanation, the amount of new credit at the bank level should decrease after the hurricane. We have tested this prediction and find the opposite result (see Web Appendix). The amount of new commercial and industrial loans increases after the hurricane for banks located in the disaster zone and for banks located in the neighborhood area relative to other banks. This result casts doubts on the possibility that the hurricane damages the entire local bank lending capacity. It is also consistent with our finding in Table 7 that the proximity of the hurricane does not negatively affect the probability of issuing new financing.

Table 10
Hurricane strike and firms operating outside the neighborhood area.

This table presents difference-in-differences estimates of the effect of the occurrence of a hurricane strike on the level of corporate cash holdings focusing on firms whose operations are less dependent on the local economy affected by the hurricane. *Cash* is the total amount of cash and cash equivalents expressed in percentage points of the total assets of the firm at the end of the quarter. *Neighbor* is a dummy variable equal to one if the county of the firm headquarters is in the neighborhood of an area hit by a hurricane over the past 12 months. *Disaster zone* is a dummy variable equal to one if the county of the firm headquarters is in the area hit by a hurricane over the past 12 months. In Column 1, we restrict the sample to firms that do not have significant connections (main provider or customer) with the disaster zone. In Column 2, *Remote neighbor* is a dummy variable equal to one if the county of the firm headquarters is in the remote neighborhood of an area hit by a hurricane over the past 12 months (i.e., the neighbors of neighbors). In Column 3, *Vulnerable* is a dummy variable equal to one if a hurricane occurred during the past 12 months, if the firm is vulnerable to the risk of hurricane disaster, and if the headquarters of the firm are neither located in the disaster area nor in the neighborhood area. Standard errors corrected for clustering of the observations at the county level. *t*-stat are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable: Cash / Assets (in percentage points)			
Effect of hurricane strike for OLS	Unconnected firms [1]	Remote neighbors [2]	Vulnerable firms outside the neighborhood area [3]
Remote neighbor		0.48*	
		(1.85)	
Vulnerable			0.66**
			(2.10)
Neighbor	0.90***	0.71***	0.89***
	(3.68)	(2.76)	(3.86)
Disaster zone	−0.25	−0.29	−0.20
	(−1.09)	(−1.34)	(−0.82)
Firm-season fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Subsample	Yes	No	No
N	392,734	411,490	411,490

A similar concern is that the hurricane hurts local insurance companies and generates insurance rationing (Froot and O'Connell, 1999; Froot, 2001). Neighboring firms may react to increased insurance costs by reducing their level of insurance and by increasing their level of cash instead. After some time, insurance premia return to normal levels. Firms then insure again and decrease their cash holdings accordingly. However, at least two of our findings are difficult to reconcile with this explanation. First, cash holdings increase over a one-year period, whereas Froot and O'Connell (1999) show that insurance prices tend to rise over a three-year period. Second, under the insurance-based explanation, the increase in cash should be concentrated on firms that depend on insurance companies to insure their business. By contrast, firms that self-insure should react less. The data do not support this prediction. Firms with many intangible assets that are more likely to self-insure react more (see Web Appendix).

7.1.4. Other forms of regional spillover effects

Because other forms of spillover effects might affect our results, we conduct another series of tests in which we focus on firms that are less exposed to the local economy shocked by the disaster and for which any increase in cash holdings is less likely to be driven by regional spillover effects. The results of these tests are reported in Table 10.

In Column 1, we re-run our main test focusing on firms that do not have business ties with other firms potentially affected by the hurricane. Using Compustat Customer Segment, we identify neighboring firms with their main customer/supplier in the disaster area. Excluding these firms does not change our main result.

In Column 2, we examine the effect of the disaster on "the neighbors of neighbors." We extend our definition of neighborhood counties to the ten nearest adjacent counties and assign firms to a "Remote neighbor" group if their headquarters are located in the ten, but not the five, closest unaffected counties. On average, firms identified as "Remote neighbors" are 80 miles from the closest affected county. Given the distance, these firms should be less affected by regional spillovers. However, Column 2 indicates that they also increase cash holdings after the hurricane.

