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 real risk remains unchanged. Both effects are temporary. Over time, the perceived risk decreases, and the bias disappears. The distortion between subjective and objective risk is large and the increase in cash is costly. Overall, managerial reaction to salient risks is consistent with salience theories of choice.

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"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**

Prior research documents significant evidence of behavioral biases in individuals' assessment of risks (e.g. Tversky and Kahneman, 1973, 1974). This literature shows that individuals are prone to use heuristics, i.e., mental shortcuts for assessing probabilities, and finds that the use of such shortcuts produces mistakes because part of the available information is ignored in the risk estimation. An important question is whether such mistakes can affect corporate decision making. Because corporate decisions are made (at least to some extent) collectively through internal procedures and committees, it is possible that biases observed at the individual level get mitigated at the corporate level. Whether managers use heuristics and make predictable risk assessment mistakes remains therefore an open question.

Addressing this question is important because of the cost that such mistakes may impose on shareholders and society as a whole. Recent examples of risk management failures abound.[1] One reason for such anecdotes could be that some risky outcomes are systematically under or overestimated because top executives use heuristics and neglect part of the information set when assessing risk.[2]

We focus on the "availability heuristic" rule. Tversky and Kahneman (1973, 1974) document the tendency to infer the frequency of an event from its availability, i.e., the ease with which concrete occurrences of the event come to mind. The drawback is that availability may be affected by the salience of the event. For many reasons (e.g., a dramatic outcome or high levels of media coverage), certain events have unusual characteristics that temporarily grab the attention. Because such events are more salient, they come to mind more easily.[3] People using the availability heuristic will then temporarily overestimate the probability that

[1] Examples include the repetitive trading losses reported in the financial sector over the past 10 years, whose total amount exceeds 40 billion dollars, or the products recalls in the automotive industry.

[2] Commenting on lessons learned by his company after the product recall, G. M. Mohatarem, Chief Economist at General Motors declared that : "There is a tendency to underestimate the risk…It is relatively easy to say, 'Well, it's a low probability risk, let's go on.'"

[3] Our definition of "salience" follows the definition given by 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))

these events will occur again. If corporate managers use the availability heuristic, salient risk situations should lead them to overreact and make inappropriate risk management decisions. Specifically, we hypothesize that managers then overestimate the probability that the risk will materialize again and take excessive precautionary measures against it.

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 use the variations in corporate cash holdings to measure how their perception of this risk changes. Given the evidence that corporate cash holdings are primarily used as a buffer against the risk of liquidity shortage, variation in cash holdings provides a good indication of the changes in the perceived liquidity risk.[4] Second, testing this hypothesis also requires the identification of a salient event whose actual distribution does not change after its occurrence. We address this problem by using hurricanes as a source of liquidity shocks.

Hurricanes are well suited for our purpose for three reasons. First, the occurrence of hurricane does not convey information about the probability of a similar event occurring again in the near future. Estimating the marginal increase in the probability of hurricane landfall in response to the occurrence of a hurricane over the past two years produces a statistically insignificant coefficient that is either negative or equal to zero. This is in line with the climate literature, which shows that, in the US mainland and over the historical period of our sample, hurricane frequency has been mostly stationary (e.g. Elsner and Bossak, 2001; Pielke et al. 2008).[5] Second, their occurrence is a salient event that is exogenous to firm or manager characteristics and represents a threat of liquidity shock. Third, hurricane events permit a difference-in-differences identification strategy because their salience is likely to decline as the distance from the disaster zone increases. This allows us to estimate the effect of risk saliency on the perceived risk by comparing how a treatment group of firms located in

[4] Froot et al. (1993) and Holstrom 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 et al., 1998; Opler et al., 1999; Almeida et al., 2004; Bates et al., 2009, Acharya et al., 2012).

[5] As we will see, this characteristic of hurricane activity in the US over our sample period is not critical for our conclusions. Even if hurricane frequency was increasing, this would not explain why the documented effects are *only temporary*.

the neighborhood area outside the disaster zone and a control group of distant firms adjust their cash holdings after a disaster.

Our main findings are as follows. First, we find that managers of unaffected firms respond to the sudden salience of liquidity risk caused by the proximity of a hurricane by increasing the amount of corporate cash holdings, although this risk remains unaffected. On average, during the 12-month period following the hurricane, unaffected firms located in the neighborhood area increase their cash holdings by approximately one percentage point of total assets relative to firms farther away. This effect represents an average increase in cash holdings of 11 million dollars and accounts for 8% of the within-firm standard deviation of cash holdings. Second, and importantly, this cash increase is temporary. The amount of cash increases sharply during the first four quarters following the disaster and then returns to pre-hurricane levels over the next four quarters. Thus, as time passes, salience decreases, people forget the event, and the bias vanishes. This bias is also weaker when the same event happens several times. Cash increases the first and second time a firm is located in the neighborhood area. However, as the salience of the event decreases because the same event repeats and becomes less unusual, the effect tends to disappear.

Next, we show that managers of firms located in the neighborhood area are also more likely to explicitly mention the risk of hurricanes in subsequent 10-Ks / 10-Qs 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 86% higher than the unconditional probability. The effect is also temporary. Two years after a hurricane, the likelihood that these firms mention hurricane risk has reverted to the pre-hurricane level. Finally, we find that firms who mention hurricane risk also increase corporate cash holdings more. The observed increase in cash is four times larger for this subset of firms. This latter test includes County x 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 probability of future hurricane perceived by the manager with the actual probability. This is not possible because the perceived probability is not observable. Another approach is to compare the increase in cash with the real amount of possible losses. When a firm is affected by a hurricane (i.e., located in the disaster zone), the loss incurred as estimated by the change in market value at the time of the landfall is 14 million dollars. In response, unaffected firms in the neighborhood area increase cash holdings by a similar amount (11 million dollars) even though the probability of hurricane hitting them is only 6%. This comparison suggests that the magnitude of the mistake that is made is economically meaningful.

In the specific context of our study, increasing cash holdings is also costly and inefficient. First, cash earns less in interest than the debt used to fund it, and interest income on cash is taxable. Second, we find that cash holdings increases via retained earnings. And 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 does not lead to an increase market capitalization, 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. Alternatively, cash holdings could increase if managers ignore the risk and its economic implications and learn about them only when the hurricane occurs. The level of cash would next revert down over time in the absence of new hurricanes as managers revise their estimate downward. However, this explanation is difficult to reconcile with our finding for two reasons. First, under the learning interpretation, cash holdings reverts down in the aftermath of the hurricane but not to pre-hurricane level because this level is suboptimal ex-post. Indeed, managers can no longer ignore the risk of hurricane. Second, we show that the learning interpretation implies that the increase in cash reverts down by half after at least 8 consecutive years without hurricane strike in the region. Instead, we find that the increase in cash fully reverts after 18 months.

Second, cash might increase temporarily if firms located in the neighborhood area are in fact indirectly affected via regional spillovers. However, if so, cash holdings should increase temporarily after each hurricane, while we find it does only the first and second time a firm is located in the neighborhood area. We also test several possible spillover effects and find 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 earn more profits and hold more cash. But this effect implies a positive change in operating performance (sales, income), which we do not find. The hurricane might also increase business uncertainty locally and neighbor firms may postpone investment and accumulate cash. However, additional uncertainty would also imply a drop in investment or greater cross-sectional variance in revenues that are not in the data. We also performed two additional tests. First, we focus on all firms vulnerable to hurricane risk located outside the affected region and the neighborhood area. Those firms may be far away from the disaster zone (e.g. firms located in 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 instances, regional spillovers are implausible and yet, cash holdings temporarily increase after the disaster.

Our paper shows that managers are prone to use the availability heuristic to assess risk, which leads them to make predictable mistakes that affect firm value. As such, this study first contributes to the behavioral corporate finance literature.[6] Our paper relates in particular to the part of this literature that examines the consequences of managers' behavioral biases. Prior research primarily focuses on how overconfidence and optimism (e.g. Malmendier and Tate, 2005; Malmendier and Tate, 2008; Landier and Thesmar, 2009; Malmendier, Tate and Yan, 2011) or reference point thinking (Loughram and Ritter, 2002; Baker et al., 2012; Dougal et al., 2015) can affect corporate policies. By contrast, current research on the use of simplifying heuristics by firm managers remains scarce. One notable exception is Krueger, Landier and Thesmar (2015), which shows that managers simplify the calculation of the weighted average cost of capital.

Next, our paper contributes to the "boom and leniency" literature. Initially propelled by Minksy (1977) and Kindelberger (1978), this literature conjectures that during periods of expansion, agents tend to extrapolate the current state of the world as if it would last forever. Prolonged economic booms then lead to over optimism and risk neglect, which introduces fragility into the financial system and increases the risk of crash (e.g. Gennaioli et al., 2012 or Baron and Xiong, 2014). By showing that managers tend to overweight the probability that

[6] See Baker and Wurgler (2012) for a comprehensive survey.

recent events will further repeat, our paper provides new evidence supporting the premise of this literature and complements recent papers showing that investors tend to wrongly extrapolate current situations in the future (e.g. Choi et al., 2009; Barberis, 2012; Cheng et al., 2013; Greenwood and Hanson, 2013, 2015; Greenwood and Shleifer, 2014).

Because saliency is experienced-based, our paper is also related to a number of studies showing that past experiences affect both investors' decisions (Malmendier and Nagel, 2011; Greenwood and Nagel, 2009) and managers' decisions (e.g. Malmandier, Tate and Yan, 2011; Bernile, Bhagwat and Rau, 2015, Dittmar and Duchin, 2015). These studies find that early-life experiences or professional experiences shape future risk-taking behavior. Our paper focuses on more recent experiences. We complement these results by showing that differences in recent experiences arising from irrelevant contextual factors (the degree of salience) also induce managers to weight the same signal differently, which leads them to undertake different risk management policies.[7]

Finally, our paper contributes to the literature on the effects of behavioral biases "in the field."[8] *A priori*, managers may act rationally because they are not uninformed and unsophisticated agents (such as home owners or insurance retail buyers as in Gallagher, 2014). Market forces should induce managers to behave in a more rational manner. Internal procedures, decision committees, and the organizational structure of the firm may also mitigate the effects of individual biases that top executives may have. Whether managers will make incorrect financial decisions in the real world because of the availability heuristic therefore 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 rest of the paper is organized as follows. Section 2 briefly summarizes what is known about hurricane risk. Section 3 proposes hypotheses based on the availability heuristic phenomenon and reviews the related scientific and anecdotal evidence. Our empirical design is presented in Section 4. Section 5 provides evidence of managers overreacting to salient

[7] Another strand of research examines how salience affects individuals' 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).

[8] DellaVigna (2009) provides a detailed survey of the real effects of behavioral economics.

risks. Section 6 investigates whether this reaction is costly. Section 7 discusses the possibility of alternative non-behavioral explanations. Finally, section 8 concludes.

2. **Hurricane activity on the US mainland**

Hurricanes are tropical cyclones that form in the waters of the Atlantic and eastern Pacific oceans with winds that exceed 32 m per second (approximately 72 miles per hour). In this section, we briefly 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, has not changed over the historical period of our sample 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, either by floods resulting from the heavy rainfalls accompanying hurricanes or by the high winds produced by the hurricane as it moves across land. In the SHELDUS database (the main database for natural disasters in the US), 1,341 distinct counties (approximately 44% of the total counties in the US) are reported to have been affected at least once by a major hurricane.

2.2. Event frequency

Hurricanes are regular events in the US. Since 1850, an average of 2 hurricanes strike the US mainland every year.

[INSERT FIGURE 1 AROUND HERE]

Figure 1 shows no particular increasing or decreasing trend in this frequency, nor does it suggest the presence of autocorrelation.[9] This absence of a trend (and autocorrelation) over the historical period of our sample is supported by the climatology literature (e.g. Elsner and

[9] The Durbin-Watson statistic for the annual series depicted in Figure 1 is 1.92, which cannot reject the null that hurricane strikes are not serially correlated.

Bossak, 2001; Landsea, 2005; Emanuel, 2005; Landsea, 2007, Pielke et al, 2008; Blake et al., 2011). In the *US mainland*, Elsner and Bossak (2001) find that the distribution of hurricane strikes have been stationary since early industrial times for all hurricanes and major hurricanes as well as for regional activity.[10] The results obtained from our own tests (exposed in Section 7) are consistent with this finding. We estimate an impulse response function to determine how the marginal probability of hurricane disaster changes over different horizons in response to the proximity of a hurricane strike. We find that in the US mainland and over the historical period of our sample, the occurrence of a hurricane never reveals information about future disaster likelihood in the neighboring counties.

Regarding possible future changes in storm frequencies, existing studies produce conflicting results. In particular, the effect of global warming on hurricane activity remains highly debated. According to the National Oceanic and Atmospheric Administration (NOAA), it is "*premature to conclude that human activities--and particularly greenhouse gas emissions that cause global warming--have already had a detectable impact on Atlantic hurricane or global tropical cyclone activity*". In existing studies, this possible impact is not expected to significantly materialize before the second half of the 21st century and does not apply to the historical period covered by our sample. Pielke et al. (2008) conclude from their survey of the literature that given "*the state of current understanding (…) we should expect hurricane frequencies (…) to have a great deal of year-to-year and decade-to-decade variation as has been observed over the past decades and longer*."

