Do firm managers properly assess risk?

Evidence from US firms proximity to hurricane strikes[1]

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Abstract

This paper provides direct evidence that firm managers rely on heuristics to assess risk, which leads them to make systematic mistakes. Consistent with Tversky and Kahneman availability bias, we find that managers overreact to salient risks. We document a significant and temporary increase in cash holdings for firms located in the neighborhood of a hurricane landfall. This bias increases when managers are less sophisticated and when firms are credit constrained. Our results also suggest that this overreaction is costly. It leads to partially reduce the investment activity as well as the shareholder compensation, and seems to marginally destroy value.

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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**

In this paper, we provide empirical evidence that managers display biases when assessing risk. In particular, they systematically respond to a near-miss liquidity shock by increasing *temporarily* the amount of corporate cash holdings. Such a reaction cannot be explained by the standard Bayesian theory of judgment under uncertainty, because the liquidity shock is provoked by a hurricane landfall whose distribution is stationary (Pielke et al 2008). However, it is consistent with a salience theory of choices (Kahneman and Tversky, 1974, Bordalo, Gennaioli and Shleifer, 2012a, 2012b, 2012c) which predicts that the *temporary* salience of the disaster leads managers to reevaluate their representation of the risk and put excessive weight on its probability.

Most corporate policy decisions are taken under uncertainty and require managers to estimate risk. Standard corporate finance models assume that managers do it by estimating probabilities through a pure statistical approach. Under this assumption, beliefs about risky outcomes are based on all the available information and are formed regardless of any context-specific factors. In practice however, assessing risk is complicated and time-consuming. Since individuals might have limited cognitive resources, psychologists argue that people may rely on heuristics, namely mental shortcuts that simplify the task of assessing probabilities (Kahneman and Tversky, 1972, 1974 and 1983) by focusing on "what first comes to mind" (Gennaioli and Shleifer, 2010). Under this alternative way of assessing risk, all information is not given the same importance. This paper proposes that managers also use such heuristic rules and that this practice leads to biased estimations which affect corporate policies.

The rule we focus on is the "availability heuristic". Tversky and Kahneman (1974) show that people have a tendency to infer the frequency of an event from its availability, namely the ease with which concrete examples of a situation where this event occurred come to mind.[3] The drawback of this rule (as the quote above suggests) is that availability can also be affected by the salience of the event. For many reasons (time proximity, dramatic outcome, media coverage), certain events exhibit contrasting features with the rest of the environment. These events then draw people's attention. Because this attention influences the event availability, its subjective probability will be different from its real likelihood. Theoretical works by Bordalo, Gennaioli and Shleifer (2012c) show that people using this heuristic behave like "local thinkers" who use only partial (i.e. salient) information to estimate probabilities. They overweight possible outcomes whose features draw their attention while neglecting the others, and thereby make incorrect inferences about the true probability of the event.

If corporate managers also use the availability heuristic, salient risk situations should lead them to overreact and take temporarily inappropriate decisions in terms of risk management.

Testing empirically this hypothesis raises two major difficulties. The first one is that the risk perceived by the manager cannot be directly observed. We address this problem by focusing on the risk of liquidity shock at the firm level. Since there is now overwhelming evidence that corporate cash holdings is used as a buffer against the risk of liquidity shortage[4], this allows us to use the variations in corporate cash holdings as an indication of the change in risk perceived by the manager.

[3] For instance, one may assess the risk of car accident by recalling such occurrences among one's acquaintances.
[4] Theoretically, Froot et al. (1993) or Holstrom and Tirole (1998, 2000) show that under imperfect financial markets, cash will be used as an insurance mechanism against the risk of a liquidity shock because firms have limited access to external finance. Empirically, several papers document a positive correlation between various possible sources of cash shortfall in the future and the current amount cash holding (Kim et al., 1998; Harford, 1999; Opler et al., 1999; Almeida et al., 2004; Bats et al. 2009; or Lins et al, 2010)

The second difficulty in testing this hypothesis is to identify a salient event whose occurrence does not convey any new information about the real distribution of its probabilities. For instance, the bankruptcy of Lehman Brothers in 2008 was a salient event which might have led bankers to reevaluate their *subjective* estimation of their risk exposure. But this event is also likely to have affected the *objective* distribution of their risks (Shleifer and Vishny, 2011). Therefore, it is impossible to disentangle the part of their reactions due to the increase in *subjective* risks from the one due to the increase in *objective* risks. Similarly here the occurrence of a salient liquidity shock may also plausibly affect the objective distribution of its probabilities.

We address this problem by using the occurrence of hurricanes as a potential source of liquidity shock. Hurricanes are indeed well suited risks for our purpose because their frequency is stationary. Their occurrence does not convey any information about the probability to occur again in the future (Pielke et al., 2008). In addition, their occurrence is a salient event which is exogenous to firm or manager characteristics and which represents a credible source of liquidity shock.[5] These events also permit a difference-in-difference identification strategy because their salience is likely to decline with the distance from the disaster zone. This allows us to estimate the *causal* effect of risk saliency on the risk perceived by comparing how a treatment group of firms located in the neighborhood of the disaster zone and a control group of distant firms adjust their cash holdings after the disaster.

We find that firm managers do respond to the sudden salience of the risk of liquidity shortage caused by the proximity of a hurricane landfall by increasing the amount of cash holdings, although nothing indicates that this risk is now bigger than it used to be. On average, firms located in the neighborhood of the disaster area increase their level of cash by 0.84% (as % of total assets) relative to firms farther away during the 12-month period

[5] Froot (2001), and Garmaise and Moskowitz (2009) show that natural catastrophe insurance market functions poorly

following the hurricane landfall. We also find that this increase in cash is temporary. The amount of cash increases sharply during the first 2 quarters following the disaster and then progressively returns to its pre-hurricane level during the next 4 quarters (Figure 6 illustrates graphically this result). So as time goes by, people forget, the salience decreases, and the bias vanishes. Over our sample period, this assessment bias leads to the immobilization over a 1-year period of an overall amount of 65 billion dollars. This bias increases when managers are likely to be less sophisticated (managers of small firms, managers of young firms, or managers of firms without previous experience of hurricane strike in their neighborhood), and when they have good reasons to care less about the risk of cash shortage either because their firm is not financially constrained, or because they are less exposed to local risks (e.g. multinational firms).

Our second set of findings focuses on the evaluation of the cost of this bias. We find that to increase their cash holdings, managers seem to reduce the overall investment activity and / or operate higher earnings retention. Using the methodology of Faulkender and Wang (2006), we also find that the value of cash decreases when firms are subject to this bias. The additional cash accrued in the balance sheet results in no particular change in market capitalization, suggesting that it would probably have been better employed otherwise.

We finally discuss alternative non behavioral explanations to the results we have, namely the possibility of change in risk, learning, or regional spillover. First, cash could increase if the real probability to be hit by a hurricane increases, or if managers ignore the risk and simply learn its existence when the hurricane occurs. However, both explanations are not consistent with the fact that the increase in cash is only temporary. Second, cash could increase because of a pure geographical externality effect (e.g. the hurricane hits a competitor and creates new business opportunities for the neighbor firms or hits some customers and creates locally higher business uncertainty). However, we find no effect of the hurricane proximity on the operating performance (sales, net income) or the stock price volatility of the neighbor firms. We further investigate these alternative explanations in many other different ways and generally find no evidence in favor of these alternative interpretations.

As a last robustness test, we also show that US firms exposed to earthquake risk slightly increase temporarily their cash holdings in response to the occurrence of a visible and violent earthquake *outside* the US. This last result allows us ruling out all the other possible explanations. Indeed, the occurrence of an earthquake outside the US provides no information about the earthquake risk in the US and the distance to the disaster area makes the possibility of regional spillover irrelevant.

Our paper contributes first to the literature on behavioral corporate finance by identifying a new bias that affects corporate decision makers. So far, the literature[6] has mainly focused on overconfidence / optimism and its effect on M&A acquisitions (Malmendier and Tate, 2005), innovation (Hirshleifer, Low and Teoh, 2012), debt contract (Landier and Thesmar, 2009), and bounded rationality (Kruger, Landier and Thesmar, 2011). The other behavioral biases that have been identified empirically are: bounded rationality (Brav et al. 2005) and reference point thinking and its effect on M&A prices (Baker, Pan and Wurgler, 2012), financing activity (Baker and Xuan, 2011), IPOs (Loughram and Ritter, 2002; Ljungqvist and Wilhelm, 2005), or debt contract (Dougal et al. 2011).

Because saliency is experience-based, ours results next complement the growing literature about the effects of individual traits, and in particular past experiences, on investment and financial decisions (Malmendier and Nagel, 2011; Malmendier and Nagel, 2012; Kaustia and Knüpfer, 2008; Choi et al., 2009; Greenwood and Nagel, 2009).

[6]: see Baker and Wurgler (2012) for a detailed survey of the literature

Finally and more generally, our paper contributes to the vast literature on the effects of behavioral biases "in the field".[7] *A priori*, managers may act rationally as they are neither uniformed and unsophisticated agents nor MBA or undergraduate students in a lab without real economic environment. Therefore, as pointed out by Levitt and List (2007), we should expect them not to be affected by behavioral biases. Whether they rely on the availability heuristic to take financial decisions is thus an open question and to the best of our knowledge, this paper is the first to empirically show that managers seem to use the availability heuristic to assess risk, and to study its effects.

The rest of the paper is organized as follows. Section 2 briefly summarizes what we know about hurricane risk. Section 3 proposes some hypotheses based on the availability heuristic phenomenon and reviews the related scientific and anecdotal evidence. Section 4 presents our empirical design. Section 5 provides evidence on whether managers are subject to an availability bias. Section 6 investigates whether the use of this heuristic is costly or not for firms shareholders. Section 7 discusses the possibility of alternative non behavioral explanations. Section 8 concludes.

2. Hurricanes activity in 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 (around 72 miles per hour). In this section, we briefly summarize what we know about the risk of hurricane strike in the US mainland.