In Column 3, we focus on all firms vulnerable to hurricane risk in the US (excluding firms in the neighborhood of the affected region). Those firms may be far from the disaster zone (e.g., firms located on the East coast when a hurricane hits Louisiana). We define a firm as vulnerable to hurricane risk if it has been strongly affected once by a hurricane during the sample period.[37] We create a

[37] To detect these firms, we look for abnormal drops in revenues after a hurricane landfall. First, we define the "normal" sales growth as the pre-

Table 11
Determinants of disaster likelihood.
This table presents impulse response functions to the proximity of a disaster. Impulse response functions are functions of time that evaluate how the marginal probability of being struck by a hurricane changes every quarter (year) in response to the occurrence of a hurricane in the neighborhood area at some point in time. The analysis is performed at the county level by quarter (Columns 1 to 4 and 7 to 10) and at the county level by year (Columns 5 to 6 and 11 to 12). The dependent variable is a dummy equal to one if the county is hit by a hurricane (only one of the 15 major hurricanes from Table 1 in Columns 1 to 6 and any hurricane in Columns 7 to 12). *Neighbor – Qi* is a dummy equal to one if the county was in the neighborhood of an area hit by a hurricane *i* quarter(s) ago. *Neighbor –Year$_i$* is a dummy equal to one if the county was in the neighborhood of an area hit by a hurricane *i* year(s) ago. Standard errors are clustered at the county level. *t*-stats are reported between parentheses. All specifications include county-season fixed effects to control for seasonality within the year. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable: Hit											
	Major 15 hurricanes only						All hurricanes					
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Neighbor -Q1	0.0057						0.0047					
	(1.01)						(0.91)					
Neighbor -Q2		−0.0001						0.0026				
		(−0.75)						(0.66)				
Neighbor -Q3			−0.0005						0.0029			
			(−1.22)						(1.15)			
Neighbor -Q4				−0.0042						−0.0018		
				(−0.70)						(−0.36)		
Neighbor -Year 1					−0.0009						0.001	
					(−0.41)						(0.49)	
Neighbor - Year 2						−0.0016						−0.0033
						(−0.52)						(−1.51)
County-season fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	154,656	154,656	154,656	154,656	154,656	154,656	154,656	154,656	154,656	154,656	154,656	154,656

dummy variable *Vulnerable* that is equal to one if (i) the firm is identified as vulnerable to hurricane risk, (ii) the firm is neither in the disaster area nor in the neighborhood area, and (iii) a hurricane made landfall over the past 12 months. We obtain a group of 614 "vulnerable firms" whose average distance from the disaster zone is 444 miles. Such a distance makes the regional spillover explanation implausible. However, these firms also increase cash holdings after the hurricane.

Overall, these results suggest that while some regional spillover effects may possibly affect neighboring firms, these effects cannot be the main explanation for our primary finding.

7.2. The possibility of a "change in risk"

Cash might also increase if the real probability of being struck by a hurricane increases. However, this explanation would imply a permanent increase in cash, which we do not find. To be consistent with a "change in risk" interpretation, the increase in risk must be temporary.

Such a temporary increase in risk might occur if hurricane strikes cluster within certain geographic areas during a one- or two-year period. The proximity of a hurricane could then indicate that the probability of being hit by a hurricane in the coming year is now higher. We are unaware of any clear evidence of such a clustering phenomenon in the climate literature. Nevertheless, we assess this possibility by testing whether the probability of being hit by a hurricane depends on the geographical location of past hurricane strikes. Specifically, we estimate an impulse response function to the proximity of a disaster that evaluates for different horizons how the probability of being struck changes when the county was previously located in the neighborhood of an affected area. We follow Jorda (2005) and proceed sequentially. We estimate the following model for every horizon h:

$$Hit_{c,t} = \alpha_c + \alpha_t + \beta\ Neighbor_{c,t-h} + \varepsilon_{c,t},$$

where c indexes county, t indexes time, and h is the horizon. *Hit* is a dummy variable equal to one if a hurricane makes landfall in county c at time t. α_c are county-season fixed effects, and α_t are time fixed effects. β estimates how the probability of county c to be hit by a hurricane at time t changes in response to the proximity of a hurricane at time $t-h$ (i.e., h quarter(s) or h year(s) ago). We report the results in Table 11.