We discuss in section 7 how a possible increase in the frequency of hurricane strikes in the US could affect the interpretation of our results.

2.3. Event cost

The total cost of hurricane strikes in terms of economic damages is now much 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. For instance, Pielke et al. (2008) find that had

[10] "the distributions of hurricanes during each [time] subinterval are indistinguishable, indicating a stationary record of hurricanes since early industrial times. Stationarity is found for all hurricanes and major hurricanes as well as for regional activity" (p. 4349)

the great 1926 Miami hurricane occurred in 2005, it would have been almost twice as costly as Hurricane Katrina; thus, they stress that "*Hurricane Katrina is not outside the range of normalized estimates for past storms.*" Overall, their results indicate 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.

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*".[11] 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 come as a surprise to the local population.[12]

3. The psychological mechanisms for probability evaluation and risk assessment

3.1. The availability heuristic

Because assessing the likelihood of uncertain events is a complex and time-consuming task, people naturally tend to use their own experiences for developing simple mental rules to rapidly adjust their beliefs and adapt to their environment. Tversky and Kahneman (1973, 1974) describe such heuristic rules and show that, although useful in general, they sometimes lead people to make mistakes. One such rule is the “availability heuristic,” which derives from the common 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. For example, people may assess the probability of a traffic accident by recalling examples of such occurrences among their acquaintances.

[11] See National Oceanic and Atmospheric Administration (NOAA) website.
[12] See NOAA website.

Tversky and Kahneman (1973, 1974) show that the use of this rule is problematic because availability may also be affected by factors that are not related to actual frequency. In particular, they argue that factors such as familiarity with the event, the salience of the event, and/or the proximity of the event can affect its availability and generate a discrepancy between subjective probability and actual likelihood. The availability of a car accident, for instance, will be higher when the person involved in the accident is famous (familiarity) or if the accident was observed in real time (salience). The subjective probability of a car accident will then be temporarily higher than its actual likelihood.

3.2. Scientific and anecdotal evidence

The availability heuristic theory is consistent with anecdotal and scientific evidence. In a series of studies by Lichtenstein et al. (1978), people were asked to estimate the frequency of several dozen causes of death in the United States. The results from this study show that salient causes that killed many people during a single occurrence were overestimated, whereas less salient causes were systematically underestimated. In a survey conducted to understand how people insure themselves against natural hazards, Kunreuther et al. (1978) observe a strong increase in the number of people willing to buy insurance at a premium immediately after an earthquake. Conversely, people were found to be reluctant to buy such insurance even at a subsidized rate in the absence of a recent major earthquake.[13]

To account for such empirical findings, Bordalo, Gennaioli, and Shleifer (2012b, 2013b) develop a theoretical framework of choice under risk in which salient attributes grab individuals' attention. In their model, individuals do not equally consider the full set of possible states of the world when it comes to assessing risk. They neglect non-salient states, and over-emphasize the salient ones. Because the salience of a state depends on contextual factors, individuals then make context-dependent risk estimations. When a good state is salient, they over-estimate the likelihood of a positive outcome. When a bad state is salient, they over-estimate the probability of a negative outcome. In both cases, individuals overreact to salient risks.[14]

[13] Likewise Gallagher (2014) finds that people buy more flood insurance policies in the year following a large regional flood.
[14] Other models based on the mechanism of salience include Bordalo, Gennaioli and Shleifer (2012a, 2013a), Gabaix (2011), Gennaioli and Shleifer (2010), Köszegi and Szeidl (2013), and Schwartzstein (2009). These models share the common

3.3. Implications and hypothesis development

In this paper, we focus on decision makers in firms. We ask whether they rely on the availability heuristic to assess risk and examine whether they overreact to salient risks (hereinafter, the *availability heuristic* hypothesis).

One challenge is that we cannot directly observe the risk perceived by firm managers. To address this difficulty, we assume that changes in risk perception can be inferred from variations in corporate cash holdings. There is indeed strong theoretical and empirical evidence in the corporate finance literature that the main driver of policies regarding cash holdings is risk management. Froot et al. (1993) and Holstrom and Tirole (1998, 2000) show that when firms have limited access to external financing because of financial markets imperfections, cash will be used as an insurance mechanism against the risk of a liquidity shock. In other words, cash holdings offer a buffer against any risk of cash shortage that would prevent firms from financing positive Net Present Value (NPV) projects.[15]

If managers rely on the availability heuristic to assess the risk of an event that would trigger a cash shortage, cash holdings should then vary in response to the salience of this event. Under the *availability heuristic* hypothesis, we thus argue that corporate cash holdings will increase in those situations in which the risk of cash shortage becomes more salient.

4. Empirical design

4.1. Identification strategy

In this paper, 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 can inflict.[16] Although firms

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assumption that individuals do not consider the whole set of available information before making a decision and neglect part of it. Significant judgment errors then occur when the neglected data are relevant for decision making.

[15] Consistent with this argument, several empirical papers document a positive correlation among various possible sources of cash shortfalls for future and current levels of cash holdings (Kim et al., 1998; Opler et al., 1999; Almeida et al., 2004; Bates et al., 2009; Acharya et al., 2012). Surveys of CFOs also confirm this link. For instance, Lins et al. (2010) find that a sizeable majority of CFOs indicate that they use cash holdings for general insurance purposes.

[16] Cash shortages can come 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.).

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 disaster is imperfect.[17] Thus, most firms prefer to self-insure by accumulating cash reserves instead of directly insuring this liquidity risk.[18] 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 likely to vary with the proximity of the landfall. Indeed, we expect the event to be salient for managers whose family members and friends are directly affected by the disaster, which is likely to occur for firms located in the disaster area and the environs nearby (referred to herein as the neighborhood), but not for more distant firms. The hurricane event should also receive more attention in situations in which firms are at risk, which again is more likely to occur when firms are located in the neighborhood of the disaster area. Fourth, the occurrence of a hurricane makes hurricane risk salient but does not imply a change in the risk itself in the near future. Over the historical period of our sample, the occurrence of a hurricane in the US mainland never predicts future hurricane strikes over the next two years in the neighboring unaffected counties (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 locations of the main hurricane landfalls in the US from the SHELDUS (Spatial Hazard and Loss Database for the United States) database at the University of South Carolina. This database provides the location for each disaster at the county level for all major hurricanes since the early 1960s. 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

[17] 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.

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

hurricanes with total direct damages (adjusted for CPI) 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.[19] We obtain detailed information about their characteristics from the tropical storm reports available in the archive section of the National Hurricane Center website and from the 2011 National Oceanic and Atmospheric Administration (NOAA) Technical Memorandum. Table 1 presents summary statistics for these 15 hurricanes.

[INSERT TABLE 1 AROUND HERE]

We obtain financial data and information about firm headquarters location from Compustat's North America Fundamentals Quarterly database.[20] We use headquarters rather than plants or clients' location 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 disaster zone, this firm will be misclassified as a neighbor firm. Because we do not have access to plant-level information, we are not able to verify whether this possible misallocation problem occurs and assume that, on average, plants are located in the same area as a firm's headquarters. This approximation should not affect our conclusions because cash holdings decreases when a firm *is* affected by a hurricane. This result implies that cash will also decrease for neighbor firms whose plants are in the disaster zone. Therefore, including those firms (if any) in our treatment group biases our main finding towards the null. Note also that in some tests, we focus on remote neighbors (the neighbors of neighbors) or more distant firms that are sensitive to the risk of hurricane. Given the distance to the disaster zone, these firms are less likely to have plants directly affected by the hurricane. These additional tests further mitigate the above misclassification concern.

[19] We obtain the same results when using all hurricanes from the SHELDUS database. Our results also remain unchanged when we remove the largest hurricanes (e.g. Katrina).
[20] One possible concern with location data 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.

Quarterly data rather than annual data are used to identify changes in cash holdings in firms near hurricane landfalls with the highest possible precision.[21] We restrict our sample to non-financial and non-utility firms whose headquarters are located in the US over the 1987-2011 period. If the county location of a firm's headquarters is missing or 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. This selection procedure leaves us with a firm-quarter panel dataset of 11,948 firms and 411,490 observations. In Panel A of Table 2, we present summary statistics for the main firm-level variables we use.[22] All variables are winsorized at the first and 99th percentile and are defined in Appendix B.

[INSERT TABLE 2 AROUND HERE]

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 through a matching procedure between affected counties and non-affected counties according to geographical distance. Under this procedure, we first assign a latitude and longitude to each county using the average latitude and average longitude of all the cities located in the county. For each affected county, we next compute the distance in miles to every non-affected county using the Haversine formula.[23] We then match with replacement each affected county with its five nearest neighbors among the non-affected counties.[24] This 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. Figure 1 presents the results of this identification procedure on a map for hurricane Katrina.

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[21] We obtain the same results with annual financial data.

[22] These statistics are in line with what is typically observed when using annual data. For example, in Compustat Annual, the average operating margin (oiadp/sale) is -64.7%.

[23] The Harversine formula gives the distance between two points on a sphere from their longitudes and latitudes.

[24] 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.

[INSERT FIGURE 1]

Firms located in the *neighborhood* area (represented by the light blue 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 that they could have been affected by the hurricane but were not by chance. For that reason, we expect the event to raise firm managers' attention. Firms located in the *rest of the US mainland* (the blank zone on the map) are assigned to the control group. 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 not of concern. Firms located in the *disaster zone* (the dark blue zone on the map) are separated in our analysis because of the direct effects of the hurricane on their cash levels. Given their location, these firms are affected by the disaster. The event is not only obviously salient for their managers but 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 of cash holdings surrounding the hurricane event is thus more likely to reflect the direct effects of the disaster rather than the change in managerial perceived risk. In practice, we do not remove these firms from our sample.[25] Instead, we control to ensure that the variation of cash holdings that we observe when these firms are affected by the hurricane does not influence our results. Panel B of Table 2 presents summary statistics for each group of firms.

[INSERT TABLE 2 AROUND HERE]

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 appear to be similar along various dimensions, including the amount of cash holdings.

[25] We do not exclude these firms because they can be in the neighborhood of another hurricane at another point in time. Because we are considering various hurricane strikes over time, it is possible that the same firm may be in each of the three groups defined in our experiment (*disaster zone*, *neighborhood*, and *the rest of the US mainland*). Note that excluding firms located in the disaster zone leads to the same results.

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-calendar 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 that we cluster at the county level to account for potential serial correlations.[26]

Firm-season fixed effects (i.e. four quarter fixed effects for each firm) control for time invariant differences among firms (which include fixed differences between treatment and control firms) for each quarter of the calendar year. Because hurricane activity is seasonal, firms in the neighborhood area might anticipate the possibility of hurricane strikes and hold more cash systematically at the end of the third quarter of the year. Therefore, controlling for this possible seasonality effect is important.[27] Time (year-quarter) fixed effects control for differences between time periods, such as aggregate shocks and common trends. The other variables, X_{iyqc}, systematically include a dummy variable $Disaster\_zone_{yqc}$ to capture the effect of the hurricane strike when the firm is located 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.

[26] Allowing for correlated error terms at the state level or firm level leads to similar inferences in the statistical significance of regression coefficients.
[27] We obtain the same results with firm fixed effects

5. **Do managers overreact to salient risks?**

5.1. Main results

We examine the effect of the event availability on the risk perceived by firm managers through differences in corporate cash holdings after a hurricane landfall. Table 3 presents our main results.

[INSERT TABLE 3 AROUND HERE]

Table 3 reports the effects of being in the neighborhood of a disaster area after a hurricane. Column 1 shows that, on average, firms located in the neighborhood of a disaster zone increase their cash holdings (as % of total assets) by approximately 1 percentage points during the four quarters following the hurricane event. This effect represents an average increase in cash holdings of 11 million dollars in absolute terms and accounts for 8% of the within-firm standard deviation of cash holdings. 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 bigger now than it was.

We investigate the dynamic of this increase in cash in Column 2. Specifically, 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 saliency of the event 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 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. However, consistent with a causal interpretation of our result, we find that the amount of cash begins to increase following the occurrence of the hurricane.[28] This effect increases during the subsequent four quarters, and the increases in cash holdings reach their maximum during *q+2*

[28] 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.

and *q+3*. Note that we do not observe cash holdings every month but only at the end of every quarter. Therefore precisely identifying when the peak of the increase in cash 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. The peak of the increase in cash thus most likely occurs somewhere between May and July, which approximately corresponds to the start of the next hurricane season (the North Atlantic hurricane season typically starts early June). The coefficient for the *Neighbor_q+2* and *Neighbor_q+3* variables show that, on average, firms located in the neighborhood area respond to the saliency of the disaster by increasing their cash levels by 1.16 and 1.06 percentage points of their total assets (approximately 15 million dollars 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 undistinguishable 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, memories fade, the salience of the event decreases, and the subjective probability of risk retreats to its initial value. Managers then reduce the level of corporate cash holdings.