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,

[7] The literature is too vast to discuss it here. DellaVigna (2009) provides a detail survey about the real effects of behavioral economics

either through the floods provoked by the heavy rainfalls or through the high winds produced by the hurricane as it moves across land. In the SHELDUS database (the prime database for natural disaster in the US), 1,341 distinct counties (about 44% of the total US counties) are reported to have been affected at least once by a major hurricane. Figure 2 to 5 plot on a map different examples of disaster area.

2.2. Event frequency

Hurricane occurrence is a regular event in the US. There are on average 17 hurricanes that strike the US mainland on any ten-year period since 1850. Figure 1 suggests no particular increasing or decreasing trend in this frequency. This lack of trend is supported by the literature in climatology. Globally, the distribution of hurricane strikes in the US is found to be stationary since early industrial times for all hurricanes, major hurricanes as well as regional activity (Elsner and Bossak, 2001; Webster et al., 2005; Elsnerand Kocher, 2000; Blake et al., 2011). As regards possible future changes in storm frequencies, our understanding of the current state of climate science is that there is still too much uncertainty to build any credible theory[8].

2.3. Event cost

The total cost of hurricane strikes in terms of economic damages is now much more important than it used to be at the beginning of the past century (Blake, Landsea and Gibney, 2011). However, after normalizing damage for change in inflation, coastal population and wealth, no trend of increasing damage appears in the data. Pielke et al. (2008) find for instance that, should the great 1926 Miami storm had occurred in 2005, it would have been almost twice as costly as Hurricane Katrina, and thus highlight that "*Hurricane Katrina is not outside the range of normalized estimates for past storms*". Overall, their results indicate that

[8] In their survey of the literature, Pielke et al (2008) conclude that given "*the state of current understanding (…) we should expect hurricane frequencies in the future to have a great deal of year-to-year and decade-to-decade variation as has been observed over the past decades and longer*"

the normalized economic cost of hurricane strikes has not changed over time, which is consistent with the lack of trends in hurricane frequency and intensity observed over the last century.

Overall, we know that hurricane risk can randomly affect an extensive number of firms throughout the US territory, has not changed over time and should remain unchanged in the coming decades in terms of both volume (frequency), and value (normalized economic cost).

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 develop simple mental rules derived from their own experience so as to quickly adjust their beliefs and adapt themselves 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 of such a rule is the “availability heuristic”. It 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 actually assess whether it is easy or not to imagine an example of a situation where this event actually occurred. That's the case when one assesses the probability of a traffic accident by recalling examples of such occurrences among one's acquaintances.

Tversky and Kahneman (1973, 1974) show that the use of this rule is problematic because availability can also be affected by other factors that are not related to actual frequency. In particular, they argue that factors such as the familiarity with the event, the salience of the event, the time proximity with the event or the preoccupation for the event outcome can affect its availability, and thus generate a discrepancy between subjective probability and actual likelihood. The availability of car accident for instance will be higher if the person involved is famous (familiarity), if the accident is observed in real time on the other side of the road (salience), if the accident occurred recently (time proximity), or if the physical pain due to the injuries resulting from traffic accidents has been recently "vividly portrayed" (preoccupation for the outcome). In all cases, 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 various 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 obtained show that salient causes that killed many people during a single occurrence were overestimated, while less salient causes were systematically underestimated. In a survey performed to understand how people insure themselves against natural hazards, Kunreuther et al. (1978) observed a strong increase in the number of people willing to buy an insurance at a premium right after an earthquake. Conversely, they were found to be reluctant to buy such an insurance even at subsidized rate when no major earthquakes had occurred recently. Johnson et al. (1993) also find that people can be willing to pay more than two times the same insurance product in situations where the risk is salient compared to situations where it is not and confirm that saliency excessively increases the risk perceived. Other similar results can be found in the housing literature where changes in housing prices can be used to infer changes in the perceived risk. In many instances, the occurrence of a salient event (floods, earthquake, nuclear accident) results in a price reduction for property that is larger than the value of the insurance premium (See for instance MacDonald et al., 1990; Bin et al., 2004, 2008; Kousky, 2010)

3.3. Implications and hypothesis development

In this paper, we focus on firm decision makers and study whether they properly assess risk by relying or not on the availability heuristic (hereafter the *availability heuristic* hypothesis). Firm decision makers are neither uninformed and unsophisticated agents like home owners or property insurance retail buyers, nor undergraduate students in a lab without real economic environment.[9] Whether managers can take wrong financial decisions in the real world because of this availability heuristic, therefore remains largely an open (and so far unexplored) question.

One challenge is that we cannot observe directly the risk perceived by firm managers. To address this difficulty, we assume here that changes in risk perception can be inferred from the variations in corporate cash holdings. There is indeed strong theoretical and empirical evidence in the corporate finance literature that the main driver of cash holdings policy is risk management. Froot et al. (1993) and Holstrom and Tirole (1998, 2000) theoretically predict that, under imperfect financial markets, cash will be used as an insurance mechanism against the risk of a liquidity shock because firms have limited access to external finance. Therefore, cash holdings provides a buffer against any risk of cash shortage that would prevent them from financing positive NPV projects. Consistent with those predictions, a large number of empirical papers document a positive correlation between various possible sources of cash shortfall in the future and the current amount cash holdings (Kim et al., 1998; Harford, 1999; Opler et al., 1999; Almeida et al., 2004; Bats et al., 2009; Ramirez and Altay, 2011). CFOs surveys also confirm this link. Lins et al (2010) find for instance that a large majority of CFOs declare using cash holdings for general insurance purposes.

If managers rely on the availability heuristic to assess the risk of an event that would trigger a cash shortage situation, cash holdings should then vary in response to the salience of

[9]: see Levitt and List (2007) for a description of the lab experiment limitations and why, placed in a familiar environment, economic agents may evolve toward more rational behaviors

this event. Under the *availability heuristic* hypothesis, we thus argue that corporate cash holdings will increase (decrease) in situations where the risk of cash shortage becomes more (less) available.

Because all firms do not exhibit the same characteristics, the effect of the event saliency on corporate cash holdings may vary in the cross section of the population. A primary source of heterogeneity is the degree of managers' sophistication. Indeed, sophisticated agents are expected to be less affected by behavioral biases. Therefore, changes in cash holdings for sophisticated firms should be less sensitive to the event saliency. Another source of heterogeneity is the degree of financial constraints. Because firms experience different levels of financial constraints, they will exhibit different degrees of concern as regards the occurrence of a cash shortage situation. In particular, firm managers with low financial constraints should feel less concerned about a potential liquidity shock. Therefore changes in cash holdings for firms with low financial constraints should also be less sensitive to the event availability.

4. Empirical design

4.1. Identification strategy

In this paper, we use both the occurrence of hurricanes and the proximity of the firm headquarter to the disaster area to identify a situation where the risk of liquidity shock becomes salient. Our motivation for the use of hurricanes relies on the following arguments. First, hurricanes can trigger a liquidity shock because of the heavy damage they produce.[10] Second, the occurrence of a hurricane is a salient event as they draw people attention and leave their marks on observers' mind. And interestingly, this saliency effect is likely to vary

[10] Cash shortage can come in many ways: a reinvestment need because of the partial destruction of the operating assets (headquarter, plants or equipment,…), a drop in earnings because of a drop in local market demand, or a new investment financing need if the hurricane creates unexpected growth opportunities (reconstruction needs, acquisition of a local competitor,…)

with the proximity of the landfall. Indeed, we expect the event to be salient for firms located in the disaster area and its neighborhood, but not for more distant firms. In particular, it could be almost totally ignored by those located in areas too far apart. Third, the occurrence of a hurricane makes the hurricane risk more available but does not imply a change in the risk itself. The distribution of hurricanes is stationary; therefore, there is no reason to think that the real risk of hurricane landfall changes after its occurrence. Finally, hurricanes are completely exogenous events which can randomly affect a large number of firms[11]. The distance to hurricane landfalls then offers a clean natural experiment framework to test for the presence of a causal link between event availability and managers' risk perception through changes in corporate cash holdings.

4.2. Data

We obtain financial data as well as information about the firm headquarter location from Compustat's North America Fundamentals Quarterly database. We use quarterly data rather than annual data in order to identify changes in cash holdings around hurricane landfalls with the highest possible precision[12]. We restrict our sample to non-financial and non-utility firms whose headquarters are located in the US over the 1987-2011 period. We also eliminate firms whose county location is missing and whose fiscal year-end month is not a calendar quarter-end month (ie. March, June, September or December). Finally, we remove firm-quarter observations for which the total assets or the amount of cash holdings is missing. This selection procedure leaves us with a firm-year-quarter panel dataset of 11,948 firms and 411,490 observations. Table 1 presents summary statistics for the main employed firm-level variables. We winsorize all our variables at the first and 99th percentile. All variables are defined in appendix 1.

[11] This last feature ensures that our findings do not correspond to something specific to the time period or the geographic location of the firms and unrelated to the availability of the hurricane risk

[12] Using annual financial data leads to the same results

[INSERT TABLE 1 AROUND HERE]

We obtain the name, date and location of the main hurricane landfalls in the US from the University of South Carolina's SHELDUS (Spatial Hazard and Loss Database for the United States) database. This database provides the location of each disaster at the county level for all major hurricanes since the early 60's. Because we want to make sure that the event is salient enough, we focus on the hurricanes with total direct damages (adjusted for CPI evolution) above 5 billion dollars. Finally we restrict the list to the hurricanes occurred after 1985 because there is no financial data available from Compustat Quarterly before that date. This leaves us with 15 hurricanes that span from 1989 to 2008. We obtain detailed information about their characteristics (start date, end date, date of landfall, direct number of deaths, total damages, and category) from the tropical storm reports available in the archive section of the National Hurricane Center website and from the 2011 NOAA Technical Memorandum. Table 2 presents summary statistics for these 15 hurricanes.