In Columns 1 to 4, we estimate the impulse response function per quarter using the 15 major hurricanes of our study. *Neighbor – Qh* is a dummy variable equal to one if the county was located in the neighborhood area h quarters ago. The coefficient is close to zero and is never statistically significant, whatever the horizon is. In Columns 5 to 6, we repeat the same analysis by year. The coefficient on the variable *Neighbor – Year*1 is negative and statistically insignificant, which means the proximity of a hurricane contains no information about the likelihood of hurricane strike for the following year. Likewise, the oc-

dicted sales growth from our baseline specification, where the dependent variable is the growth of sales relative to the same quarter of the previous year. Next, we calculate the difference between actual and predicted sales growth. A firm is vulnerable if it is in the disaster zone and the abnormal sales growth is below the median of all observed negative abnormal sales growth.

currence of a disaster in the neighborhood area two years before has no predictive power on the likelihood of being affected by a hurricane in a given year. Columns 7 to 12 show similar results when we repeat the same analysis using all hurricanes from the SHELDUS database. Whatever the time horizon is, the occurrence of a hurricane never reveals information about future disaster likelihood in the neighboring counties.

7.3. The possibility of "risk learning"

Finally, cash holdings might increase if managers ignore or underestimate the risk before the occurrence of the hurricane and learn about its true probability after the disaster. However, this explanation cannot easily explain why cash holdings return to the pre-hurricane level and why the reversal occurs only after 21 months. If managers completely ignore the risk before the hurricane, then cash holdings after the hurricane cannot return to the pre-hurricane level because this level is suboptimal ex post. Indeed, after the hurricane, managers no longer ignore this risk. If managers know the risk but ignore the probability, then the learning explanation predicts that they will revise their estimate upward when a disaster occurs and downward when nothing happens. However, for low-probability events, the magnitude of the revision made when nothing happens is small, so cash will revert down in the aftermath of the disaster, but only after a long period without hurricanes.

To illustrate this, let us consider that the number of hurricanes follows a continuous time process N_t with constant probability $\lambda = 6\%$, where 6% is the actual unobserved probability of disaster. Before the shock, the prior of the manager is that, on average, the likelihood of a hurricane is 6% with variance 0.03^2. Every year, managers update both the probability and the variance depending on whether a hurricane is observed ($dN_t = 1$) or not ($dN_t = 0$). Immediately after a hurricane, the updated probability is approximately $6\% + (3\%^2/6\%) = 7.5\%$.[38] The variance is also updated, and the new estimate is lower than the previous one because the precision of the estimation increases over time. The following year, no hurricane occurs, and the probability is updated downward. Assuming that the variance is lower but still very close to 0.03^2, the updated probability is approximately $7.5\% - 3\%^2 = 7.41\%$. After a year without a hurricane, the estimated probability reverts down by only 6% (i.e., $(7.5\% - 7.41\%)/(7.5\% - 6\%)$). Note that this is a conservative estimate because of our assumption that the estimated variance remains unchanged. If we make the same conservative assumption for the subsequent years, the learning interpretation predicts that cash holdings should revert down by half after 8.3 consecutive years without a hurricane in the region. Instead, we find that it fully reverts after 21 months.

Another learning interpretation is that managers learn about the economic consequences of the disaster. However, the total cost of hurricanes has been increasing over time, so this explanation also implies a permanent increase in cash. Moreover, while the absence of hurricanes reveals information about the probability of a disaster, it provides no information about its cost. Therefore, this explanation does not easily explain why we observe a decrease in cash when no more hurricanes occur in the region.

Finally, it is difficult to reconcile any learning explanation with our results regarding the value of cash. If managers learn the true probability (or the true cost) of suffering a liquidity shock and increase their cash holdings accordingly, investors should value this decision positively and should not discount the additional cash in the balance sheet.