[INSERT FIGURE 4 AROUND HERE]

We plot the result of this analysis in a graph in which we also display the evolution of the difference in corporate cash holdings between firms located in the *disaster zone* and control firms. This graph is presented in Figure 4. 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 their cash holdings (significant at the 5% level). Second, it suggests that managers’ response to hurricane proximity is disproportionate compared to the real risk. Indeed, the graph demonstrates that the additional amount of cash accrued in the balance sheet (+1.2 percentage points of total assets), presumably to insure against the risk of cash shortage after a hurricane strike, exceeds the actual loss of cash (-0.6 percentage points) that firms experience when this risk materializes. This finding suggests that the mistake that is made about the real risk incurred is economically meaningful. [29]

Assessing the exact magnitude of this mistake is difficult. Ideally, we would like to compare the probability of future hurricane strikes estimated by the manager with the real probability. Because we only observe the former but not the latter, we cannot perform this comparison. However, we can compare the observed amount of additional cash buffer 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 dollars, or 1.03% of the total assets of the firm (significant at the 5% level), which roughly corresponds to the magnitude of the increase in cash (+15 million dollars).[30] Next, we estimate the true probability to be affected by a hurricane for firms located in the neighborhood area using all hurricanes reported in the SHELDUS database and find that this probability is approximately 6%. Therefore, the real amount of expected losses for firms located in the neighborhood area is 0.8 million dollars (14 x 6%), i.e. 0.06% percentage points of total assets. This means that a manager who learns of the existence of hurricanes and wishes to self-insure this risk should increase corporate cash holdings by approximately 1 million dollar.[31] Instead, we find that cash increases by 15 million dollars, which is what this manager should do if the risk to be affected in the short run by the same event was certain. Note that this comparison implicitly assumes that the losses that we observe for the group of firms located in the disaster zone would be the same for our group of unaffected neighbors. This may not be the case. One concern then, is that we may underestimate the amount of incurred losses for firms located in the neighborhood area. However, even if the cost for firms located in the neighborhood area was twice bigger, the

[29] This finding is also useful to determine 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. Here, we cannot (and do not) rule out the possibility of risk neglect in normal times. However, we can rule out the possibility that managers correctly adjust cash holdings when a disaster occurs. Indeed, the magnitude of the increase in cash compared to the magnitude of the possible liquidity shock suggests that managers overshoot and increase cash holdings too much, which is more consistent with an overreaction-based explanation.

[30] The results of this event study are presented in Table 9 and further discussed in section 7

[31] Under standard insurance utility theory, the maximum premium an agent is willing to pay for insuring a given risk is the value of the loss incurred weighted by the probability that this loss materializes.

amount of the increase in cash would still be higher than the expected loss. Therefore, what this second-best comparison suggests is that the magnitude of the distortion between subjective and objective risk induced by the salience of the danger is large.

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), one way to test this prediction is to examine whether the increase in cash holdings documented above disappears when the same event is repeated and becomes less unusual. To this end, we create an indicator variable *Occurence* 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 a firm has never been located in the neighborhood area, when it has been once located in this area, and when it has been located in this area in multiple instances, respectively.[32] We then estimate the effect of the hurricane proximity conditioning on the number of past occurrences of the same event by interacting all three dummy variables with the *Neighbor* variable. To estimate a proper diff-in-diff effect, all three dummy variables are interacted with the firm-fixed effects and time fixed effects. This is achieved by augmenting our baseline specification with Occurrence-firm-season fixed effects and Occurrence-time fixed effects. The Occurrence-firm-season fixed effects ensures that we are not capturing the effect of the number of past occurrences on cash holdings that is independent of the proximity of a new disaster. The Occurrence-time fixed effects ensures that firms used as a control group are distant firms with the *same* experience in terms of hurricane proximity. For instance, when we estimate the effect of being in the neighborhood area for the second time, adding Occurrence-time fixed effects allows us to tailor the control group such that control firms are distant firms that have the same hurricane history (i.e. exactly one treatment in the past), but are not in the neighborhood area a second time.[33] Because we compare firms at different points of their life cycle, it is also necessary to control

[32] 1,321 firms are located multiple times in the neighborhood of an area affected by a hurricane
[33] Note that these fixed effects absorb the variables *First time, Second time,* and *Third time (or more)*

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.

[INSERT TABLE 4 AROUND HERE]

Column 1 shows that managers significantly increase corporate 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 further repeats, the effect tends to disappear. The coefficient on the interaction between *Neighbor* and *Third time (and more)* is close to zero and is statistically insignificant. As expected, managers' response to the proximity of the hurricane strike decreases when the salience of the event is lower. 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, the overreaction decreases. 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 consistently be observed after each hurricane, which is not what we find.

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 and 10-Qs filed by the firms of our sample to detect when hurricane risk is explicitly mentioned as a risk factor. Specifically, we search for expressions such as "hurricane risk", "hurricane threat", "hurricane likelihood" or "possibility of hurricane". 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 comas.[34] Note that we search for the word hurricane only when it appears with an adjective (or in a sentence) indicating that managers express concerns about the *likelihood* of this event, and that we never search for the word "hurricane" alone. We find that the risk of hurricane is explicitly mentioned in 2,110 documents filed by 552 distinct firms over the 1998-2010 period.[35] We then test whether the proximity of a hurricane strike affects the probability that hurricane risk is explicitly mentioned by the manager. The specification of this test is the same as in Table 3. The only difference is that the dependent variable is a dummy variable (denoted *Hurricane risk*) equal to 1 if a concern is expressed about the risk of hurricanes and zero if not. The estimation results are reported in Table 5.

[INSERT TABLE 5 AROUND HERE]

Column 1 shows that when firms are located in the neighborhood of the disaster zone, the likelihood that managers explicitly mention the risk of hurricanes increases by 0.4 percentage points. This effect represents an average increase of 50% relative to the unconditional probability that hurricane risk is mentioned.[36] Column 2 shows that the dynamic of this effect is similar to the one observed for cash holdings.[37] Nothing happens before the hurricane and the likelihood that hurricane risk is mentioned starts increasing after the occurrence of the disaster. The peak of the increase occurs again at q+2. At this date, the increase in the probability that hurricane risk is mentioned is particularly large. The point estimate indicates that the likelihood that hurricane risk is mentioned is 84% higher than the unconditional probability. The documented effect is also temporary. Two years after the disaster, the probability that hurricane risk is mentioned in 10K/10Q filings by neighboring firms is the same as before the event.[38]

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[34] The exact list of expressions that we search is: "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)", "such as hurricane(s)", ",hurricane(s),", "and hurricane(s)."

[35] Coverage by Edgar of 10-K/10-Q filings under electronic format is too sparse before 1998

[36] The unconditional probability that hurricane risk is mentioned is 0.8%.

[37] We start estimating the dynamic at q-2 instead of q-4 as is the case in Table3 because of data limitation. Estimating the dynamic of the effect requires to have at least one of year of data available before the first hurricane (here Floyd 1999).

[38] Note that 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 (or almost significant) at the 10% level).

[INSERT FIGURE 4 AROUND HERE]

To better compare the dynamic of this effect with the dynamic of the increase in corporate cash holdings, we plot the results of this analysis in a graph in which we also display the evolution of the difference in corporate cash holdings between neighboring firms and control firms. This graph is presented in Figure 4 and shows that the dynamic of both effects is exactly the same. In particular, both cash holdings and the likelihood that hurricane risk is mentioned strongly increase in quarters q+2 and q+3. As already pointed out, 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 early June). This coincidence suggests that the documented effect may not only be a within-hurricane season effect, and that managers also increase corporate cash holdings in expectation of the *next* hurricane season.

Finally, to further cement the risk perception channel behind the increase in corporate cash holdings, we test whether managers that express more concerns about hurricane risk also increase corporate cash holdings more. We perform this test using a triple-difference approach. That is, we compare how managers of firms located in the neighborhood area who mention the risk of hurricane increase cash holdings relative to managers of more distant firms *who also* explicitly mention the risk of hurricane. This estimate is obtained by interacting *Hurricane Risk* with *Neighbor* in our baseline specification.[39] Table 6 reports the results.

[INSERT TABLE 6 AROUND HERE]

Column 1 shows that the increase in cash holdings is four times bigger when firms explicitly mention the risk of hurricane. Column 2 shows that this result is robust to the inclusion of county-time fixed effects.[40] In other words, the effect survives when controlling for local economic shocks at the county level. Because firms that express concerns about hurricane risk may be smaller firms, younger firms or firms with different sets of investment

[39] 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. The base line variable *Hurricane risk* is then omitted from the regression because it is fully interacted with the fixed effects.
[40] Neighbor and Disaster Zone are omitted from the regression because they are absorbed by the county-time fixed effects.

opportunities, we control for size, age and market-to-book in column 3. The magnitude of the coefficient remains exactly the same. Finally, unaffected neighboring firms that mention the risk of hurricane may be indirectly "affected" by the hurricane proximity. For instance, the disaster may create new business opportunities for them which would explain why they hold more cash. Column 4 reports the results of a placebo test that rules out this possibility. The test shows that firms in the neighborhood area that mention the risk of hurricane are not more "affected" than the other neighboring firms in terms of sales growth.

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.1, we investigate whether the increase in corporate cash holdings documented above is robust to alternative specifications. First, we use SIC3-time fixed effects rather than time fixed effects to remove any time varying unobserved heterogeneity across industries. We find that the inclusion of this high-dimension fixed effects does not alter our estimation (Column 1). The effect also survives when controlling for local economic trends by adding location state-time fixed effects (Column 2). Likewise, the inclusion of the usual firm-specific control variables used by the cash literature does not change our finding that cash increases after the landfall (Column 3).[41] 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 4).

In panel A.2, we check that our results on cash over total assets is not driven by a decrease in total assets. The table shows that whatever the specification we use, the total assets of neighbor firms is not affected by the hurricane proximity.

Finally, in unreported tests, 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,

[41] 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. That's why we do not include them in our baseline specification. See for instance Roberts and Whited (2012) or Angrist and Pischke (2008) for a discussion about the effect of including covariates as controls when they are potentially affected by the treatment.

working capital requirements, investment, and dividends.[42] Overall, this analysis leads to the same conclusion as the one 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. Is managers' reaction costly?

Because the liquidity risk remains unchanged, managers' decisions to temporarily increase cash holdings after a hurricane event are likely to be suboptimal in terms of resource allocation. In this section, we examine whether this temporary increase in cash is costly for shareholders. First we note that holding extra cash when it is not necessary is costly. Second, we analyze the counterparts to this cash increase. Next, we study whether this response to risk saliency 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 (2008), the cost of holding extra cash is twofold. First, cash earns less in interest than the debt used to fund it. Second, the interest income on cash is taxable which generates a loss of tax shield. Therefore, the cost of the increase in cash documented above is non zero. However because the increase in cash is only temporary, the magnitude of such direct costs here is modest. Indeed interests earned on cash for neighbor firms is 0.6% and the average cost of debt is approximately 4%. Assuming a corporate tax rate of 35%, the average cost of holding 11 million dollars of extra cash over a year is 273 thousand dollars. The aggregate cost for the group of 3,102 firms that increase cash holdings then amounts at 846 million dollars.

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

[42] The results of this analysis as well as a detailed description of our matching procedure are presented in a technical appendix (Appendix C) that is not intended for publication.

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 and instead use the amount of sales (unless the literature suggests another more relevant normalization method). [43] Next, we replicate our difference-in-differences analysis and apply our basic specification to each item separately. The results of this analysis are reported in Table 7.

[INSERT TABLE 7 AROUND HERE]

In Panel A, we begin by examining whether hurricanes affect operating activity. Column 1 shows that, on average, the occurrence of a hurricane has no significant effect on revenues for firms located in the neighborhood area of the disaster zone. While sales growth decreases by 2.4 percentage points relative to the control group for firms hit by the hurricane, we find no evidence that the relative sales growth for neighborhood firms is affected by the proximity of the disaster. Column 2 confirms that neighborhood firms are truly unaffected in terms of operating activity. Unlike firms in the disaster zone, firms located in the neighborhood area suffer no significant decrease in operating margin (the coefficient on the *Neighbor* variable is not statistically different from zero).[44]

In the rest of panel A, we examine other possible channels through which the change in cash holdings may occur. 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 neighborhood 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. Indeed, column 6 indicates that firms in the neighborhood area tend to pay lower dividends and retain more earnings after the hurricane (the coefficient on the Neighbor variable is negative and statistically significant at the 5% level); but the point estimate is small. On average the pay-out ratio decreases by 0.5

[43] We have re-run all regressions on the log-transformation of the dependent variable without scaling (i.e. Ln(Sales), Ln(EBIT), Ln(Net Working Capital), Ln(Investment), etc) and find similar results.