[INSERT TABLE 2 AROUND HERE]

4.3. Assignment to treatment and control group

For each hurricane, we identify the degree of salience of the event according to the distance between the firm headquarter and the landfall area. For this purpose, we define three different geographic perimeters corresponding to various levels of distance: the *disaster zone*, the *neighborhood* area, and the *rest of US mainland*. The *disaster zone* includes all counties which are reported to be affected by the hurricane in 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 by 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. We then match with replacement each affected county with its 5 nearest neighbors among the non-affected counties.[13] This procedure leaves us with a set of matched counties which is our neighborhood area and a set of non-matched counties which forms the *rest of US mainland* area. Figures 2 to 5 present on a map the result of this identification procedure for hurricanes Fran, Floyd, Allison and Katrina.

[INSERT FIGURES 2 TO 5 AROUND HERE]

Firms located in the *neighborhood* area (light blue zone on the map) are assigned to the treatment group because the hurricane landfall should be a salient event for their managers. Given their proximity to the disaster zone, the hurricane is indeed a near-miss event. They could have been affected by the hurricane but by chance were not. For that reason, we expect the event to have raised firm managers' attention. Firms located in the *rest of the US mainland* (blank zone on the map) are assigned to the control group. Given their distance to the landfall area, the hurricane should not be a salient event for the firm managers. Some of them may even completely ignore the event if they are located in an area where the risk of hurricane strike is not a concern at all. Firms located in the *disaster zone* (dark blue zone on the map) are left apart from our analysis because of the direct effects of the hurricane on their level of cash. Given their location, these firms are affected by the disaster. The event is then obviously salient for their managers, but it is also a potential source of direct cash outflow (e.g. operating assets destruction) or cash inflow (e.g. insurance payment). The variation of cash holdings around the hurricane is thus likely to reflect more the direct effects of the disaster rather than the change in risk perceived by their managers. In practice, we do

[13] We find that on average, a county has around 5 adjacent counties. Our results remain the same when we use 3 or 4 rather than 5 nearest non affected counties.

not remove these firms from our sample[14] but we control that they do not influence our results when they are in this situation. Table 3 presents summary statistics for each group of firms.

[INSERT TABLE 3 AROUND HERE]

The statistics reported are mean values computed one quarter before the hurricanes occurrence. The last column shows the t-statistic from a two-sample test for equality of mean across treated and control firms. Treatment firms and control firms appear to be very similar along various dimensions including the amount of cash holdings.

4.4. Methodology

We examine the effect of the hurricane saliency on managers risk perception through changes in corporate cash holdings by using a differences-in-differences methodology. We follow the specification proposed by Bertrand and Mullainathan (2003) to handle situations with multiple time period and multiple treatment groups. The basic regression we estimate is

$$Cash_{itc} = \alpha_i + \delta_t + \gamma X_{itc} + \beta Neighbor_{tc} + \varepsilon_{itc}$$

where *i* indexes firm, *t* indexes time, *c* indexes county location, $Cash_{itc}$ is the amount of cash as a percentage of total assets at the end of a quarter, α_i are firm fixed-effects, δ_t are time fixed effects, X_{itc} are control variables, $Neighbor_{tc}$ is a dummy variable that equals 1 if the county location of the firm is in the neighborhood of an area hit by a hurricane over the last 12 months and 0 if not, and ε_{itc} is the error term that we cluster at the county level to account for potential serial correlations (Bertrand, Duflo and Mullainathan, 2004).[15]

Firm fixed-effects control for time invariant differences between firms[16], and the time (year-quarter) fixed-effects control for global differences between time periods such as aggregate shocks and common trends. The other variables X_{itc} systematically include fiscal

[14] In fact, we cannot exclude them because we are considering various hurricanes here. So they can belong to the other two categories (*neighborhood*, and *rest of US mainland*) during the time period of our analysis.
[15] Allowing for correlated error terms at the state level or firm level leads to similar inferences as regards statistical significance
[16] This includes fixed differences between treatment and control firms

quarter dummy variables to control for the possibility of window dressing at the end of the fiscal year (Khokhar 2012), and a dummy variable $Disaster\_zone_{tc}$ to capture the effect of the hurricane strike when the firm is located in the disaster zone. This $Disaster\_zone_{tc}$ variable allows to strictly compare firms in the neighborhood area with firms further away (rest of US mainland) by isolating the changes in cash holdings observed when firms are located in the disaster zone[17] from the rest of our estimation. Our estimate of the effect of the hurricane landfall proximity is β. This is our main coefficient of interest. It measures the change in cash holdings observed right after a hurricane strike for firms located in the neighborhood of the disaster area, with respect to a control group of more distant firms.

5. Are managers subject to an availability bias?

5.1. Main results

We examine the effect of the event availability on the risk perceived by firm managers through the variations in corporate cash holdings after a hurricane landfall. Table 4 and 5 present our main results.

[INSERT TABLE 4 AROUND HERE]

Table 4 reports the effects of having been in the neighborhood of a hurricane in the last 12 months. Column 1 shows that on average, firms located in the neighborhood of a disaster zone increase their cash holdings (as % of total assets) by 0.84 percentage point during the 4 quarters following the hurricane landfall. This effect represents an average increase by 16 million dollars in absolute terms and accounts for 8% of the within-firm standard deviation in cash holdings. We investigate the robustness of this effect in the rest of the table. First, we control for the situations where the firm is simultaneously located in the neighborhood area and the disaster area by creating a dummy variable *Overlap*. This phenomenon can occur if

[17] and which are likely to be due to the direct effects of the hurricane

different hurricanes make landfall at different places within a short period of time (e.g. Ivan and Jeanne in 2004, Rita and Wilma in 2005). Column 2 shows that this control does not affect our result. Second, we control for the influence of industry level-specific shocks. In column 3, we include quarterly mean cash of the firm industry (excluding the firm itself). The effect of hurricane proximity on cash holdings remains exactly the same. In column 4, we include basic firm characteristics controls: age, size and market-to-book. Again, we obtain the same result. Because such controls are likely endogenous[18], we follow Bertrand and Mullanaithan (2003). We do not include them in our basic regression and only check that our findings are not modified by their inclusion[19]. Overall, the effect is extremely robust to the different specifications and the magnitude of the coefficient is nearly always the same. Consistent with the *availability heuristic* hypothesis firm managers respond to the sudden salience of the danger by increasing the amount of cash holdings, although nothing indicates that this danger is now bigger than it used to be.

[INSERT TABLE 5 AROUND HERE]

In table 5, we further investigate the effect of this availability bias over time. In practice, we replace the *Neighbor* variable by 13 *Neighbor_q+i* dummy variables to capture the effect of the event saliency at the end of every quarter around the hurricane occurrence. The *Neighbor_q+i* variable is then equal to 1 if the county location of the firm headquarter at quarter *q+i* is in the neighborhood of an area hit by a hurricane during quarter *q0*. We do the same for the *Disaster_zone* variable. This approach allows identifying when the effect starts and how long it holds over time. Column1 first shows that no statistically significant change in cash holdings appears before the occurrence of the hurricane for firms located in the neighborhood area. However, and consistent with a causal interpretation of our result, we do

[18] See Roberts and Whited (2011) for a discussion about the effect of including covariates as controls when they are potentially affected by the treatment

[19] Similarly, this result does not change either when adding other control variables which are frequently associated with the level of cash holding in the cash literature, such as capital structure, working capital requirements, capital expenditures, or R&D expenses.

find that the amount of cash starts increasing right after the occurrence of the hurricane.[20]This effect increases during the 3 following quarters and the rise of cash holdings reaches its maximum at time *q+2* and *q+3*. The variables *Neighbor_q+2* and *Neighbor_q+3* show that on average, firms located in the neighborhood area respond to the disaster saliency by increasing their level of cash by respectively 1.15 p.p. and 1.13 p.p.as a percentage of total assets (ie. around 20 million dollars and about 11% of the within-firm standard deviation of *cash*). Interestingly, the level of cash holdings then starts decreasing and the effect progressively vanishes during the next 3 quarters. The variable *Neighbor_q+8* shows that the average change in cash holdings for neighborhood firms is not statistically different from zero 2 years after the hurricane landfall. This drop in the amount of cash holdings is consistent with our behavioral interpretation. As time goes by, the salience of the event decreases, people forget, and the subjective probability of risks goes back to its initial value. Managers then reduce the level of corporate cash holdings.

[INSERT FIGURE 6 AROUND HERE]

We plot the result of this analysis in a graph displayed in figure 6 and also display the evolution of the change in corporate cash holdings for firms located in the *disaster zone*. 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 interesting for two reasons. First it confirms that the hurricane occurrence can trigger a liquidity shock, as firms hit by a hurricane experience a significant drop of 0.6p.p of their cash holdings. Second it gives an indication to appreciate the magnitude of the increase in cash observed when firms are located in the neighborhood area. It shows that the additional amount of cash accrued in the balance sheet (+1.1p.p) presumably for insurance purposes against the risk of cash shortage after a hurricane strike exceeds the actual loss of cash (-0.6 p.p.) that has to be

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

supported when this risk materializes. So even if the increase in cash observed for the neighbor firms were rational, the magnitude of this increase looks excessive compared to the real loss of cash at risk. However, we do recognize that the loss of cash (-0.6%) we observe here may not correspond to the real economic cost of the hurricane. We address this issue in section 7 where we examine the market reaction at the time of the landfall. We find that on average, the present value of losses due to the disaster represents 1.03% of the total assets of the firm, which is still lower than the increase in cash observed on firms located in the neighborhood area (+1.1%).

5.2. Cross sectional variation in firm's response

Because firms exhibit different characteristics, they may not respond in the same way to the salience of hurricane risk. We first investigate whether this response changes according to the degree of sophistication of firm managers. We use three proxies to measure sophistication: the firm size, its age, and its past experiences. We use the size of the firm because we expect large firms to be run by more sophisticated CEOs and CFOs (see for instance Krueger Landier and Thesmar, 2011). We use the age of the firm because various studies in the behavioral literature show that young age is more associated with behavioral biases (Greenwood and Nagel, 2009; or Malmendier and Nagel, 2011). Finally, we use the number of instances in which a firm has been located in the neighborhood area in previous occasions, because we expect firms to learn from past experiences and to be less sensitive to the danger saliency if they have already been "fooled" once. For each criterion, we split our sample into three categories of sophistication (low, medium and high) and then define three dummy variables corresponding to each sophistication degree. Further details about the construction of these dummy variables are provided in appendix 1.