7.4. Reaction to extreme earthquakes outside the US

To alleviate even further the concern that our results are driven by a non-behavioral explanation, we perform one final experiment based on earthquake risk rather than hurricane risk. We test the validity of the *availability heuristic* hypothesis by looking at US firms whose headquarters are located in urban communities in which earthquakes are frequently felt. We then focus on the announcement of extremely violent (and therefore salient) earthquakes outside the US and examine whether these firms respond to such announcements by changing their cash holdings. Finding an increase in cash holdings would be consistent with our hypothesis while allowing to rule out other explanations. It would neither be consistent with the *change in risk* hypothesis nor with the *risk-learning* hypothesis because the occurrence of an earthquake outside the US provides no information about earthquake risk in US territory. It would also be inconsistent with the *regional spillover* hypothesis because of the distance to the disaster area. We obtain information about the level of intensity felt by zip code address for each earthquake from the "*Did you feel it?*" surveys. For each zip code, we compute the average earthquake intensity felt over the past 20 years. We assign this average earthquake intensity felt to each firm using the zip code of the headquarters' address. We then assign firms within the top 10% of the average intensity felt distribution to the treatment group. All other firms are assigned to the control group. Next, we focus on the strongest earthquakes that have occurred outside the US in the past 30 years according to descriptions of magnitude, total deaths, and total damage.[39] These selection criteria lead to the list of 11 major non-US earthquakes described in the Web Appendix. We then estimate the average change in cash holdings for the treatment group around the announcement of the earthquake outside the US using the same matching methodology as that used for hurricanes and described in our Web Appendix. The results of this analysis are depicted in the graph of Fig. 6.[40]

[38] In continuous time, the revision of the estimated probability $\hat{\lambda}$ is $d\widehat{\lambda}_t = \frac{Var(\lambda_t/N_t)}{\widehat{\lambda}_t}\,(dN_t - \widehat{\lambda}_t dt)$ if λ is constant.

[39] We obtain this information from the Significant Earthquake Database. National Geophysical Data Center/World Data Center (NGDC/WDC) Significant Earthquake Database, Boulder, CO, USA.

[40] See Web Appendix for a detailed description of our methodology and the results obtained.