[44] Using RoA as an alternative measure of operating profitability leads to the same results

percentage points. This is a low effect both in absolute terms and relative to the increase in cash. In addition, many firms in the neighborhood area do not pay dividends. 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 further investigate whether hurricanes affect the payout policy or the financing policy. We use a linear probability model to assess whether hurricane landfalls affect the likelihood of stock repurchases, dividend payment, and new financing issues. In column 1, we find that the likelihood of a stock repurchase is lower in the case of hurricane proximity. Similarly, column 2 indicates a decrease in the probability of dividend payment. 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 of a disaster zone, firm managers slightly increase earnings retention and also 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 an efficient decision, 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 accrued in the balance sheet 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 (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 same specification as Faulkender and Wang (2006).[45] Next, we examine how this value changes for firms located in the neighborhood relative to control firms by interacting *Change in cash* with *Neighbor*. We also interact the firm fixed effects and the time fixed effects with all

[45] 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 recommended in Gormley and Matsa (2014)

explanatory variables (Note that the base line variables are then omitted from the regression because they are fully interacted with the firm and time fixed effects). Doing so allows to control for heterogeneity across firms and to absorb trends in the value of a marginal dollar of cash. The results of this analysis are reported in Table 8.

[INSERT TABLE 8 AROUND HERE]

Column 1 shows than on average, the value of a marginal dollar of cash is 0.72. In other words, when cash holdings increases by one dollar, market value increases by 72 cents.[46] In column 2, we find that this increase in market value is lower when cash holdings increases because of the proximity of a hurricane strike. The interaction term between *Neighbor* and *Change in cash* indicates that when both neighbor 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, and this loss of market of value relative to control firms is 29 cents. On average, firms in the neighborhood area increase corporate cash holdings by $11 million. Therefore, the opportunity cost in terms of loss value for their shareholders is 3.2 million dollar (11 x 0.29).

Overall, these results suggest that the managerial decision to increase the amount of corporate cash holdings temporarily 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. Next, we propose and 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 geographical externalities. Indeed, firms located in the neighborhood area could be indirectly affected by the hurricane. Such

[46] Faulkender and Wang (2006) find that the average value of a marginal dollar of cash is 75 cents

indirect effects may then explain why the amount of cash holdings temporarily increases. However, one implication of such spillover effects is that cash holdings should increase *systematically* after a hurricane event, which is not what we find. Instead, we find that as the salience of the disaster decreases because the same event repeats, the increase in cash holdings is weaker. Hence, this finding already mitigates the concern that the increase in cash is driven by regional spillover effects. To further alleviate this concern, we review the main possible regional spillover effects and test whether they are likely to drive 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, neighborhood firms may temporarily hold more cash because they make more profits or because they plan to invest in the disaster zone.[47] Under this possible 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. Indeed, 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 neighborhood firms invest more after the hurricane. We have investigated further how the hurricane affects the growth of sales for neighborhood firms relative to the control group at every quarter surrounding the disaster. The graph in Figure 7 illustrates the main outcome of this analysis.[48]

[INSERT FIGURE 7 AROUND HERE]

This graph shows that growth in revenues for neighborhood firms does not increase significantly relative to the control group after the hurricane. Therefore, and unlike firms located in the disaster zone, firms located in the neighborhood area are on average truly unaffected. This conclusion is also supported by the analysis of the market reaction at the time of the hurricane landfall.

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[47] 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.

[48] The graph plots the coefficients of the same regression as the one performed in Table 3 Column 2, except that the dependent variable is the growth of sales relative to the same quarter of the previous year. This regression is not reported for brevity.

[INSERT TABLE 9 AROUND HERE]

In Table 9, we report the results of a simple event study analysis. For each group of firms (disaster area, neighborhood area, and the rest of the US mainland), we estimate the average Cumulated Abnormal Return (CAR) of the stock price over the hurricane event period. Because the events we are looking at overlap in time, we cannot assume the independence between the variances of security abnormal returns. To address this issue, we form an equally-weighted portfolio whenever the event windows perfectly overlap, and run the event study at the portfolio level rather than the stock level.[49] Unsurprisingly, we find a negative abnormal return for firms located in the disaster zone. However, we find no significant reaction for neighbor firms, which suggests that investors perceive that there are no benefits (new business and/or investment opportunities) from the proximity of the natural disaster.[50]

7.1.2. Higher business uncertainty

A second form of spillover effect might arise if the hurricane creates locally higher business uncertainty. In this case, managers may decide to stop and/or postpone their investment projects. Neighborhood firms would then temporarily hold more cash. However, this explanation would imply a *negative* market reaction at the announcement of the hurricane, which we do not find. We also do not find that firms in the neighborhood area significantly reduce their investments in Table 7 (Panel A - Column 4).

To further mitigate this concern, we have also explicitly tested whether the proximity of the disaster creates higher uncertainty. First, we have tested whether the proximity of the hurricane affects the volatility of firm revenues. We find that the standard deviation of sales for neighborhood firms is not higher after the hurricane. We also calculated the standard deviation of sales growth by period across firms at the county level and find that revenue volatility by county is unaffected by the hurricane proximity. Second, we have looked at stock return volatility and find that it is also unaffected by the disaster proximity, which indicates that investors do not perceive higher uncertainty after the hurricane.[51]

[49] A more detailed description of our methodology is described in a technical appendix (Appendix C)
[50] We also note that at the time of the event study, the change in cash holdings is not yet observable by market participants. Thus, finding no market reaction here is not inconsistent with the decrease in the market value of cash observed afterwards
[51] Results of all these complementary tests are reported in the technical appendix (Appendix C)

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 effectively finance the local economy. Firms in the neighborhood 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 credits at the bank level should decrease after the hurricane. We have tested this prediction and find the opposite result. In fact, the amount of new commercial and industrial loans increases after the hurricane event 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. [52] It is also consistent with our findings in Table 7 that the proximity of the hurricane does not negatively affect the probability of issuing new financing.

A similar alternative story could be that the hurricane hurts local insurance companies and generates insurance rationing (Froot and O'Connell (1999), Froot (2001)). Neighboring companies 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 increases over a one-year period whereas Froot and O'Connell (1999) show that prices for insurance tend to rise over a *3-year* period. Second, under the insurance-based explanation, the increase in cash holdings should be concentrated on firms that depend on external insurance companies to insure their business. By contrast, firms that self-insure should react less. The data does not support this prediction. In fact, firms with a lot of intangible assets that are more likely to self-insure react more. [53]

7.1.4. *Other forms of regional spillover effects*

Because a variety of other forms of regional spillover effects might affect our results, we conduct another series of tests in which we focus on firms operating outside of the disaster

[52] Note that after a major disaster, banks are given access to a special liquidity window at the FED to refinance their balance sheet more easily and re-inject liquidities in the local economy, which explains why the amount of new credits increases
[53] Results of this complementary test are reported in the technical appendix (Appendix C)

zone *and* outside of the neighborhood area. Because these firms are more isolated from the local economy that is shocked by the disaster, any increase in cash holdings is less likely to be driven by a regional spillover effect. The results of these tests are reported in Table 10.

[INSERT TABLE 10 AROUND HERE]

In the first column, we re-run our main test and focus on firms that do not have significant business connections with other firms potentially affected by the hurricane event. Using the Compustat Customer Segment database, we identify neighborhood firms from our sample that have their main customer and/or provider in the disaster area. Column 1 indicates that excluding those firms from our sample does not change our main result.

In the second column, we examine the effect of the disaster on "the neighbors of neighbors". We define two groups of neighbors according to geographical distance by creating a fourth category of firms that correspond to firms located in the neighborhood of the disaster zone but not in its close neighborhood (hereafter, a "Remote Neighbor"). To identify these firms, we match with replacement each affected county with its ten nearest neighbors among the non-affected counties. Firms are then assigned to the Remote Neighbor group if their headquarters are located in the ten nearest non-affected counties but not in the five closest. For each firm identified as a "Remote Neighbor", we calculate the distance between its headquarters and the headquarters of the closest affected firm. On average, we find that firms from our Remote Neighbor group are 80 miles away from the disaster zone. Despite the distance, the regression in Column 2 indicates that these firms also respond to the occurrence of the hurricane by increasing the amount of cash holdings.

In the third column, we focus on all vulnerable firms (excluding firms in the neighborhood of the affected region). Those firms may be far away from the disaster zone (e.g. firms located in the East coast when a hurricane hits Louisiana). We define a firm as sensitive to the risk of hurricane strike if it has been strongly affected once by a hurricane during the sample period.[54] We create a dummy variable *Vulnerable* that is equal to one if (i) the firm is identified as sensitive to the risk of hurricane disaster, (ii) the firm is neither in the

[54] To detect these firms, we look for significant drop in revenues after a hurricane landfall. Our methodology is the following. We first compare the growth in revenues observed in the data after each disaster with the prediction obtained from the same regression as the one performed in Table 3 Column 2, except that the dependent variable is the growth of sales relative to the same quarter of the previous year. A firm is defined as vulnerable if the difference between its actual and predicted sales growth is in the bottom tercile of the distribution.

disaster area nor in the neighborhood area, and (iii) a hurricane made landfall over the past twelve months. We obtain a group of 614 "vulnerable firms", whose average distance from the disaster zone is 444 miles. Despite such a distance, the regression in Column 3 indicates that the managers of these firms increase cash holdings after the hurricane.[55]

Overall, these results suggest that while some regional spillover effects may possibly affect firms in the neighborhood area, these effects cannot be the main explanation of 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 in certain geographic areas during a one-year or two-year period. In this case, being a neighbor could indicate that the probability of being hit by a hurricane in the coming year is now higher than it used to be. We are not aware of any clear evidence of such a clustering phenomenon in the climate literature (see section 2). 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 time horizons how the probability of being struck changes when the county was previously located in the neighborhood of an area affected by a disaster. We follow Jorda (2005) and Favara and Imbs (2015) and proceed sequentially. For every horizon *h* (e.g. 1 quarter ago, 2 quarters ago, etc…), we estimate the following model

$$Hit_{ct} = \alpha_c + \gamma_t + \beta Neighbor(h)_{ct} + \varepsilon_{c,t}$$

Where *h* indexes the horizon (e.g. *h* quarter(s) / year(s) ago), *c* indexes county, and *t* indexes time. *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 that control for heterogeneity across county and

[55] This finding rules out the possibility that cash increases here because of a local negative sentiment as in Addoum, Kumar and Le (2014)

season, γ_t are time fixed effects. $\beta(h)$ estimates how the probability for county *c* to be hit by a hurricane at time *t* changes in response to the proximity of a hurricane strike occurred *h* quarter(s) / year(s) ago. We report the results in Table 11

[INSERT TABLE 11 AROUND HERE]

In column 1 to 4, we estimate the impulse response function by quarter using the 15 major hurricanes of our study. *Neighbor – Qh* is a dummy variable equal to 1 if the county was located in the neighborhood area *h* quarters ago. The point estimate is close to zero and is never statistically significant whatever the horizon we consider. In column 5 to 6, we repeat the same analysis by year. The coefficient on the variable *Neighbor – Year1* is negative and statistically insignificant, which means that the proximity of a hurricane contains no information about the likelihood of hurricane strike for the following year. Likewise, the occurrence of a disaster in the neighborhood area two years before has no predictive power on the likelihood to be affected by a hurricane in a given year. Column 7 to 12 show similar results when we repeat the same analysis using all hurricanes from the SHELDUS database. Whatever the time horizon that is considered, the occurrence of a hurricane never reveals information about future disaster likelihood in the neighboring counties. [56]

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 the true probability of a disaster after the hurricane's landfall. However, this explanation would again imply a permanent increase in cash, which we do not find.[57]

It is also difficult to reconcile such a risk-learning hypothesis with our results regarding the value of cash. If managers learn the true probability 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.

[56] We also estimated the impulse response function by month and find the same results. We plotted the results of this analysis in a graph presented in the technical appendix (Appendix C).

[57] Managers could also learn about the economic consequences of this type of natural disaster. But since the total cost of hurricanes has been increasing over the past decades, this explanation should also imply a permanent increase in cash.

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 the amount of their cash holdings. Finding an increase in cash holdings would then be consistent with the *availability heuristic* hypothesis while allowing us to rule out other possible explanations. Indeed, 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 (for instance in Pakistan) provides no information about the likelihood of experiencing an earthquake in US territory.[58] It would also not be consistent with the *geographical 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 performed under the Earthquake Hazard Program by the USGS. For each zip code, we compute the average earthquake intensity felt over the past 20 years. We assign the average earthquake intensity felt to each firm in Compustat using the zip code from the headquarters' address. We then focus on firms within the top 10% of the average intensity felt distribution and assign them to a seismic zone group (treatment group). All other firms are assigned to a non-seismic zone group (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. We obtain all this information from the Significant Earthquake Database.[59] These selection criteria lead to the list of 11 major non-US earthquakes described in the technical Appendix. We then estimate the average change in cash holdings for the seismic zone group around the announcement of the earthquake outside

[58] An earthquake in Japan, Chile or Mexico *does not* provide information about earthquake risk in California. See U.S. Geological Survey website: "Often, people wonder if an earthquake in Alaska may have triggered an earthquake in California (…). Over long distances, the answer is no. Even the Earth's rocky crust is not rigid enough to transfer stress efficiently over thousands of miles."