[INSERT TABLE 6 AROUND HERE]

Columns 1 to 3 of table 6 show that a low degree of sophistication systematically leads to a strong increase in the amount of cash holdings. Conversely, we find no statistically significant change in cash for firms whose managers are likely to be more sophisticated. In all three cases, an F-test indicates that the difference between the two coefficients (high vs. low) is statistically significant at the 1% or 5% level.

Next we investigate whether this response also changes according to the degree of financial constraints. Firms with low constraints should care less about the risk of hurricane since they can easily raise new funds in case of cash shortage. Conversely, firms more vulnerable to capital market imperfections should be more precautionary and more sensitive to this risk. We follow the literature and create a dummy variable *FC* which is equal to 1 if the firm is considered as financially constrained according to the following criteria[21]: the lack of debt rating, the absence of dividend payment, and the firm dependence to external finance[22]. Further details about the construction the FC dummy variable are provided in appendix 1.

[INSERT TABLE 7 AROUND HERE]

Columns 1 to 3 of table 7 show that the cash holdings policy is no longer sensitive to the hurricane saliency when firms are not financially constrained. However, the interaction term between *Neighbor* and the *FC* dummy indicates that on average the level of cash holdings increases substantially when the firm is financially constrained. For firms which depend strongly on external finance for instance, having been in the neighborhood of a hurricane in the last twelve month entails an increase in cash by 1.61 p.p (column 3).

Another dimension along which firms in the neighborhood of a hurricane differ is the degree to which their operating activity is vulnerable to the occurrence of a hurricane. Just like firms which are not credit constrained should respond less to the saliency of the risk

[21] These criteria are used as proxies for the degree of credit constraint in a vast empirical literature. See for instance Whited (1992), Gilchrist and Himmelberg (1995), Opler et al. (1999), Almeida et al. (2004), Faulkender and Wang (2006), Pinkowitz and Williamson (2006), Denis and Sibilkov (2010), or De Angelo et al. (2011)

[22] We follow the methodology proposed by Rajan and Zingales to measure the firm dependence to external finance

because they will have the ability to cushion the liquidity shock, firms whose operating activities are not concentrated around the headquarter location will be less vulnerable in case of a similar disaster and therefore should react less.

We identify three dimensions according to which firms differ in terms of vulnerability. First, firms are likely to be less vulnerable if they are not too much dependent on the US for both products sales and products manufacturing. Conversely, they should be more vulnerable if they operate in the US only. To identify these firms, we follow Foley et al. (2007) and create a dummy equal to one if the firm is not a multinational and zero if not. Second, firms are also likely to be more vulnerable when they strongly depend on the US market demand. To identify these firms, we use a strategy similar to Frésard and Valta (2012). We use Compustat Segment Data to calculate for each firm the share of total sales realized abroad. We consider that a firm is less exposed to the US market and then less vulnerable if at least 20% of sales are made abroad.[23] Third, firms are also more likely to be vulnerable if they evolve in a highly competitive environment. In this case, the presence of unaffected competitors should exacerbate the cost of the temporary difficulties (e.g. plants destruction) provoked by the hurricane. We calculate the Herfindal-Index at the SIC 3 level for every year-quarter using sales and defined firms as being "more vulnerable" if they belong to the first tercile of the HHI distribution and as "less vulnerable" if they belong to the third tercile. Finally, we also hypothesis that some industries are more vulnerable than others in case of hurricane strike. For each industry, we identify this degree of vulnerability by looking at the average cumulative abnormal return observed at the time of the hurricane strike for firms located in the disaster zone.[24] Our intuition is that industries whose CAR is in the lowest part of the industry-average CAR distribution are industries which suffer the highest damages. Practically, we split the industry-average CAR into tercile. We then define industries as

[23] These firms represent about 30% of our sample
[24] appendix 3 explains in detail how we calculate the CAR.

"vulnerable" if they are in the first tercile (ie. with the lowest CAR) and industries as "less vulnerable" if they belong to the third tercile.

Columns 1 to 4 of table 8 report the results for these different proxies. The insignificant sign for *Neighbor* implies that cash holdings policy is no longer sensitive to the risk saliency. On the contrary, the interaction term *Neighbor x Vulnerable dummy* is positive and significant, implying that firms which are more vulnerable react more compared to those which are not. The third measure of vulnerability is particularly interesting because it also allows us to test the effect of competition on behavioral biases. Some papers (see for instance List and Levitt, 2007) argue that a more competitive environment should "discipline" managers and therefore should dampen the effects of behavioral biases. We find on the contrary that in our context, a greater competition amplifies the availability bias.

[INSERT TABLE 8 AROUND HERE]

5.3. Robustness and validity check

Our main source of concern is the slight heterogeneity between treated firms and control firms. Although fairly comparable along various dimensions, Table 2 indicates that some differences exist as regards to age, market-to-book and capital expenditures. To make sure that our results are not driven by this heterogeneity, we combine our diff-in-diff approach with a matching approach. We match on SIC3 industry, size, age, market-to-book, financial leverage, working capital requirement, and capital expenditures. Appendix 2 describes our matching procedure in detail. We make this analysis for different periods of time around the hurricane landfall (which occurs at q0). Ours results are presented in Table 9 and in the graph of figure 7.

[INSERT TABLE 9 AND FIGURE 7 AROUND HERE]

Table 9 and the graph from figure 7 show the same kind of pattern as the one already observed with the simple diff-in-diff approach. Firms located in the neighborhood area temporarily increase their level of cash holdings after the hurricane. Because we wanted to make sure that this result is both valid and robust, we also conducted many additional tests which are reported in the appendix 4. We run a placebo test to make sure that the results we have are driven by the hurricane landfalls. We randomly change the dates of the hurricanes and find nothing (column 1). Then we re-run our main regression and find that our effect is robust to different specifications: we add as controls the main determinants of cash (size, age, market-to-book, debt, net working capital, capex and R&D) (column 2), we use all 23 major hurricanes reported in the SHELDUS database (and not only the ones with total damages above 5 billion dollars) (column 3), we change the definition of neighbor counties and use the three closer (column 4) or the seven closer (column 5) and finally we use annual data and find again a temporary increase in cash.

6. Is it costly to rely on the availability heuristic for risk assessment?

In this section, we examine whether this temporary increase in cash is costly. We start by analyzing the counterparts of this cash increase and then study whether market investors positively or negatively value this change in cash holdings.

6.1. Source of cash

The cash increase observed after the hurricane landfall can come from various sources: an increase in profits (*Net_profit* variable), a drop in net working capital requirements (*NWC* variable), a drop in investments (*Net_investment* variable), a decrease in repurchases (*Repurchases* variable), a reduction of dividends (*Dividend* variable), or an increase in new financings (debt or equity) (*New_financing* variable). Because total assets include the amount of cash holdings, we do not normalize these items by the total assets and rather use the amount of sales (unless the literature suggests another more relevant normalization method). We then replicate our diff-in-diff analysis and apply our basic specification to each item separately. The result of this analysis is reported in table 10.

[INSERT TABLE 10 AROUND HERE]

We start by examining whether the occurrence of the hurricane affects the level of sales so as to make sure that the other effects we may identify afterwards are not driven by our normalization process. Column 1 confirms that on average the occurrence of a hurricane has no significant effect on the growth of sales. The rest of the table examines the different channels through which a change in cash may occur. We find that the proximity of the hurricane does not modify the operating activity (column 2 and 3) or the financing activity (column 7). But it changes the investment activity and the payout policy. Indeed, column 4 indicates that the overall investment activity decreases, which suggests that managers may be willing to postpone some investments and accelerate some disposals to increase their amount of cash available right after the hurricane; and column 6 indicates that firms tend to pay lower dividends.

Column 8, 9 and 10 further investigate whether the occurrence of the hurricane affects both the pay-out policy and the financing policy. We use a linear probability model to assess whether hurricane landfalls affects the likelihood of stock repurchase, dividend payment, and new financing issue. In column 8, we find that the likelihood of a stock repurchase is lower in case of hurricane proximity. Similarly, column 9 indicates a decrease in the probability of dividend payment. However, we find no change in the probability of new security issue in column 10.

Overall, these results suggest that, when located in the neighborhood area of a disaster zone, firm managers increase the amount of cash holdings by reducing the investment activity, and/or the payout policy.

6.2. Value of cash

We next investigate whether this change in cash holdings policy is an efficient decision or a source of wealth destruction from the investors' perspective. If this 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 practice, we follow the literature on the value of cash (Faulkender and Wang, 2006; Dittmar and Mahrt-Smith, 2007; Denis and Sibilkov, 2010) and examine whether neighbor firms marginally improve this value. We estimate the additional equity value resulting from a change in a firm's cash position over a given time window by regressing the abnormal stock return over this period on the change in cash over the same period and various control variables. The coefficient on the change in cash is then interpreted as a measure of the value on a marginal dollar of cash. We then interact this coefficient with a dummy variable *Neighbor_q0* which is equal to 1 if the firm is in the neighborhood area at time *q0.* This allows us to assess whether being in the neighborhood area of a hurricane marginally deteriorates or improves the value of a marginal dollar of cash. The abnormal return we use is the stock return in excess of the Fama and French (1993) size and book-to-market portfolio return. All control variables are the ones used in the cash value literature. We exclude from our analysis the observations corresponding to firms located in the disaster zone as well as stocks which are not sufficiently liquid[25]. Finally, we perform this analysis for different time windows around the hurricane occurrence to examine how the effect varies over time. The results of this analysis are reported in table 11.