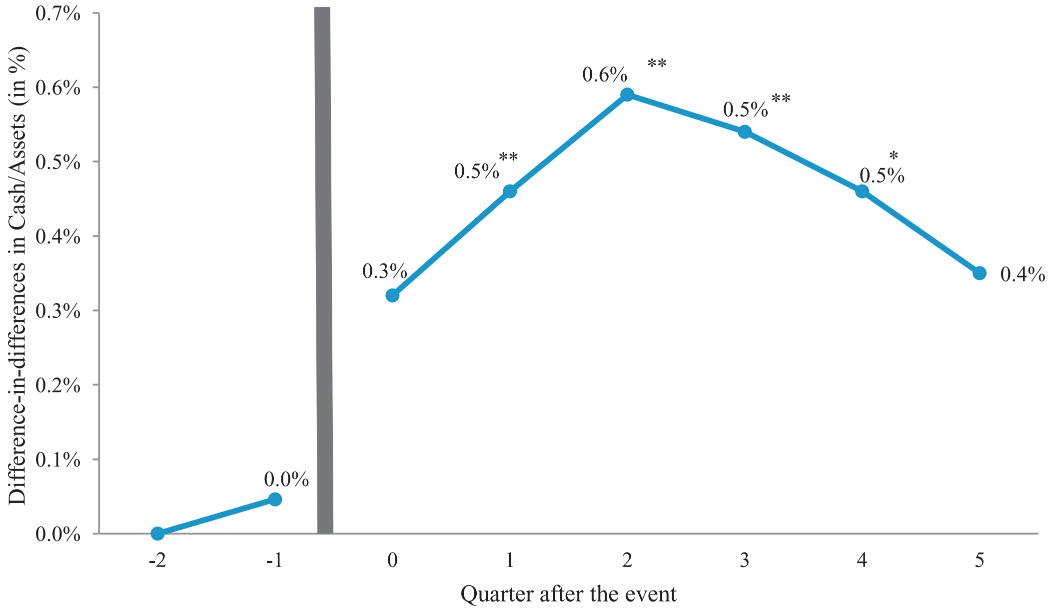

Fig. 6. Effects of earthquakes outside the US on corporate cash holdings of US firms. This graph presents difference-in-differences in the level of corporate cash holdings at different quarters surrounding the announcement of a violent earthquake outside the US (quarter $q0$) for a sample of US firms located in a seismic area. This sample comprises 1,191 distinct treated firms whose headquarters are located in an urban community where an earthquake is frequently felt according to the U.S. Geological Survey agency ("Seismic zone firms"). For each treated firm, the counterfactual outcome is the weighted average of the change in the level of cash holdings relative to $q-2$ over all control firms with the same SIC 3 code ("Matched firm"). The weighting is achieved through a kernel function so that the control firms that are closer in terms of Mahalanobis distance to the treated firm receive greater weight. The Mahalanobis distance is computed at quarter $q-2$ (i.e., three months before the earthquake occurrence) along four dimensions: size, age, market-to-book, and financial leverage. The graph plots the estimates from Table E reported in Web Appendix. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Fig. 6 shows qualitatively the same pattern as that previously observed. Firms located in seismic areas respond to the sudden salience of earthquake risk by temporarily increasing the level of cash holdings compared to firms located outside a seismic zone.

8. Conclusions

This paper provides empirical evidence that managers exhibit biases when assessing risk. We show that managers respond to near-miss liquidity shocks by temporarily increasing the amount of corporate cash holdings and expressing more concerns about this type of liquidity shock in regulatory filings. Such a reaction cannot easily be reconciled with the standard Bayesian theory of judgment under uncertainty because the liquidity shock stems from a hurricane landfall whose probability of reoccurrence is not higher after the shock. Instead, this reaction is consistent with salience theories of choice (Tversky and Kahneman, 1973, 1974; Bordalo, Gennaioli, and Shleifer, 2012a, 2012b, 2013) that predict that the temporary salience of the danger leads managers to reevaluate their representation of risk and place excessive weight on its probability. We also show that this mistake is costly and inefficient. More importantly, we provide evidence suggesting that the magnitude of this mistake is meaningful. While the economic cost of temporarily increasing cash holdings is modest, the amount of additional cash accrued in the balance sheet relative to the real amount of expected losses is large, suggesting that the distortion between perceived and actual risk induced by the salience of the danger is high. Given the large and increasing diversity of risks that must be assessed every day by firms' decision makers, our results suggest that the total real economic cost of this bias could be considerable.

Appendix A. Robustness tests

Table A1

This table presents additional tests examining whether the effects of hurricane proximity on the main variable outcomes are robust to alternative specifications. In Panel A, the dependent variable is the total amount of cash and cash equivalents scaled by the total assets at the end of the quarter. In Panel B, the dependent variable is the log of total assets at the end of the quarter. *Neighbor* is a dummy variable equal to one if the county of the firm headquarters is in the neighborhood of an area hit by a hurricane over the past 12 months. *Disaster zone* is a dummy variable equal to one if the county of the firm headquarters is in an area hit by a hurricane over the past 12 months. All other variables are defined in Appendix B. Standard errors are corrected for clustering of the observations at the county level. *t*-stats are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A

Dependent variable: Cash / Assets (in percentage points)

Robustness test	Industry x time fixed effects [1]		Location state x time fixed effects [2]		CEO fixed effects [3]		More controls [4]		Placebo [5]	
	coef.	*t*-stat	coef.	*t*-stat	coef.	*t*-stat	coef.	*t*-stat	coef.	*t*-stat
Neighbor	0.83***	(3.63)	0.64**	(2.09)	0.76*	(1.68)	0.68***	(2.67)	0.05	(0.22)
Disaster zone	−0.22	(−1.07)	-0.06	(−0.19)	−0.22	(−0.69)	−0.38	(−1.57)	0.11	(0.18)
Size							−1.00***	(−6.87)		
Age							−7.65***	(−12.86)		
Market-to-book							0.07***	(7.46)		
Debt							−11.52***	(−28.97)		
Net working capital							−0.54***	(−9.50)		
Investment							0.06	(0.85)		
R&D							−23.98***	(−4.40)		
Firm-season fixed effects	Yes		Yes		Yes		Yes		Yes	
Time fixed effects							Yes		Yes	
SIC3-time fixed effects	Yes		Yes		Yes					
State-time fixed effects			Yes							
CEO fixed effects					Yes					
N	411,490		411,490		93,759		344,057		411,490	