[59] National Geophysical Data Center/World Data Center (NGDC/WDC) Significant Earthquake Database, Boulder, CO, USA. (Available at http://www.ngdc.noaa.gov/nndc/struts/form?t=101650&s=1&d=1)

the US using the same matching methodology as the one used for hurricanes and also described in our technical Appendix. The results of this analysis are depicted in the graph of Figure 6.[60]

[INSERT FIGURE 6 AROUND HERE]

Figure 6 shows qualitatively the same pattern as that previously observed. Firm managers 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 shocks in regulatory filings. Such a reaction is difficult to reconcile with the standard Bayesian theory of judgment under uncertainty because the liquidity shock stems from a hurricane landfall whose probability to occur again in the near future is not higher than it was before the shock. And if it were, the observed reaction should be *permanent* rather than *temporary*. 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 put 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 economically 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 subjective risk and objective 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 firm managers, our results suggest that the total real economic cost of this bias is likely to be considerable.

[60] More details about our methodology and the detailed results are provided in the technical appendix (Appendix C).

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Figure 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 (2011).

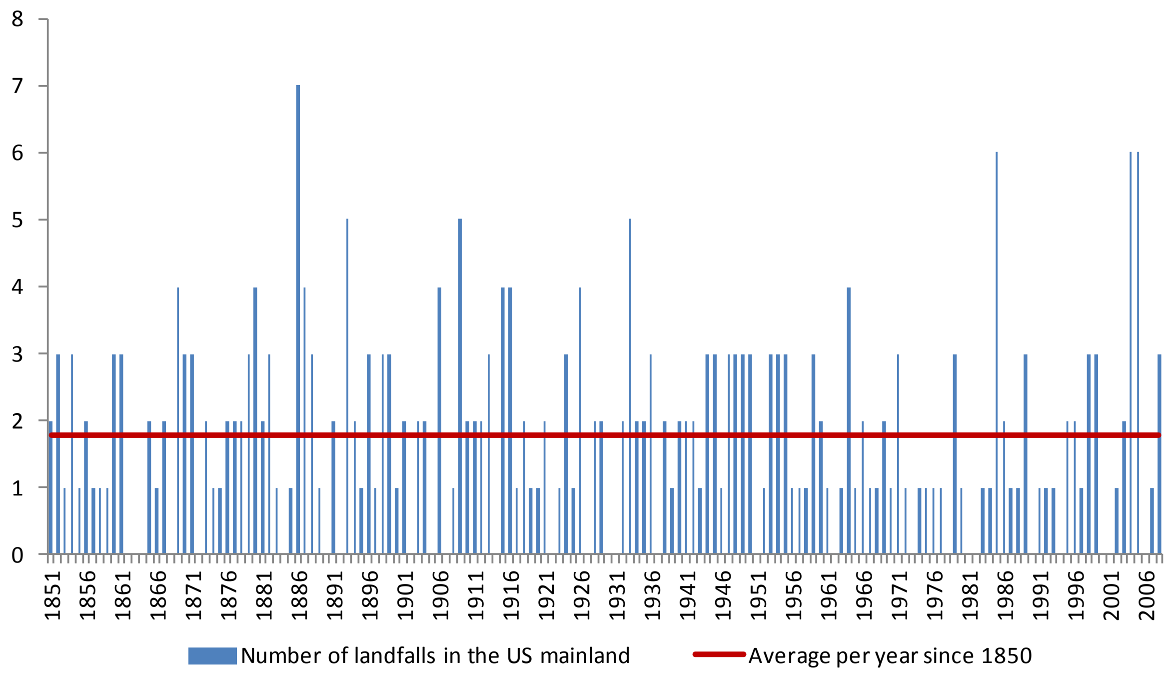


Figure 2

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 the urban communities of the county. Firms located in the Neighborhood (dark blue counties on the map) are assigned to treatment group. Firms located in the rest of the US mainland (White counties on the map) are assigned to control group. Firms located in the disaster zone (light blue counties on the map) are not considered in the analysis.

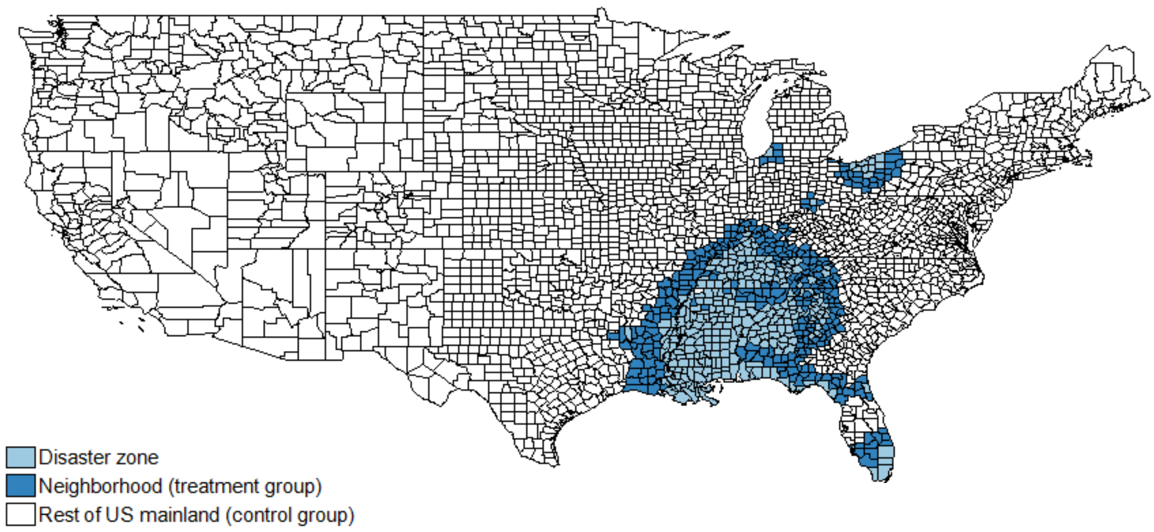


Figure 3

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 q0). The blue line plots the difference-in-differences in the level of corporate cash holdings for firms located in the neighborhood area. The red 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.

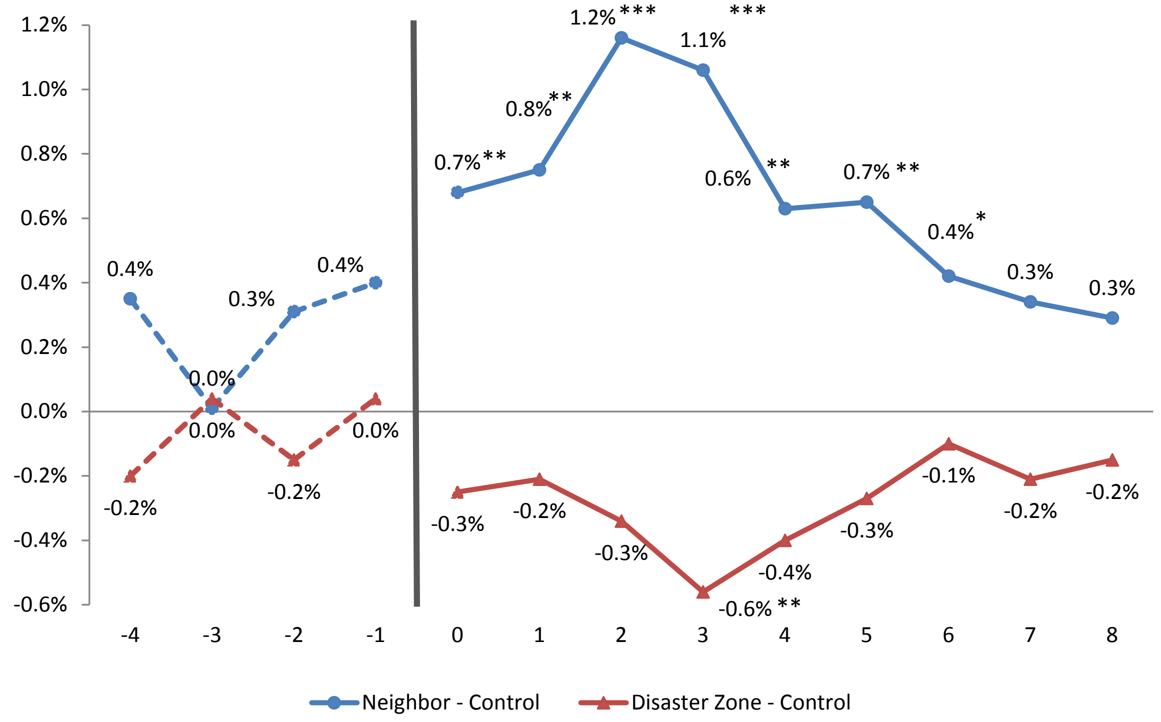


Figure 4

Hurricane Proximity and the Likelihood that Hurricane Risk is Mentioned in 10-K/10-Q Filings

This graph compares the effects of the hurricane proximity on the probability that hurricane risk is explicitly mentioned as a risk factor in 10-K/10-Q filings with the effects of the hurricane proximity on the level of corporate cash holdings at different quarters surrounding the hurricane event (quarter q0). The vertical bars plot the difference-in-differences estimates in the probability that hurricane risk is mentioned in 10-K/10-Q filing for firms located in the neighborhood area (left-hand side axis). The blue line plots the difference-in-differences in the level of corporate cash holdings for firms located in the neighborhood area (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.

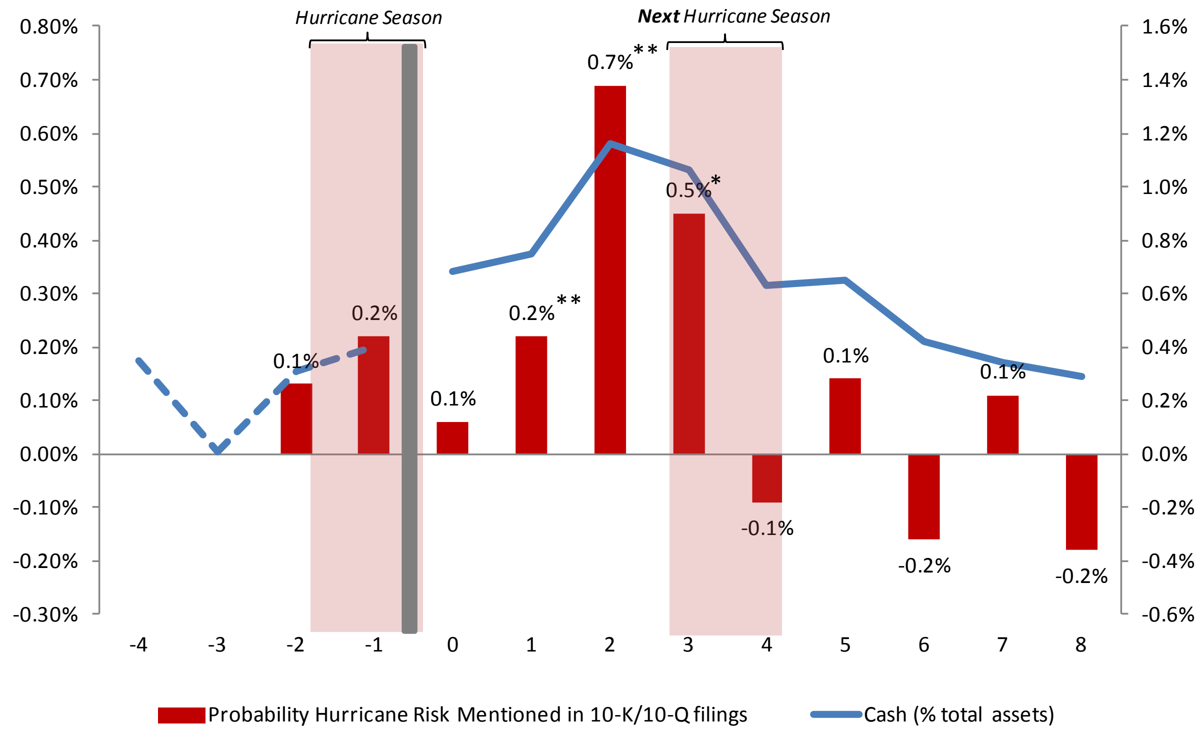


Figure 5

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 blue line plots the difference-in-differences in sales growth for firms located in the neighborhood area. The red 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 the Internet appendix. ***, **, and * denote significance at the 1%, 5% and 10% levels.