[INSERT TABLE 11 AROUND HERE]

Column 1 and 2 estimate the value of cash during two time periods preceding the occurrence of the hurricane. They show that whether firms are located in the neighborhood area at time *q0* does not change the value of cash before the occurrence of the hurricane. This result is reassuring as cash variations for these firms (Neighborhood area) are not yet statistically different from the other firms (rest of US mainland). However when the time window starts capturing the hurricane landfall event, the same analysis shows that the value of cash decreases if firms are in the neighborhood area. In column 3 for instance, the interaction term between *Neighbor_q0* and *Change in cash* is negative and statistically significant. This result means that on average and over a 6 months period around the hurricane landfall, the value of a marginal dollar of cash decreases by 22 pence when the firm is located in the neighborhood area compared to an average value of 88 pence otherwise. Column 4 and 5 lead to similar results with larger time windows around the event. Unsurprisingly the effect disappears when the time window becomes too large (column 6), as firms located in the neighborhood area only increase temporarily their level of cash.

7. Are there any other alternative explanations?

In this section, we discuss possible alternative non behavioral stories behind the results we have.

7.1. The possibility of "change in risk"," learning", or "regional spillover"

We have identified three possible alternative (and non behavioral) explanations. The first one is that firm managers temporarily increase the amount of cash holdings because the

[25] : this corresponds to stocks with more than 50% of zero daily returns during the time window considered for the analysis.

real risk rises temporarily. This could happen 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 to be hit by a hurricane in the coming year is now higher than it used to be.

We are not aware of any evidence of such a clustering phenomenon in the climate literature (see section 2). Still, we assess this possibility by testing whether the probability to be hit by a hurricane depends on the geographical location of the last recent hurricane strikes. Practically, we use a linear probability model where the dependent variable is a dummy equal to 1 if the county is hit by the hurricane during a given quarter and where the main explanatory variable is a dummy equal to 1 if that county was in the neighborhood of a disaster area over the past 12 months. We add county fixed effects to account for the fact that the risk of a hurricane strike varies geographically. We also add quarter dummies to account for hurricane seasonality and cluster the observations at the state level. The results of this analysis are reported in table 12.

[INSERT TABLE 12 AROUND HERE]

Column 1 shows that being in a county located in the neighborhood of an area affected by a hurricane over the past 12 months conveys no particular information about the probability to be hit during a given quarter. Similarly, column 2 shows that being in a county located in the neighborhood of an area affected by a hurricane over the past 24 months does not convey either any particular information about this risk. Column 3 and 4 show similar results when taking into account all hurricanes from the SHELDUS database (and not only the 15 biggest). Overall, these results go against the hypothesis of a change in risk.

Another possible explanation is that firms ignore or underestimate the risk before the occurrence of the hurricane and learn the true probability after the landfall. In this case the increase in cash would merely reflect a learning process. However, it is hard to explain why the level of cash decreases after a while and eventually returns to its initial suboptimal level. It is also difficult to reconcile this learning hypothesis with our result on the marginal value of cash holdings. If managers learn the true probability of suffering a liquidity shock and increase their cash holdings accordingly, the stock market should value positively this decision and therefore should not discount the additional cash in the balance sheet.

One last possible story concerns regional spillover. Cash could temporary increase because firms benefit from unexpected growth opportunities in the disaster area. As a result, they temporarily make more profits and hold more cash. Or they could also temporarily accumulate cash to size new investment opportunities in the disaster area (e.g. acquiring a competitor, opening additional stores). Under this hypothesis, firms hold more cash because they benefit from positive externalities. A first difficulty with this hypothesis is that the externalities created by the hurricane can go either ways: an increase and / or a decrease in cash.[26] To be valid, the effects of positive externalities must be higher than the effects of negative externalities, which is *a priori* not obvious. A second caveat to this hypothesis is that these externalities can also affect the control group, so our diff-in-diff estimator should already partly control for this effect. Indeed, assume that the hurricane creates some new growth opportunities because a competitor located in the disaster area went bankrupt, both firms in the treatment group and in the control group will benefit from that. Finally, our results in table 10 show that the occurrence of the hurricane has no impact on sales growth (column 1) and on the amount of operating profits (column 2). This result contradicts the presence of a clear geographical spillover effect (in one sense or the other) driving temporarily the average operating performance.

7.2. Investors' risk perception

[26]: for instance neighbor firms could have their main suppliers or clients in the affected counties. It could then slow down their own activities and generate a decrease in cash holdings

We further study the validity of these three alternative stories (*change in risk*, *learning*, or *geographical spillover*) by examining the investors' reaction to the occurrence of hurricanes. This reaction provides a benchmark to evaluate the reaction of firm managers. Since investors (unlike managers) are not necessarily located in the neighborhood of the landfall, the event should be on average less salient for them. Therefore, they should be less subject to the availability bias. [27] Finding no significant market reaction would then be consistent with the *availability heuristic* hypothesis while invalidating the alternative stories (which should translate into a change in price). We start with a simple event study analysis. For each group of firms (disaster area, neighborhood area, and the rest of US mainland), we estimate the average CAR of the stock price over the hurricane strike period. Appendix 3 describes the methodology used to perform this event study. The results are presented in table 13.

[INSERT TABLE 13 AROUND HERE]

We find zero abnormal returns for firms located in the rest of the US mainland and a negative abnormal return for firms located in the disaster zone.[28]

Interestingly, we also find no significant reaction on firms located in the neighborhood area. This result is compatible with the *availability heuristic* hypothesis but casts doubts on the three alternative hypotheses. If the event is less salient for market investors, finding no reaction is consistent with the *availability heuristic* hypothesis.[29] However, a real *change in risk* or some risk *learning* should on average materialize by lower profits expectations and generate a decrease in price. Finding no market reaction suggests that investors perceive no change in risk and learn nothing about hurricane risk. Similarly, the presence of positive externalities should have translated into a positive market reaction. Again, finding no reaction

[27]: They should even be perfectly rational if, as is often assumed in the behavioral corporate finance literature, the managers subject to cognitive biases operate in an efficient market (see the review of Baker and Wurgler, 2012)
[28] This confirms that hurricanes are costly for firms and therefore the market react negatively when they are in a zone hit
[29] We also note that at the time of the event study, the change in cash holdings is not yet observable by market investors. So finding no market reaction here is not inconsistent with the decrease in the value of cash observed afterwards in table 10.

casts doubt on the validity of the *regional spillover* hypothesis. One last interesting result is the magnitude of the negative reaction observed for firms affected by the hurricane. We find that on average investors value the total present loss of the hurricane strike at 0.82% of the firm market equity value. When expressed as a percentage of the total assets (one quarter before the hurricane occurrence), this loss amounts to 1.03% which is slightly inferior to the increase in cash observed on firms located in the neighborhood area (+1.1%). So increasing cash by 1.1% to insure against the risk of such a cost looks very excessive[30]. This means that even if it was justified to increase cash holdings because of higher actual risk (*change in risk* or *learning*), the magnitude of the change in cash observed would be inadequate compared to the real cost at risk.

We further investigate whether investors perceive higher risk after the hurricane landfall by comparing the stock price volatility before and after the hurricane. We follow a methodology proposed by Kalay and Loewenstein (1985). For each security within each group, we compute the variance of the daily return over the pre event period and the variance over the post event period. We then run an F-test to evaluate the equality of the two variances and count the number of occurrences where this test is statistically significant from zero. We also compute the total variance of all stock returns (after forming portfolios to capture covariance effects) for each period and run again an F-test for variance equality. We run the test with different lengths of time window and remove the observations corresponding to hurricane Ike because the hurricane occurred two days before Lehman Brothers bankruptcy. The results of this analysis are reported in table 14.

[INSERT TABLE 14 AROUND HERE]

[30] In fact, this result suggests that managers react as if the probability of being hit in the coming year were certain, which is obviously unrealistic.

We first compute the variance over a 10 day window.[31] We find a significant decrease in stock price volatility for 9% of the firms located in the neighborhood area (column 1), and a significant increase in stock price volatility for 12% of them (column 2). For the vast majority (80%), we find no statistically significant change (column 3). Finally, columns 4 and 5 show no statistically significant change in the variance of the sum of all stock returns variances.[32] We obtain similar results when looking at firms located in the disaster zone or in the rest of the US. Overall these results confirm that investors perceive no particular change in risk after the occurrence of the hurricane. Again, this result goes against both the change in risk hypothesis and the learning hypothesis.

7.3. Reaction to extreme earthquakes outside US

We finally perform one last validity check of the *availability heuristic* hypothesis by looking at US firms whose headquarter is located in a urban community where earthquakes are frequently felt. We then focus on the announcement of extremely violent (and thus salient) earthquakes outside the US and examine whether these firms respond to this announcement by changing their amount of cash. Finding an increase in cash holdings would then be consistent with the *availability heuristic* hypothesis while allowing us to reject all the other possible explanations. It would neither be consistent with the *change in risk* hypothesis, nor with the *learning* hypothesis because the occurrence of an earthquake outside the US (for instance in Pakistan) provide no information about the earthquake likelihood in the US territory[33]. 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 surveys "*Did you feel it?*" performed under the

[31] Using other lengths of time window for variance calculation purposes does not change our results.
[32] We use the variances of the returns generated at the portfolios level (see event study methodology) to account for covariance effects. The total variance is then the sum of the portfolio return variances (these portfolios returns do not overlap in time, so their variances can be considered as independent).
[33] In addition, this test focuses on US firms whose managers frequently feel earthquakes. So they cannot ignore this risk. This also casts doubts about the possibility of a learning reaction.

Earthquake Hazard Program by the USGS. For each zip-code, we compute the average earthquake intensity felt over the past 20 years. We assign to each firm in Compustat this average earthquake intensity felt using the zip-code from the headquarter 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). We next focus on the biggest earthquakes occurred during the past 30 years according to magnitude, total deaths, and total damages description. We obtain all this information from the Significant Earthquake Database[34]. Table 15 describes our list of major non US earthquakes using these selection criteria.

[INSERT TABLE 15 AROUND HERE]

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 presented in table 16 and the graph of figure7.