Panel B

Dependent variable: Total assets (in log)

Robustness test	Base line specification [1]		Industry x time fixed effects [2]		Location state x time fixed effects [3]		CEO fixed effects [4]		More controls [5]	
	coef.	*t*-stat	coef.	*t*-stat	coef.	*t*-stat	coef.	*t*-stat	coef.	*t*-stat
Neighbor	0.00	(0.18)	−0.00	(−0.15)	−0.01	(−0.23)	0.00	(0.08)	0.01	(1.09)
Disaster zone	0.03	(1.27)	0.01	(0.85)	0.00	(0.22)	−0.01	(−0.69)	0.03	(1.05)
Age									0.38***	(16.29)
Market-to-book									0.00***	(−2.62)
Debt									−0.37***	(−11.76)
Net working capital									0.04***	(10.89)
Investment									0.06***	(18.15)
R&D									−7.92***	(−25.79)
Firm-season fixed effects	Yes		Yes		Yes		Yes		Yes	
Time fixed effects	Yes								Yes	
SIC3-time fixed effects			Yes		Yes		Yes			
State-time fixed effects					Yes					
CEO fixed effects							Yes			
N	411,490		411,490		411,490		93,759		344,057	

Appendix B. Variables used in tests (in alphabetical order)

Age	Log-transformed number of years between the date of the current quarterly financial accounts and the date of the first quarterly financial accounts reported in Compustat
Assets	Total assets.
Cash	Cash and cash equivalents scaled by total assets.
Change in cash	Change in cash and cash equivalents scaled by market value at the beginning of the quarter.
Change in dividends	Change in common dividends scaled by market value at the beginning of the quarter.
Change in earnings	Change in net income before extraordinary items scaled by market value at the beginning of the quarter.
Change in interest	Change in interest expenses scaled by market value at the beginning of the quarter.
Change in net assets	Change in total assets minus all cash and cash equivalents scaled by market value at the beginning of the quarter.
Change in R&D	Change in R&D expenses (set to zero if missing) scaled by market value at the beginning of the quarter.
Debt	Total debt: short-term debt + long-term debt scaled by total assets.
Disaster zone	Dummy equal to one if the county location of the firm headquarters is in an area hit by a hurricane over the past 12 months.
Dividend	Total dividends over last year's net income.
First time	Dummy equal to one if a firm has never been located in the neighborhood area and zero if not.
Hurricane risk	Dummy equal to one if the risk of hurricane is mentioned at least once in the contents of 10-K/10-Q/8-K filings and zero if not.
Investment	Total cash flow from investing activities (capital expenditures + acquisition expenditures) scaled by net property, plant, and equipment (PPE).
Lagged cash	Cash and cash equivalents at the end of the previous quarter.
Market leverage	Total debt (long-term debt + short-term debt) over total debt + equity market value.
Market-to-book	Market-to-book ratio. Equity market value over total equity.
Neighbor	Dummy variable equal to one if the county location of the firm headquarters is in the neighborhood of an area hit by a hurricane over the past 12 months.
New financing	Issuance of long-term debt + sale of new stocks scaled by equity market value.
NWC	Net Working Capital: Inventories + receivables - payables scaled by total revenues.
Occurrence	Number of times a firm has been located in the neighborhood of an area hit by a hurricane. The variable is equal to zero if the county location of the firm has never been in the neighborhood area, to one if it has been in this area only once, and two if it has been in the neighborhood area in multiple instances.
Operating margin	Operating income after depreciation over total revenues.
R&D	R&D expenses over total assets.
Repurchases	Purchase of common and preferred stocks over last year's net income.
Sales growth	Growth in total revenues relative to the same quarter of the previous year.
Second time	Dummy equal to one if the firm has been located once in the neighborhood area and zero if not.
Size	Log of total assets.
Third time (and more)	Dummy equal to one if the firm has been located in the neighborhood area multiple times and zero if not.
Vulnerable	Variable equal to one if a hurricane occurred over the last year, if the firm is vulnerable to hurricanes, and if the firm is located outside the disaster area and its neighborhood.

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