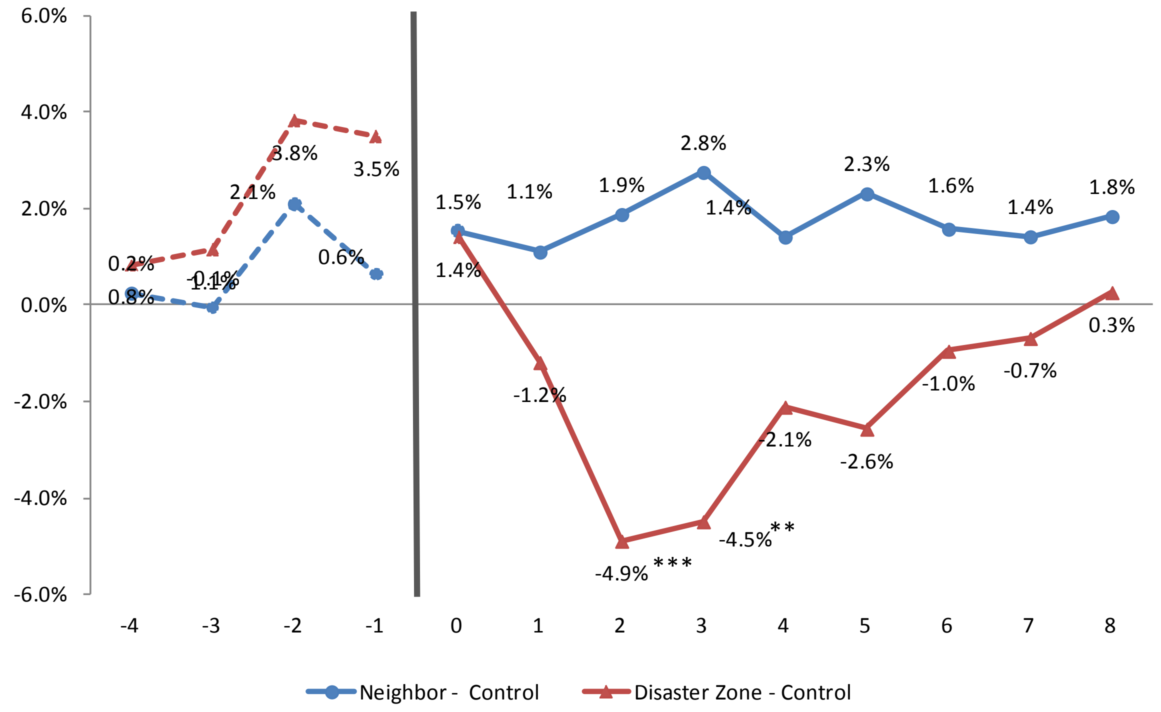


Figure 6

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 treated firms whose headquarters are located in a urban community where an earthquake is frequently felt according to the U.S. Geological surveys ("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 closer control firms in terms of Mahalanobis distance to the treated firm receive greater weight. The Mahalanobis distance is computed at quarter q-2 (ie. three months before the earthquake occurrence) along four dimensions: size, age, market-to-book, and financial leverage. ***, **, and * denote significance at the 1%, 5% and 10% levels.

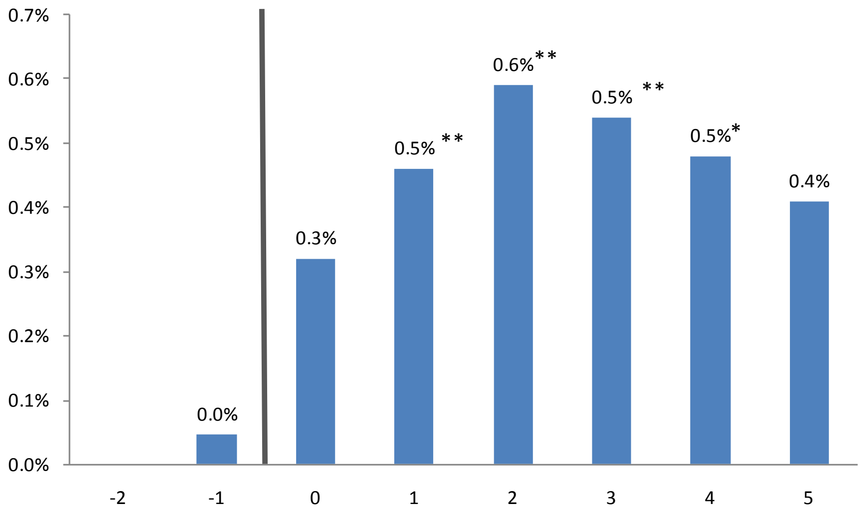


Table 1

Major Hurricanes Landfall 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 billion dollars. Damages (CPI adjusted) is the estimated value of total damages expressed in billion dollars adjusted for the Consumption Price Index as of 2010. Category measures the wind intensity according to the Saffir and Simpson Hurricane Wind Scale which ranges from 1 (lowest intensity) to 5 (highest intensity). Primary source of information is the SHELDUS database. 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 (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	1,500	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

(*) "TS" : Tropical Storm

Table 2

Descriptive Statistics

This table reports firm-level summary statistics. Panel A reports statistics of the main firm-level variables over the 1987-2011 period. 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-statistic from a two-sample test for equality of mean across treated and control firms. All variables are from Compustat Quarterly, excluding financial, utilities and non US firms. All variables are winsorized at the 1st and 99th percentiles. The variables are defined in Appendix B.

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	408,392	13.8%	47.6%	5.8%	16.0%	27.1%
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	Disaster Zone	Neighborhood	Rest of US	*t* -statistic
Group Assignement	Excluded	Treatment	Control	
Age	11.1	11.3	10.3	2.19**
Assets	1,316	1,308	1,135	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	10.2%	12.2%	13.5%	-1.02
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	

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 1 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 1 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 1 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*-stat are reported in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels.

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	

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 1 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 1 if the firm is located in the neighborhood area for the first, second, and third time (or more), respectively. *Occurrence* is the number of times the firm was located in the neighborhood of an area hit by a hurricane. 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. Base line 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-stat are reported in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels.

Dependent Variable: Cash / Assets (in percentage points)		
OLS	[1]	[2]
Neighbor x First time	2.15***	2.04*
	(2.62)	(1.94)
Neighbor x Second time	1.94**	1.98*
	(2.33)	(1.66)
Neighbor x Third time (and more)	0.07	0.08
	(0.06)	(0.06)
Neighbor x Age	-0.60*	-0.64
	(-1.81)	(-1.48)
Disaster zone	-0.26	-0.26
	(-1.18)	(-0.95)
Occurence x Firm-Season Fixed Effects	Yes	Yes
Occurence x Time Fixed Effects	Yes	Yes
Occurence x Age Fixed Effects	Yes	Yes
Subsample		Yes
N	411,490	333,596
Neighbor x First time - Neighbor x Third time (and more)	2.08	1.96
F -test	6.81***	4.44**

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 as a risk factor in 10-K/10-Q filings. Hurricane Risk is a dummy variable equal to 1 if the risk of hurricane is mentioned at least once in the contents of 10-K/10-Q filings. *Neighbor* is a dummy variable equal to 1 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 1 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 1 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-stat are reported in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels.

	Dependent Variable: Hurricane Risk			
	[1]		[2]	
Linear Probability Model	coef.	t-stat	coef.	t-stat
Neighbor	0.36***	(2.60)		
Disaster zone	0.51**	(1.97)		
Neighbor_q-2			0.13	(0.44)
Neighbor_q-1			0.22	(0.82)
Neighbor_q0			0.06	(0.33)
Neighbor_q+1			0.21**	(2.01)
Neighbor_q+2			0.67**	(2.26)
Neighbor_q+3			0.45*	(1.68)
Neighbor_q+4			-0.1	(-0.72)
Neighbor_q+5			0.14	(0.49)
Neighbor_q+6			-0.16	(-0.57)
Neighbor_q+7			0.11	(0.46)
Neighbor_q+8			-0.19	(-0.95)
Disaster Zone_q-2			1.35	(1.44)
Disaster Zone_q-1			-0.39	(-0.81)
Disaster Zone_q0			0.28	(0.94)
Disaster Zone_q+1			0.58*	(1.70)
Disaster Zone_q+2			1.64	(1.41)
Disaster Zone_q+3			-0.38	(-1.31)
Disaster Zone_q+4			0.07	(0.29)
Disaster Zone_q+5			0.02	(0.09)
Disaster Zone_q+6			0.1	(0.18)
Disaster Zone_q+7			-0.26	(-1.28)
Disaster Zone_q+8			0.22	(0.94)
Firm-Season Fixed Effects	Yes		Yes	
Time Fixed Effects	Yes		Yes	
N	196,149		196,149	

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 10-K/10-Q 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 1 if the risk of hurricane is mentioned at least once in the contents of 10-K/10-Q filings. *Neighbor* is a dummy variable equal to 1 if the county of the firm headquarters is in the neighborhood of an area hit by a hurricane over the past 12 months. In column 3, control variables (interacted with *Neighbor*) include *Size*, *Age* and *Market-to-book*. All other variables are defined in Appendix B. Base line 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*-stat are reported in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels.

Dependent variable	Cash / Assets			Sales Growth
OLS	[1]	[2]	[3]	[4]
Neighbor x Hurricane Risk	2.96*	3.61**	3.68**	1.35
	(1.72)	(2.14)	(1.98)	(0.21)
Neighbor	0.77***			
	(2.96)			
Disaster zone	-0.16			
	(-0.54)			
Hurricane Risk x Firm-Season FE	Yes	Yes	Yes	Yes
Hurricane Risk x Time FE	Yes	Yes	Yes	Yes
County x Time FE		Yes	Yes	Yes
Controls (Interacted)			Yes	
N	196,149	196,149	196,149	196,149

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 1 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 1 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 1 if the examined outcome is different from zero, and all regression coefficients are multiplied by 100 for readability purposes. 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.

Panel A

Dependent variable	Sales growth (%)	Operating Margin (%)	NWC (% Sales)	Investment (% PPE)	Dividend (% Earnings)	Repurchase (% Earnings)	New financing (% Mark. Cap.)
OLS	[1]	[2]	[3]	[4]	[6]	[5]	[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	408,392	384,494	210,680	209,049	352,257

Panel B

Dependent variable	Dividend dummy	Repurchases dummy	New financing dummy
Linear Probability Model	[1]	[2]	[3]
Neighbor	-0.66*	-1.17**	0.35
	(-1.67)	(-2.31)	(0.81)
Disaster zone	0.34	0.03	-0.06
	(0.62)	(0.05)	(-0.13)
Season-Firm Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
N	382,848	353,584	406,324

Table 8

Change in the Value of Cash after the 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 1 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 1 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 (2005). Controls include *Change in Earnings*, *Change in Interests*, *Change in Dividends*, *Change in Net Assets*, *Change in R&D*, *Market Leverage*, *New Financing* and *Cash Lagged*. 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*, as well as the firm and time fixed effects. Base line 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-stat are reported in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels.

Dependent Variable: Change in Market Value				
OLS	[1]		[2]	
	Coef.	t-stat	Coef.	t-stat
Change in cash	0.72***	(20.93)		
Change in cash x Neighbor			-0.29**	(-2.19)
Change in cash x Disaster Zone			-0.15	(-1.11)
Controls	Yes			
Time Fixed Effects	Yes			
Controls (Interacted)			Yes	
Time Fixed Effects (Interacted)			Yes	
Firm Fixed Effects (Interacted)			Yes	
N	293,225		293,225	

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 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 Internet 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.

Group	N (firms)	N (portfolios)	ACAR (%)	*Z*	Economic gain (% of assets)
Neighbor	2,583	15	-0.04%	(-0.16)	-0.10%
Disaster zone	1,991	74	-0.82%**	(-2.23)	-1.03%
Control (Rest of US)	30,350	15	-0.08%	(-0.56)	-0.11%

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 1 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 1 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 have not significant connections (main provider or customer) with the disaster zone. In column 2, *Remote Neighbor* is a dummy variable equal to 1 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 1 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.

Dependent variable: Cash / Assets (in percentage points)			
Effect of Hurricane Strike for	Unconnected Firms	Remote Neighbors	Vulnerable Firms Outside the Neighborhood area
OLS	[1]	[2]	[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

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 stroke 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 done 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 1 if the county is hit by a hurricane (Only one of the 15 major hurricanes in columns 1 to 6 and any hurricane in columns 8 to 12). *Neighbor – Qi* is a dummy equal to 1 if the county was in the neighborhood of an area hit by a hurricane *i* quarter(s) ago. *Neighbor –Yeari* is a dummy equal to 1 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-stat 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.

	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	38,664	38,664	154,656	154,656	154,656	154,656	38,664	38,664

Appendix A - Robustness Tests

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.1, 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 A.2, the dependent variable is the log of total assets at the end of the quarter. *Neighbor* is a dummy variable equal to 1 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 1 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 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.