[INSERT TABLE 16 AND FIGURE 7 AROUND HERE]

Figure 7 and Table 16 show qualitatively the same pattern as the one already observed. Firm managers located in seismic area respond to the sudden salience of the earthquake risk by temporarily increasing the level of cash holdings compared to firms located outside a seismic zone. This analysis confirms that firm managers are subject to the availability bias while rejecting the other explanations.

8. Conclusions

In their seminal paper, Tversky and Kahneman (1973, 1974) observe that people have a tendency to develop heuristic rules to reduce the complex task of estimating probabilities.

[34]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)

They show that, although useful in general, relying on these rules can also be a source of mistake. This paper provides direct evidence that firm managers rely on one of such a rule to assess risk: the availability heuristic. Using cash holdings as a proxy for risk management, we find that managers located in the neighborhood of a hurricane landfall temporarily perceive more risk after the event although the real risk remains unchanged. We show that this mistake, which is due to the temporary salience of the danger, is costly and inefficient. It leads to reduce the overall investment activity as well as the shareholder compensation, and marginally destroys value. Over our sample period, almost 65 billion dollars were temporarily immobilized in the firm financial accounts because of this assessment bias. Given the large and increasing diversity of risks which have to be assessed every day by firm managers, our results suggest that the total real economic cost of this bias is likely to be considerable.

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Appendix 1 :Variables used in tests (in alphabetical order)

Age	Current year minus first year of appearance in Compustat
Assets	Total assets (atq)
Cash	Cash and cash equivalents (cheq) normalized by total assets (atq)
Debt	Total debt: short term debt (dlcq) + long term debt (dlttq) normalized by total assets (atq)
Dependence on External Finance	Industry (SIC3) mean of one minus ((cash flow + capex) /capex)). Cash flow is the sum of Income Before Extraordinary Items (ibcomq)
Disaster_zone	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
Dividend	Total dividends paid (dvq) normalized by the last year net income (niq)
Experience	Number of times a firm has been in the neighborhood of a disaster area
FC	Dummy equal to 1 if the firm is considered as financially constrained according to various criteria. Bond rating : FC is equal to 1 if the firm has a S&P Long-term Senior Debt Rating and the debt is not in Default (D), Selective Default (S.D.) or Not Meaningful (N.M.) Dividend : FC is equal to 1 if the total payout is zero
High Sophistication	According to size criteria : Dummy equal to 1 if the sales are in the top 3 deciles of the sales distribution during the year, and 0 if not. According to age criteria : Dummy equal to 1 if the age is in the top 3 deciles of the the sales distribution during the year, and 0 if not. According to experience criteria; Dummy equal to 1 if the firm has at least 2 previous experiences of a hurricane landfall in its neighborhood.
Industry Cash	Average amount of cash in the industry (SIC3), excluding the firm itself
Low Sophistication	According to size criteria : Dummy equal to 1 if the sales are in the bottom 3 deciles of the sales distribution during the year, and 0 if not. According to age criteria : Dummy equal to 1 if the age is in the bottom 3 deciles of the the sales distribution during the year, and 0 if not. According to experience criteria; Dummy equal to 1 if the firm has never experienced a hurricane landfall in its neighborhood.
Mb	Market to book ratio. Equity market value (cshoq * prccq) over total equity (ceqq)
Medium Sophistication	Dummy equal to 1 if both High Sophistication and Low Sophistication are equal to zero
Neighbor	Dummy variable equals 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
Net capex	Total change in net property plant & equipment (ppegtq) + depreciation (dpq) normalized by total assets (atq)
Net Income	Income before extraordinary items (ibq) over sales (saleq)
Net Investment	Total cash flow from Investing Activities (invcfq) normalized by sales (saleq)
Net Working Capital	Inventories (invtq) + receivables (retcq) - payables (apq) normalized by total assets (atq)
New Financing	Issuance of long term debt (dltisq) + sale of new stocks (sstkq) normalized by total

	market value (cshoq * prccq)
Sales growth	Total sales (saleq) divided by the last year total sales minus 1
Operating margin	Operating Income After Depreciation (oiadpq) divided by sales (saleq)
Overlap	Dummy variable equal to 1 if both Neighbor and Disaster_zone are equal to 1
Payout Ratio	Sum of dividend and share repurchase
Repurchases	Purchase of common and preferred stocks (prstkcq) normalized by the last year net income (niq)
Size	Log of total assets

Appendix 2 :Matching Methodology

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 6 dimensions : size, age, market-to-book, financial leverage, working capital requirement, 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).

Appendix 3: Event Study Methodology

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))

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

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

$$CAR_p = w_p AR_p$$

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

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

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

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

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

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

Appendix 4: Robustness checks

Table 1-Appendix 4 – Robustness checks

This table presents the effects of hurricane proximity on corporate cash holdings according to the level of sophistication of the firm managers. *Cash* is the total amount of cash and cash equivalents held by the firm expressed as a percentage of its total assets at the end of the quarter. *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. *Overlap* is a dummy variable equal to 1 if both *Neighbor* and *Disaster_zone* are equal to 1. Standard errors are corrected for clustering of the observations at the county of location level. *T*-statistics are reported between parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels.

Dependent variable	Cash	Cash	Cash	Cash	Cash	Cash
	Random Date	Additional Controls	All Hurricanes	Smaller Neighbor	Larger Neighbor	Compustat Annual
	(1)	(2)	(3)	(4)	(5)	(6)
Neighbor	0.03	0.62***	0.69***	0.74***	0.85***	0.57**
	(0.14)	(2.76)	(3.08)	(2.68)	(4.03)	(2.05)
Disaster zone	0.11	-0.27	-0.24	-0.30	-0.23	-0.14
	(0.60)	(-1.14)	(-1.10)	(-1.24)	(-0.95)	(-0.61)
Overlap	0.24	0.21	0.17	-0.19	-0.39	-0.28
	(0.33)	(0.36)	(0.31)	(-0.29)	(-0.68)	(-0.47)
Size		-0.83***				
		(-5.92)				
Age		-0.12***				
		(-5.77)				
Mb		0.82***				
		(20.72)				
Debt		-14.71***				
		(-33.82)				
Net Working Capital		-29.07***				
		(-18.31)				
Capex		-29.98***				
		(-9.94)				
R&D		-42.37***				
		(-10.23)				
Constant	17.86***	32.93***	17.86***	17.86***	17.86***	19.27***
	(52.56)	(36.69)	(52.40)	(52.45)	(52.33)	(70.30)
Fiscal quarter FE	Yes	Yes	Yes	Yes	Yes	
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
N	400 619	373 576	400 619	400 619	400 619	134 483

Table 1 – Firm level descriptive statistics

This table reports summary statistics of the main employed firm-level variables over the 1987-2009 period. All variables are from Compustat Quarterly, excluding financial, utilities and non US firms. All variables are winsorized at the first and 99th percentile. The variables are defined in Appendix 1.

	N	Mean	SD	P25	Median	P75
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%
Net working capital	408,392	13.8%	47.6%	5.8%	16.0%	27.1%
Net capex	389,101	1.5%	2.2%	0.3%	0.8%	1.8%
Net investment	365,374	-16.5%	116.0%	-14.0%	-3.9%	-0.5%
Repurchases	209,049	25.7%	88.8%	0.0%	0.0%	0.4%
Dividend	210,680	11.0%	20.7%	0.0%	0.0%	14.4%
New financing	352,256	6.4%	20.1%	0.0%	0.2%	2.9%
Sales growth	371,702	10.0%	65.0%	-6.4%	7.8%	24.8%
Net income	408,453	-109.0%	496.9%	-13.8%	1.7%	6.8%
Mb	359,449	2.84	6.74	0.99	1.89	3.51
Age	411,490	10.0	7.8	3.8	8.0	14.5

Table 2 – Major hurricanes landfall in the US mainland since 1987

This table describes the 15 major hurricanes according to total damages (adjusted for inflation) occurred in the US mainland since 1987. 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 dollar. Damages (CPI adjusted) is the estimated value of total damages expressed in billion dollar 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	9/10/1989	9/22/1989	9/22/1989	21	7.0	12.3	4
Andrew	1992	8/16/1992	8/28/1992	8/24/1992	26	26.5	41.2	5
Opal	1995	9/27/1995	10/5/1995	10/4/1995	9	5.1	7.4	3
Fran	1996	8/23/1996	9/8/1996	9/6/1996	26	4.2	5.8	3
Floyd	1999	9/7/1999	9/17/1999	9/14/1999	56	6.9	9.0	2
Alison	2001	6/5/2001	6/17/2001	6/5/2001	41	9.0	11.1	TS
Isabel	2003	9/6/2003	9/19/2003	9/18/2003	16	5.4	6.4	2
Charley	2004	8/9/2004	8/14/2004	8/13/2004	10	15.1	17.4	4
Frances	2004	8/25/2004	9/8/2004	9/5/2004	7	9.5	11.0	2
Ivan	2004	9/2/2004	9/24/2004	9/16/2004	25	18.8	21.7	3
Jeanne	2004	9/13/2004	9/28/2004	9/26/2004	4	7.7	8.8	3
Katrina	2005	8/23/2005	8/30/2005	8/25/2005	1,500	108.0	120.6	3
Rita	2005	9/18/2005	9/26/2005	9/24/2005	7	12.0	13.4	3
Wilma	2005	10/15/2005	10/25/2005	10/24/2005	5	21.0	23.5	3
Ike	2008	9/1/2008	9/14/2008	9/13/2008	20	29.5	29.9	2

(*) "TS" : Tropical Storm

Table 3 – Descriptive statistics for treated and control firms

This table presents statistics for each group of firms defined according their headquarter location. The statistics reported are mean values computed one quarter before the hurricanes occurrence. All variables are from Compustat Quarterly, excluding financial and non US firms. The last column shows the *t*-statistic from a two-sample test for equality of mean across treated and control firms. All variables are winsorized at the first and 99th percentile and are defined in Appendix 1.