Panel A.1

Dependent Variable	Cash / Assets (in percentage points)							
Robustness test	Industry x Time Fixed Effects		Location State x Time Fixed Effecs		More Controls		Placebo	
	[1]		[2]		[3]		[4]	
	coef.	t-stat	coef.	t-stat	coef.	t-stat	coef.	t-stat
Neighbor	0.83***	(3.63)	0.64**	(2.09)	0.65***	(3.17)	0.05	(0.22)
Disaster Zone	-0.22	(-1.07)	-0.06	(-0.19)	-0.23	(-1.08)	0.11	(0.18)
Size					-0.92***	(-6.32)		
Age					-0.11***	(-4.94)		
Market-to-Book					0.84***	(21.03)		
Debt					-14.72***	(-33.55)		
Net Working Capital					-29.25***	(-18.09)		
Investment					-29.15***	(-9.28)		
R&D					-44.98***	(-9.83)		
Firm-Season Fixed Effects	Yes		Yes		Yes		Yes	
Time Fixed Effects					Yes		Yes	
SIC3 x Time Fixed Effects	Yes		Yes					
State x Time Fixed Effects			Yes					
N	411,490		411,490		373,576		411,490	

Panel A.2

Dependent Variable	Total Assets (in log)							
Robustness test	Base Line Specification		Industry x Time Fixed Effects		Location State x Time Fixed Effecs		More Controls	
	[1]		[2]		[3]		[4]	
	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)	0.01	(1.09)
Disaster Zone	0.03	(1.27)	0.01	(0.85)	0.00	(0.22)	0.03	(1.05)
Size								
Age							0.38***	(16.29)
Market-to-Book							-0.00***	(-2.62)
Debt							-0.37***	(-11.76)
Net Working Capital							0.00***	(10.89)
Investment							0.00***	(18.15)
R&D							-0.08***	(-25.79)
Firm-Season Fixed Effects	Yes		Yes		Yes		Yes	
Time Fixed Effects	Yes						Yes	
SIC3 x Time Fixed Effects			Yes		Yes			
State x Time Fixed Effects					Yes			
N	411,490		411,490		411,490		340,183	

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 Dividend	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 Interests 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 1 if the county location of the firm headquarter is in an area hit by a hurricane over the past 12 months
Dividend	Total dividends over last year net income
First Time	Dummy equal to 1 if a firm has never been located in the neighborhood area and zero if not
Hurricane Risk	Dummy equal to 1 if hurricane risk is explicitly mentioned in 10K/10Q filing and zero if not
Investments	Total cash flow from investing activities (capital expenditures + acquisition expenditures) scaled by net property, plant and equipment
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 1 if the county location of the firm headquarter 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
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 net income
Sales growth	Growth in total revenues relative to the *same* quarter of the previous year
Second Time	Dummy equal to 1 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 1 if the firm has been located in the neighborhood area multiple times and zero if not
Vulnerable	Variable equal to 1 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

Appendix C – Technical Appendix (Not Intended for Publication)

In this appendix, we present some complementary results not intended for publication that are mentioned in the paper but not reported there for brevity. We also provide further details about the methodology used to implement our matching approach in section 5.4 and to perform the event study presented in section 7.3.1. The structure of this appendix follows the structure of the paper.

A. Matching approach (Mentioned in Section 5.4)

We use a kernel matching approach similar to the one proposed by Heckmann, Ichimura and Todd (1998) where the matched outcome for each treated firm is a weighted average of the effects observed on several non-treated firms. In this approach, the weights are chosen so that the observations closer in terms of distance receive greater weight. In practice, we match each treated firm (neighborhood area) with all the control firms (rest of US mainland) from the same industry (SIC3) 6 months before the occurrence of the hurricane (ie. time q-3) . For each treated firm, we then compute the Mahalanobis distance to all matched firms along seven dimensions : size, age, market-to-book, financial leverage, working capital requirement, dividend and capital expenditures. The weight assigned to each matched firm is then given by

$$w_{i,j} = \frac{K\left(\frac{d_{i,j}}{h}\right)}{\sum_{k=1}^{k=n} K\left(\frac{d_{i,k}}{h}\right)}$$

where i indexes the treated firm, j indexes the matched firm, n_i is the number of firms matched to i, $d_{i,j}$ is the Mahalanobis distance between i and j, $K(.)$ is the Gaussian density function and h is a bandwidth parameter. For each treated firm i, we follow Todd (1999) and simply set the bandwidth equal to the distance to the nearest matched j. This methodology allows to use a smaller bandwidth when the treated firm has more matched firms in its local neighborhood. The matched outcome is then the weighted average of the change in cash observed for all matched firms (ie. control firms from the same SIC3 industry).

The results of this analysis are presented in Table A.

B. Event Study Methodology (mentioned in section 7.1.1)

The event window is defined as [$BOH_{c,h}$-1 ; $EOH_{c,h}$+1], where c indexes county and h hurricane, and where *BOH* (*EOH*) is the beginning (end) of hazard date reported in the SHELDUS database. By definition, firms assigned to Treatment group or Control group are not located in a county reported by SHELDUS. In this case, the event window is defined as [$Min(BOH_h)$-1 ; $Max(EOH_h)$+1], where $Min(BOH_h)$ ($Max(EOH_h)$) is the minimum (maximum) of the beginning (end) of hazard dates reported in the SHELDUS database for hurricane h. Because the events we are looking at overlap in time, we cannot assume the independence between the variances of security abnormal returns. To address this issue, we form an equally-weighted portfolio whenever the event windows perfectly overlap. For firms assigned to the neighbor group and control group, we obtain 15 portfolios because there are 15 hurricanes (and thus 15 different event windows). We obtain 74 portfolios for firms assigned to the disaster zone category (instead of 15) because all affected counties are not affected at the same time by the same hurricane. While some are affected on Monday, other can be affected on Tuesday and Wednesday as the hurricane moves across land.

For each portfolio p, the average abnormal return over the event window is then estimated as the parameter AR_p in the equally-weighted market model (see Betton, Eckbo, Thorburn (2008))

$$r_{p,t} = \alpha_j + \beta_p rm_t + AR_p w_t + \epsilon_{p,t}, \quad \text{with } t = \text{day}\{BOH_p - 201; EOH_p + 1\}$$

where r_{jt} is the return to portfolio p over day t, rm_t is the crsp equally-weighted market return, and w_t is a dummy variable that takes a value of one if day t is in the event window and zero otherwise. This conditional event parameter approach allows us to easily incorporate variable-length event windows across portfolios and directly produces an estimate of the standard error of the Abnormal Return *AR*. To be included in the portfolio, a security must have at least 150 non missing and non zero returns over the estimation period (200 days), and no missing return over the event window (See Savickas (2003)). The cumulative abnormal return (CAR) to portfolio *p* over event window *w* is

$$\mathrm{CAR_p = w_p AR_p}$$

where w_p is the number of trading days in the event window. For each group, the average CAR is

$$\mathrm{ACAR} = \left(\frac{1}{\mathrm{N}}\right)\sum_{\mathrm{p=1}}^{\mathrm{T}} \mathrm{n_p CAR_p}$$

where N is the total number of securities, n_p is the total number of securities in portfolio p, and T is the total number of equally-weighted portfolios. Since the event windows do not overlap between portfolios, we can assume that the variances of the portfolio abnormal returns are independent. For each category, the variance of the average abnormal return is

$$\mathrm{V(ACAR)} = \left(\frac{1}{\mathrm{N}^2}\right)\sum_{\mathrm{p=1}}^{\mathrm{T}} \mathrm{n_p^2 w_p^2}\, \sigma^2_{\mathrm{AR_p}}$$

where σ_{AR_p} is the estimated standard error of AR_p. The z-values are determined as

$$\mathrm{z} = \frac{\mathrm{ACAR}}{\sqrt{\mathrm{V(ACAR)}}}$$

C. Effects of hurricane proximity on Sales Growth Volatility (mentioned in section 7.1.2)

We examine whether the proximity of the hurricane affects the volatility of firm revenues. We use two different approaches to conduct this examination. In Panel A of Table B, we estimate revenue volatility at the firm level using the standard deviation of sales growth in a time series. We estimate the standard deviation of the growth in revenues before and after the hurricane for each firm over a four-quarter period. We then test whether this standard deviation is higher for firms in the neighborhood are after the hurricane. In panel B of Table B, we estimate revenue volatility at the county level using the standard deviation of sales growth in cross section. We estimate the standard deviation of the growth in revenues across all firms from the same county at every quarter surrounding the hurricane event. We then test whether this standard deviation at the county level is affected by the hurricane.

D. Effects of hurricane proximity on Stock Return Volatility (mentioned in section 7.1.2)

Our analysis of stock return volatility in Table C provides evidence that the hurricane does not create higher uncertainty for firms in the neighborhood area. In Panel A, we follow a methodology proposed by Kalay and Loewenstein (1985) and use an F-test to assess whether a hurricane event affects stock return variances. We find that an F-test cannot reject at the 5% level the null hypothesis that the pre-hurricane and post-hurricane stock return variances are equal for the majority of firms in the neighborhood area (64.8%). We next compute stock return volatility at each quarter and test in Panel B whether this volatility changes for firms in the neighborhood area using our baseline specification; we again find that the proximity of the hurricane does not affect stock return volatility.

E. Effects of hurricane proximity on Bank Loans (mentioned in section 7.1.3)

We examine the effect of hurricane proximity on Commercial and Industrial Loans (C&I Loans) at the bank level using the data from the FDIC database. This database provides "Reports of Income and Condition" (Call Reports) that include detailed quarterly financial and regulatory bank data for all commercial and domestic banks in the U.S. We include all banks in our sample provided that standard viability conditions of the bank are respected.[64] The outcome variable we are interested in is the amount of new commercial loans at the bank level. This variable corresponds to the change in commercial and industrial loans (RCON1766) relative to the previous quarter scaled by total assets (RCFD2170). We then use the same difference-in-differences methodology as the one used to measure how the proximity of the hurricane affects cash holdings over time. The results of this analysis are reported in Table D.

[64] To be included in our sample, banks must have non zero or negative equity, total assets above 25 million dollars, consumer loans representing less than 50% of total assets, more than two years of existence, and non missing values on the commercial and industrial loans variable

F. Hurricane proximity and Self Insurance (mentioned in section 7.1.3)

We investigate how managers' response to hurricane proximity changes when the business operated by the company is less dependent on external insurance. We use the share of total assets which are intangible assets to identify when the business of the firm is more likely to be self-insured. Firms are identified as more likely to be self-insured if this share is in the top tercile of the distribution. We define a dummy variable *Self-Insurance* that is equal to one if the firm is more likely to be self-insured and zero if not. We then interact this variable with the *Neighbor* variable to study how the response to the salience of hurricane risk varies when firms are more likely to self-insure. The results of this analysis are reported in Table E.

G. Monthly Impulse Response Function (mentioned in section 7.4)

Graph A plots the monthly impulse response function to the proximity of the county to a hurricane disaster on future hurricane likelihood.

H. Reaction to extreme earthquakes outside the US (mentioned in section 7.4)

We focus on the biggest earthquakes occurred during the past 30 years according to magnitude, total deaths, and total damages description. These selection criteria leads to the list of major non US earthquakes described in Table G, Panel A. We then estimate the average change in cash holdings for the seismic zone group around the announcement of the earthquake outside the US using exactly the same matching methodology as the one already used for the hurricanes. The results of this analysis are reported in Table F, Panel B.

Technical Appendix - Table A

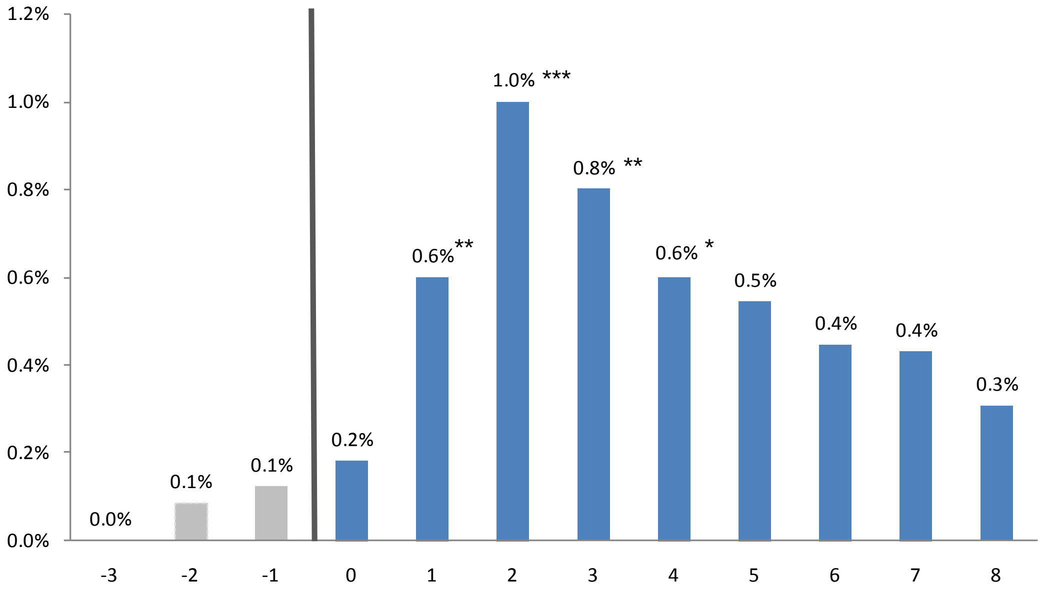
Effects of Hurricane Proximity on Corporate Cash holdings (Matching Approach)