Firm headquarter location **Group assignement**	**Disaster zone** **Excluded**	**Neighborhood** **Treatment**	**Rest of US** **Control**	***t*-statistic**
Assets	1,871	1,950	1,656	1.21
Cash	14.8%	18.3%	18.8%	-1.18
Debt	33.2%	30.2%	29.2%	1.63
Net working capital	9.8%	12.3%	13.6%	-1.51
Net capex	1.5%	1.3%	1.4%	-4.09***
Repurchases	28.7%	24.2%	23.7%	0.21
Dividend	18.8%	17.8%	18.4%	-0.47
Mb	2.95	3.12	2.87	1.78*
Roe	-4.9%	-5.2%	-4.8%	-0.72
Age	11.1	11.2	10.2	6.84***
N	3,207	3,016	39,301	
N distinct firms	1,992	2,137	9,760	

Table 4 – Effects of Hurricane Proximity on Corporate Cash holdings

This table presents changes in corporate cash holdings caused by the proximity of a hurricane. *Cash* is the total amount of cash and cash equivalents held by the firm expressed as a percentage of its total assets at the end of a quarter.*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. *Overlap* is a dummy variable equal to 1 if both *Neighbor* and *Disaster_zone* are equal to 1 (which can occur if two hurricanes hit similar geographical areas in a short time interval). *Industry cash* refers to the mean level of cash and cash equivalents as percentage of total assets of the firm's industry (SIC3) excluding the firm itself. All other variables are defined in appendix 1. Standard errors are corrected for clustering of the observations at the county of location level. *t*-statistics are reported between parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels.

Dependent variable OLS	Cash (1)	Cash (2)	Cash (3)	Cash (4)
Neighbor	0.84*** (3.70)	0.84*** (3.43)	0.84*** (3.47)	0.81*** (3.00)
Disaster zone	-0.30 (-1.37)	-0.30 (-1.24)	-0.23 (-1.00)	-0.26 (-0.92)
Overlap		-0.04 (-0.06)	0 (0.00)	0.08 (0.11)
Industry cash			0.16*** (8.37)	0.16*** (7.59)
Size				-1.09*** (-7.10)
Age				-0.16*** (-5.89)
Mb				0.13*** (17.04)
Constant	17.23*** (49.88)	17.23*** (49.88)	13.99*** (23.52)	23.86*** (33.82)
Fiscal quarter FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
N	411,490	411,490	409,675	357,830

Table 5 – Effects of Hurricane Proximity on Corporate Cash holdings over time

This table presents changes in corporate cash holdings over time caused by the proximity of a hurricane occurred at quarter *q0*.*Cash* is the total amount of cash and cash equivalents held by the firm expressed as a percentage of its total assets at the end of a quarter. *Neighbor_q+i* is a dummy equal to 1 if the county location of the firm 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 firm headquarter at quarter *q+i*is in the area hit by a hurricane during quarter *q0*. Standard errors are corrected for clustering of the observations at the county of location level. *t*-statistics are reported between parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels.

Dependent variable OLS	Cash (1)	
	Coef.	*t* -statistic
Neighbor_q-4	0.31	(1.19)
Neighbor_q-3	0.02	(0.06)
Neighbor_q-2	0.26	(0.93)
Neighbor_q-1	0.42	(1.24)
Neighbor_q0	0.64**	(1.98)
Neighbor_q+1	0.72**	(2.34)
Neighbor_q+2	1.15***	(4.16)
Neighbor_q+3	1.13***	(4.26)
Neighbor_q+4	0.62**	(2.02)
Neighbor_q+5	0.62**	(2.21)
Neighbor_q+6	0.42*	(1.73)
Neighbor_q+7	0.41	(1.50)
Neighbor_q+8	0.27	(0.96)
Disaster zone_q-4	-0.11	(-0.49)
Disaster zone_q-3	0.04	(0.18)
Disaster zone_q-2	-0.17	(-0.67)
Disaster zone_q-1	0.05	(0.18)
Disaster zone_q0	-0.26	(-0.91)
Disaster zone_q+1	-0.26	(-1.02)
Disaster zone_q+2	-0.37	(-1.38)
Disaster zone_q+3	-0.57**	(-2.36)
Disaster zone_q+4	-0.31	(-1.24)
Disaster zone_q+5	-0.33	(-1.24)
Disaster zone_q+6	-0.11	(-0.35)
Disaster zone_q+7	-0.16	(-0.52)
Disaster zone_q+8	-0.06	(-0.22)
Constant	17.23***	(49.76)
Fiscal quarter FE	Yes	
Firm FE	Yes	
Year-quarter FE	Yes	
N	411,490	

Table 6 – Cross Sectional Effects According to Sophistication Degree

This table presents the effects of hurricane proximity on corporate cash holdings according to the level of sophistication of the firm managers. *Cash* is the total amount of cash and cash equivalents held by the firm expressed as a percentage of its total assets at the end of the quarter. Management sophistication is identified according three criteria : the size of the firm (total assets), the age of the firm (number of years in compustat), and the experience (number of occurrence where the firm is located in the neighborhood area). *High (Medium) (Low) sophistication* is a dummy variable equal to 1 if the sophistication degree of the company is identified as high (medium) (low) by the respective criterion. *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. *Overlap* is a dummy variable equal to 1 if both *Neighbor* and *Disaster_zone* are equal to 1 (which can occur if two hurricanes hit similar geographical areas in a short time interval). All other variables are defined in appendix 1. Standard errors are corrected for clustering of the observations at the county of location level. *T*-statistics are reported between parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels.

Dependent variable OLS	Cash (1)	Cash (2)	Cash (3)
Sophistication criteria	Size	Age	Experience
Neighbor x High sophistication	0.30	0.26	-0.55
	(1.06)	(0.72)	(-0.78)
Neighbor x Medium sophistication	0.63	0.64	0.62
	(1.63)	(1.63)	(1.21)
Neighbor x Low sophistication	1.67***	1.83***	1.16***
	(3.17)	(3.45)	(3.23)
High sophistication dummy	-3.11***	1.51***	0.36
	(-8.50)	(4.05)	(0.79)
Low sophistication dummy	0.26	4.67***	-0.16
	(0.54)	(15.62)	(-0.42)
Disaster zone	-0.29	-0.27	-0.28
	(-1.18)	(-1.07)	(-1.15)
Overlap	0.04	-0.11	0.05
	(0.06)	(-0.16)	(0.08)
Constant	18.06***	16.46***	17.24***
	(54.02)	(42.70)	(40.92)
Fiscal quarter FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes
N	411,490	411,490	411,490
High - Low sophistication	1.37**	1.57***	2.00***
F -test	(4.47)	(6.01)	(5.12)

Table 7 – Cross Sectional Effects According to Financial Constraints Degree

This table presents the effects of hurricane proximity on corporate cash holdings according to the level of financial constraints of the firm. *Cash* is the total amount of cash and cash equivalents held by the firm expressed as a percentage of its total assets at the end of the quarter. Financial constraints degree is identified according three criteria : the presence of a bond rating, the payout policy, and the dependence on external financing. *FC* is a dummy variable equal to 1 if the company is identified as financially constrained by the respective criterion. *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. *Overlap* is a dummy variable equal to 1 if both *Neighbor* and *Disaster_zone* are equal to 1 (which can occur if two hurricanes hit similar geographical areas in a short time interval). All other variables are defined in appendix 1. Standard errors are corrected for clustering of the observations at the county of location level. *t*-statistics are reported between parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels.

Dependent variable OLS	Cash (1)	Cash (2)	Cash (3)
Financial Constraints criteria	Bond Ratings	Payout ratio	Dependence on External Financing
Neighbor x FC dummy	1.09***	0.88**	1.61***
	(2.73)	(2.23)	(4.04)
Neighbor	0.14	0.22	0.00
	(0.49)	(0.66)	(0.01)
Disaster zone	-0.18	-0.33	-0.29
	(-0.67)	(-1.35)	(-1.21)
Overlap	0.67	0.07	0.00
	(1.34)	(0.11)	(-0.01)
FC dummy	1.01***	-0.63***	
	(2.94)	(-4.34)	
Constant	13.74***	16.90***	17.23***
	(33.60)	(41.02)	(49.93)
Fiscal quarter FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes
N	354,476	390,097	411,490

Table 8 – Cross Sectional Effects According to the Degree of Vulnerability

This table presents the effects of hurricane proximity on corporate cash holdings according to the degree of vulnerability to the hurricane risk. *Cash* is the total amount of cash and cash equivalents held by the firm expressed as a percentage of its total assets at the end of the quarter. Degree of vulnerability is identified according four criteria: whether the firm realizes at least 20% of its sales abroad (*Export*), whether the firm is a multinational (*Multinational*), whether the firm is in a highly competitive industry, namely in the bottom tercile of the HHI based on sales at the SIC4 level (*Competition*) and finally whether the firm is in an industry which suffers the most from a hurricane (*Most Affected Firms*). *Vulnerability* is a dummy variable equal to 1 if the company is identified as being more vulnerable to the hurricane risk by the respective criterion. The other variables are those previously defined. Standard errors are corrected for clustering of the observations at the county of location level. *t*-statistics are reported between parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels.

Dependent variable OLS	Cash (1)	Cash (2)	Cash (3)	Cash (4)
Financial Constraints criteria	Export	Multinational	HHI	Most Affected Firms
Neighbor x Concern dummy	0.78*	1.19***	1.68***	1.47***
	(1.74)	(3.23)	(3.00)	(2.71)
Neighbor	0.28	-0.14	0.29	0.03
	(0.73)	(-0.42)	(0.71)	(0.07)
Disaster zone	-0.29	-0.29	-0.28	-0.26
	(-1.19)	(-1.20)	(-0.97)	(-0.91)
Overlap	-0.09	-0.08	0.53	-0.02
	(-0.14)	(-0.13)	(0.77)	(-0.03)
Concern dummy	1.65***	0.88***		
	(5.72)	(3.58)		
Constant	16.22***	16.54***	18.22***	18.29***
	(40.91)	(41.54)	(41.41)	(49.36)
Fiscal quarter FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
N	411 490	411 047	249 484	295 096

Table 9 – Effects of Hurricane Proximity on Corporate Cash holdings over time (with Matching)

This table 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 firm*s* 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 6 months before the hurricane landfall at quarter q-3 along 6 dimensions: size, age, market-to-book, financial leverage, capital expenditures and net working capital. *t*-statistics are reported between parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels.