Panel A presents changes in corporate cash holdings over time caused by the proximity of a hurricane occurred at quarter *q0*. The sample comprises 2,060 treated firms whose headquarter is located in the neighborhood of an area hit by a hurricane during quarter *q0* ("Neighbor firms"). For each treated firm, the counterfactual outcome is the weighted average of the change in cash over all control firms with the same SIC 3 code ("Matched firm"). The weighting is achieved through a kernel function so that the closer control firms in terms of Mahalanobis distance to the treated firm receive greater weight. The Mahalanobis distance is computed six months before the hurricane landfall at quarter q-3 along seven dimensions: size, age, market-to-book, financial leverage, capital expenditures and net working capital. *t*-statistics are reported in the last column. ***, **, and * denote significance at the 1%, 5% and 10% levels. Panel B plots the results in graph

Panel A

Average change in cash from q-3 to	**Neighbor firms**	**Matched firms**	**Diff-in-diffs**	***t*-statistic**
q-2	-0.5%	-0.6%	0.1%	0.51
q-1	-0.7%	-0.8%	0.1%	0.55
q0	-0.6%	-0.8%	0.2%	0.69
q+1	0.0%	-0.6%	0.6%**	1.96
q+2	0.4%	-0.6%	1.0%***	2.97
q+3	0.1%	-0.7%	0.8%**	2.38
q+4	-0.3%	-0.9%	0.6%*	1.71
q+5	-0.1%	-0.6%	0.5%	1.47
q+6	-0.5%	-0.9%	0.4%	1.18
q+7	-0.7%	-1.1%	0.4%	1.12
q+8	-0.9%	-1.2%	0.3%	0.79

Panel B



Technical Appendix - Table B

Change in Sales Growth Volatility after the Hurricane Landfall

This table presents difference-in-differences estimates of the effect of the hurricane proximity on sales growth volatility. In panel A, we estimate the volatility of the growth in revenues at the firm level after (before) the hurricane by measuring the standard deviation of sales growth over the four quarters following (preceding) the occurrence of the disaster. In panel B, we estimate the volatility of the growth in revenues at the county level using the standard deviation of sales growth across firms for each quarter around the hurricane. The specification in panel B is weighted by the average number of firms in the county. 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.

Panel A: Impact of Hurricane Proximity on Sales Growth Variance at the Firm level

Dependent variable: Sales Growth Standard Deviation (in percentage points)		
	Coefficient	*t* -stat
Neighbor	0.21	(0.38)
Disaster zone	-1.24*	(-1.85)
Firm Fixed Effects	Yes	
Time Fixed Effects	Yes	
N	89,990	

Panel B: Impact of Hurricane Proximity on Sales Growth Variance at the County level

Dependent variable: Sales Growth Standard Deviation at the County Level (in percentage points)		
	Coefficient	t-stat
Neighbor_q-1	-0.95	(-0.53)
Neighbor_q0	0.98	(0.37)
Neighbor_q+1	1.24	(0.50)
Neighbor_q+2	2.94	(1.05)
Neighbor_q+3	3.10	(1.02)
Neighbor_q+4	-1.70	(-0.70)
Neighbor_q+5	-1.85	(-0.88)
Neighbor_q+6	-1.84	(-0.76)
Neighbor_q+7	-2.26	(-1.02)
Disaster zone_q-1	0.70	(0.27)
Disaster zone_q0	-2.83*	(-1.90)
Disaster zone_q+1	-2.97*	(-1.83)
Disaster zone_q+2	-4.26	(-1.30)
Disaster zone_q+3	-3.88	(-1.43)
Disaster zone_q+4	-0.85	(-0.27)
Disaster zone_q+5	0.21	(0.07)
Disaster zone_q+6	0.75	(0.40)
Disaster zone_q+7	-1.18	(-0.54)
County Fixed Effects	Yes	
Time Fixed Effects	Yes	
N	42,540	

Technical Appendix - Table C

Change in Stock Returns Volatility after the Hurricane Landfall

This table presents results of two tests examining the effect of the hurricane proximity on stock returns volatility. Panel A presents results of an F-test of the equality of stock return variances around the hurricane period for each group of firms (Neighbor, Disaster Zone, and Control). Stock return variances are estimated over two 30-days periods, one before the start of the hurricane period and the other after the end of the hurricane period. Column 1 (2) reports the percentage of firms experiencing a decrease (increase) in stock return variance that is statistically significant at the 5% level. Column 3 reports the percentage of firms for which the F-test cannot reject the null hypothesis of stock variances equality between the two periods at the 5% level. In Panel B, we presents difference-in-differences estimates of the effect of the hurricane proximity on stock returns volatility. The dependent variable is the (annualized) stock returns volatility measured by the standard deviation of daily stock returns over the quarter. Neighbor is a dummy variable equal to 1 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 1 if the county of the firm headquarters is in the area hit by a hurricane over the past 12 months. 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.

Panel A: F-test of the Equality of Stock Returns Variances

		Change in Stock Returns Variance		
Group	# Firms	% Down	% Up	% No change
		[1]	[2]	[3]
Neighbor	1,773	16.6%	18.6%	64.8%
Disaster zone	2,299	16.7%	19.7%	63.5%
Control	27,539	16.4%	17.9%	65.8%

Panel B: Impact of Hurricane Proximity on Stock Returns Volatility

	Dependent variable: Stock Returns Volatility (in percentage points)
Neighbor	0.95
	(0.94)
Disaster zone	1.33**
	(2.22)
Firm-Season Fixed Effects	Yes
Time Fixed Effects	Yes
N	314,383

Technical Appendix - Table D

Impact of Hurricane Proximity on Bank Loans

This table presents difference-in-differences estimates of the effect of the proximity of a hurricane strike on the amount of new commercial and industrial loans of the bank at different quarters around the occurrence of the hurricane. *ΔC&I Loans* is the amount of new commercial and industrial loans granted during the quarter at the bank level expressed in percentage points of the total assets at the end of the quarter. *Neighbor_q+i* is a dummy equal to 1 if the county location of the bank headquarter at quarter *q+i* is in the neighborhood of an area hit by a hurricane during quarter *q0*. *Disaster_zone_q+i* is a dummy equal to 1 if the county location of the bank headquarter at quarter *q+i* is in the area hit by a hurricane during quarter *q0*. Standard errors corrected for clustering of the observations at the county level. *t*-stat are reported between parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels.

Dependent variable: ΔC&I Loans / Assets (in percentage points)

	Coefficient	t-stat
Neighbor_q-4	-0.02	(-0.74)
Neighbor_q-3	0.00	(-0.07)
Neighbor_q-2	0.02	(0.90)
Neighbor_q-1	0.00	(-0.20)
Neighbor_q0	-0.01	(-0.68)
Neighbor_q+1	0.00	(0.05)
Neighbor_q+2	0.04*	(1.93)
Neighbor_q+3	0.00	(-0.20)
Neighbor_q+4	-0.01	(-0.53)
Neighbor_q+5	0.00	(-0.15)
Neighbor_q+6	0.00	(-0.01)
Neighbor_q+7	-0.01	(-0.48)
Neighbor_q+8	-0.04	(-1.60)
Disaster zone_q-4	0.00	(0.01)
Disaster zone_q-3	-0.01	(-0.19)
Disaster zone_q-2	0.02	(0.78)
Disaster zone_q-1	-0.01	(-0.51)
Disaster zone_q0	0.02	(0.68)
Disaster zone_q+1	0.03	(1.26)
Disaster zone_q+2	0.03	(0.88)
Disaster zone_q+3	0.06**	(2.30)
Disaster zone_q+4	0.09***	(3.11)
Disaster zone_q+5	0.05**	(2.07)
Disaster zone_q+6	0.01	(0.47)
Disaster zone_q+7	0.03	(1.24)
Disaster zone_q+8	0.00	(-0.16)
Bank Fixed Effects	Yes	
Year-Quarter Fixed Effects	Yes	
N	787,595	

Technical Appendix - Table E

Hurricane Proximity and Assets Insurability

This table presents difference-in-differences estimates of the effect of the proximity of a hurricane strike on the level of corporate cash holdings conditional on the dependence on external insurance. *Cash* is the total amount of cash and cash equivalents scaled by the total assets of the firm at the end of the quarter. We use the share of total assets which are intangible assets to identify when firms are more likely to self-insure and less likely to rely on external insurance companies. *Self-Insurance* is a dummy equal to 1 if the share of total assets which are intangible assets is in the top tercile of the distribution *Neighbor* is a dummy equal to 1 if the county location of the firm headquarter is in the neighborhood of an area hit by a hurricane over the past 12 months. *Disaster_zone* is a dummy equal to 1 if the county location of the firm headquarter is in the area hit by a hurricane over the past 12 months. Note that the dummy *Self Insurance* is omitted from the regression because it is already fully interacted with the firm and time fixed effects. Standard errors corrected for clustering of the observations at the county level. t-stat are reported between parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels.

Dependent variable: Cash / Assets (in percentage points)	
	[1]
Neighbor x Self-Insurance	0.86*
	(1.67)
Neighbor	0.40**
	(1.97)
Disaster zone	-0.27
	(-1.37)
Firm-Season Fixed Effects (Interacted)	Yes
Time Fixed Effects (Interacted)	Yes
N	392,734

Technical Appendix - Table F

Effects of Earthquakes outside the US on Corporate Cash holdings of US Firms

Panel A describes the 11 major earthquakes occurred outside the US since 1980. See the text for the details of the selection criteria. *Magnitude* measures the energy contained in an earthquake according to the Richter scale, *Tsunami* is a dummy equal to one if the earthquake generated a Tsunami, *Fatalities* is the total number of deaths, and *Damages* is the estimated value of total damages expressed in billion dollar. *Damages (CPI adjusted)* is the estimated value of total damages expressed in billion dollar adjusted for the Consumption Price Index as of 2011. Primary source of information is the Significant Earthquake Database from the National Geophysical Data Center. Panel B presents changes in corporate cash holdings over time for US firms located in a seismic area after the occurrence of a major earthquake outside the US at quarter *q0*. The sample comprises 3,668 treated firm*s* whose headquarter is located in an urban community where an earthquake is frequently felt according to the U.S. Geological surveys ("Seismic zone firms"). For each treated firm, the counterfactual outcome is the weighted average of the change in cash over all control firms with the same SIC 3 code ("Matched firm"). The weighting is achieved through a kernel function so that the closer control firms in terms of Mahalanobis distance to the treated firm receive greater weight. The Mahalanobis distance is computed at quarter *q-2* (ie. three months before the earthquake occurrence) along four dimensions: size, age, market-to-book, and financial leverage. *t*-statistics are reported in the last column. ***, **, and * denote significance at the 1%, 5% and 10% levels.

Panel A - Major Earthquakes outside the US since 1980

Country	**Year**	**Date**	**Magnitude**	**Tsunami**	**Fatalities**	**Damages**	**Damages (CPI adjusted)**
Mexico	1985	9/19/1985	7.5	Yes	9,500	4,000	8,362
Iran	1990	6/20/1990	7.1	No	40,000	8,000	13,768
Turkey	1999	8/17/1999	7.2	Yes	17,118	20,000	27,003
Taiwan	1999	9/20/1999	7.3	No	2,297	14,000	18,902
India	2001	1/26/2001	7.5	No	20,005	2,623	3,332
Indonesia	2004	12/26/2004	8.3	Yes	227,898	10,000	11,908
Pakistan	2005	10/8/2005	7.4	No	80,361	5,200	5,989
China	2008	5/12/2008	7.6	Yes	87,652	121,000	126,415
Indonesia	2009	9/30/2009	7.3	Yes	1,117	2,200	2,307
Haiti	2010	1/12/2010	7.0	Yes	222,570	8,000	8,253
Japan	2011	3/11/2011	8.2	Yes	15,854	210,000	210,000

Panel B - Effects of Earthquakes outside the US on Corporate Cash holdings of US Firms

Average change in cash from q-2 to	**Seismic zone firms**	**Matched firms**	**Diff-in-diffs**	***t*-statistic**
q-1	-0.63%	-0.68%	0.05%	0.30
q0	-0.73%	-1.05%	0.32%	1.62
q+1	-0.74%	-1.20%	0.46%**	2.03
q+2	-0.49%	-1.09%	0.59%**	2.35
q+3	-0.70%	-1.24%	0.54%**	1.97
q+4	-0.77%	-1.25%	0.48%*	1.68
q+5	-0.83%	-1.22%	0.39%	1.36

Technical Appendix - Figure A

Hurricane Proximity and Future Hurricane Likelihood

This graph represents the monthly impulse response function to the proximity of a hurricane strike. The analysis is made at the county level. The line plots the probability for a county of being hit by a hurricane if it was in the neighborhood of a disaster zone x-month ago. Dot-lines plot the upper and lower bounds of the 10% interval confidence.