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

Table 10 – Source of Change in Cash due to Hurricane Landfall Proximity

This table presents changes in sources of cash holdings caused by the proximity of a hurricane. *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. *Overlap* is a dummy variable equal to 1 if both *Neighbor* and *Disaster_zone* are equal to 1 (which can occur if two hurricanes hit similar geographical areas in a short time interval). All other variables are defined in appendix 1. Standard errors are corrected for clustering of the observations at the county of location level. *t*-statistics are reported between parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels.

Dependent variable	Sales growth (log)	Net income (% sales)	NWC (% sales)	Net investment (% sales)	Repurchase (% earnings)	Dividend (% earnings)	New financing (% mark. Cap.)	Repurchase dummy	Dividend dummy	New financing dummy
	OLS							Linear Probability Model		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Neighbor	1.44	-8.15	-0.42	-3.56***	-0.32	-0.49*	0.25	-0.01**	-0.01*	0.01
	(1.21)	(-1.56)	(-0.99)	(-2.71)	(-0.22)	(-1.86)	(1.03)	(-2.31)	(-1.67)	(1.18)
Disaster zone	-2.00*	-4.02	-0.61	-1.56	-0.24	-0.59**	-0.69**	0.00	0.00	0.00
	(-1.78)	(-0.66)	(-0.88)	(-1.00)	(-0.15)	(-2.27)	(-2.25)	(0.11)	(0.58)	(0.72)
Constant	2.97**	-57.56***	12.17***	-29.27**	33.78***	12.96***	3.55***	0.32***	0.28***	0.65***
	(2.01)	(-5.80)	(14.95)	(-2.54)	(12.60)	(26.36)	(8.12)	(29.26)	(35.63)	(69.59)
Fiscal quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	371,703	408,453	408,392	365,375	209,049	210,680	352,257	357,831	386,532	389,921

Table 11 –Change in Value of Cash around Hurricane Landfall

This table presents changes in the value of corporate cash holdings over different time windows around the hurricane landfall. The dependent variable is the excess return of the firm relative to the Fama and French (1993) 25 size and book-to-market portfolios over the specified time window. Hurricane landfall occurs at quarter *q0*. *Neighbor_q0* is a dummy equal to 1 if the county location of the firm headquarter was in the neighborhood of the area hit by the hurricane at quarter *q0*. All other independent variables are calculated over the specified time window and normalized by the market value of equity of the firm at the beginning of this time window. These variables are defined in appendix 1. Standard errors are corrected for clustering of the observations at the county of location level. *T*-statistics are reported between parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels.

Dependent variable	Stock return - Fama & French 25 portfolio					
Over time window	[q-2 , q-1]	[q-2 , q0]	[q-2 , q+1]	[q-2 , q+2]	[q-2 , q+3]	[q-2 , q+4]
OLS	(1)	(2)	(3)	(4)	(5)	(6)
Change in cash * Neighbor_q0	-0.23	-0.15	-0.22**	-0.27**	-0.24*	-0.12
	(-1.60)	(-1.13)	(-2.04)	(-2.14)	(-1.65)	(-0.85)
Change in cash	0.32***	0.59***	0.88***	1.08***	1.27***	1.29***
	(5.00)	(7.41)	(10.47)	(10.53)	(15.58)	(12.73)
Change in earnings	0.04	0.17***	0.22***	0.33***	0.60***	0.89***
	(1.59)	(4.90)	(6.26)	(3.72)	(8.63)	(9.16)
Change in dividends	-0.26	1.56	2.73**	6.15***	1.31	4.24**
	(-0.27)	(1.18)	(2.53)	(3.43)	(0.81)	(2.51)
Change in interest expenses	0.46	-0.65	-2.67***	-3.86***	-4.08***	-0.23
	(1.03)	(-1.20)	(-4.94)	(-4.55)	(-5.07)	(-0.74)
Change in non cash assets	0.06***	0.08***	0.13***	0.14***	0.15***	0.12***
	(5.24)	(6.08)	(10.79)	(10.59)	(10.67)	(8.83)
Change in R&D	-0.5	-0.43	0.80***	0.51	-0.67	-0.51
	(-1.56)	(-1.19)	(2.81)	(0.77)	(-1.20)	(-0.95)
Lagged cash	0.05***	0.12***	0.21***	0.34***	0.37***	0.33***
	(4.37)	(7.79)	(11.13)	(12.28)	(12.42)	(10.42)
Change in cash x Lagged cash	-0.03	-0.24**	-0.22**	-0.25**	-0.41***	-0.36***
	(-0.43)	(-2.24)	(-2.05)	(-2.05)	(-5.19)	(-4.20)
Leverage	-0.13	-0.13***	-0.20***	-0.25***	-0.30***	-0.32***
	(-1.01)	(-10.00)	(-10.28)	(-12.72)	(-12.35)	(-10.84)
Change in cash x Leverage	-0.07***	-0.36***	-0.63***	-0.74***	-0.94***	-1.31***
	(-6.98)	(-2.94)	(-4.79)	(-4.62)	(-5.84)	(-7.19)
Net financing	0	-0.04*	-0.08***	-0.05**	-0.02	-0.06***
	(-0.03)	(-1.93)	(-3.64)	(-2.14)	(-1.03)	(-2.90)
Neighbor_q0	0.01**	0.01	0.00	0.00	-0.01	-0.03
	(1.99)	(1.15)	(0.18)	(0.21)	(-0.81)	(-1.48)
Constant	-0.01	-0.02***	-0.04***	-0.04***	-0.07***	-0.08***
	(-1.38)	(-3.32)	(-4.59)	(-4.07)	(-5.45)	(-5.69)
N	12,196	11,808	11,466	10,894	10,359	10,136

Table 12 – Determinants of Disaster Likelihood

This table presents the effect of past proximity to hurricane strikes on the likelihood to be affected by a hurricane during the quarter. The analysis is performed at the county level. 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 column 1 and 2, and any hurricane in column 3 and 4).*Neighbor* is a dummy equal to 1 if the county is in the neighborhood of an area hit by a hurricane over the past 12 months. *Neighbor_last_24* is a dummy equal to 1 if the county is in the neighborhood of an area hit by a hurricane over the past 24 months. Standard errors are clustered at the state level. *t*-statistics are reported between parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels.

Dependent variable Linear Probability Model	Major hurricane (1)	Major hurricane (2)	Any hurricane (3)	Any hurricane (4)
Neighbor	0.01		0.00	
	(1.38)		(0.47)	
Neighbor_last_24		-0.01*		-0.01
		(-1.78)		(-1.38)
Constant	0.01**	0.01**	0.00	0.00
	(2.37)	(2.74)	(0.68)	(0.95)
Quarter FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
N	65,604	65,604	94,600	94,600

Table 13 – Market Reaction at Hurricane Landfall

This table presents the average cumulative abnormal (ACAR) stock return over the hurricane period (hereafter the "event window") according to the proximity of the firm headquarter to the disaster area. For each hurricane, firms are assigned to the *Disaster zone* group, the *Neighbor* group, or the *Control* group according to the location of their headquarter. The event windows starts one day before the beginning of the hurricane strike and ends one day after the end of hurricane strike. For each group of firm, ACAR and *z* statistics are estimated using equally weighted portfolios of firms with similar event windows. See appendix 2 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 the 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 14 –Change in Stock Prices Volatility around Hurricane Landfall

This table presents the results of an F-test of the equality of stock return variances around the hurricane period for different group of firms .For each hurricane, firms are assigned to the *Disaster zone* group, the *Neighbor* group, or the *Control* group according to the location of their headquarter. Stock return variances are estimated over two time periods, one before the start of the hurricane period (time window before hurricane) and the other after the end of the hurricane period (time window after hurricane). 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. Column 4 reports the F-statistic testing for the equality of the total variance of all stock returns included in each group and column 5 reports the corresponding p-value. ***, **, and * denote significance at the 1%, 5% and 10% levels.

Group	Time window before hurricane (nb days)	Time window after hurricane (nb days)	N (firms)	Change in stock return variance: % Down (1)	Change in stock return variance: % Up (2)	Change in stock return variance: % No change (3)	Change in total variance: *F*-statistic (4)	Change in total variance: P-value (5)
Neighbor	10	10	1,773	9%	12%	80%	1.17	0.82
	20	20	1,773	14%	15%	71%	1.02	0.97
	30	30	1,773	17%	19%	65%	1.17	0.68
	40	40	1,773	19%	19%	62%	1.21	0.56
Disaster zone	10	10	2,299	8%	13%	79%	1.31	0.70
	20	20	2,299	13%	17%	70%	1.28	0.60
	30	30	2,299	17%	20%	64%	1.14	0.73
	40	40	2,299	19%	21%	60%	1.01	0.98
Control (Rest of US)	10	10	27,538	9%	12%	80%	1.08	0.91
	20	20	27,539	14%	15%	71%	1.06	0.90
	30	30	27,539	16%	18%	66%	1.12	0.76
	40	40	27,539	19%	17%	63%	1.05	0.89

Table 15 – Major Earthquakes outside the US since 1980

This table 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.

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

Table 16 – Effects of Earthquakes outside the US on Corporate Cash holdings of US Firms

This table 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. 3 months before the earthquake occurrence) along 4 dimensions: size, age, market-to-book, and financial leverage. *t*-statistics are reported between parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels.

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%	-1.24%	0.41%	1.36

Figure 1 – Number of Hurricanes by Decade since 1850

This graph presents the total number of hurricanes by decade that made landfall in the US mainland since 1850. The source of the information is the NOAA Technical Memorandum (2011)

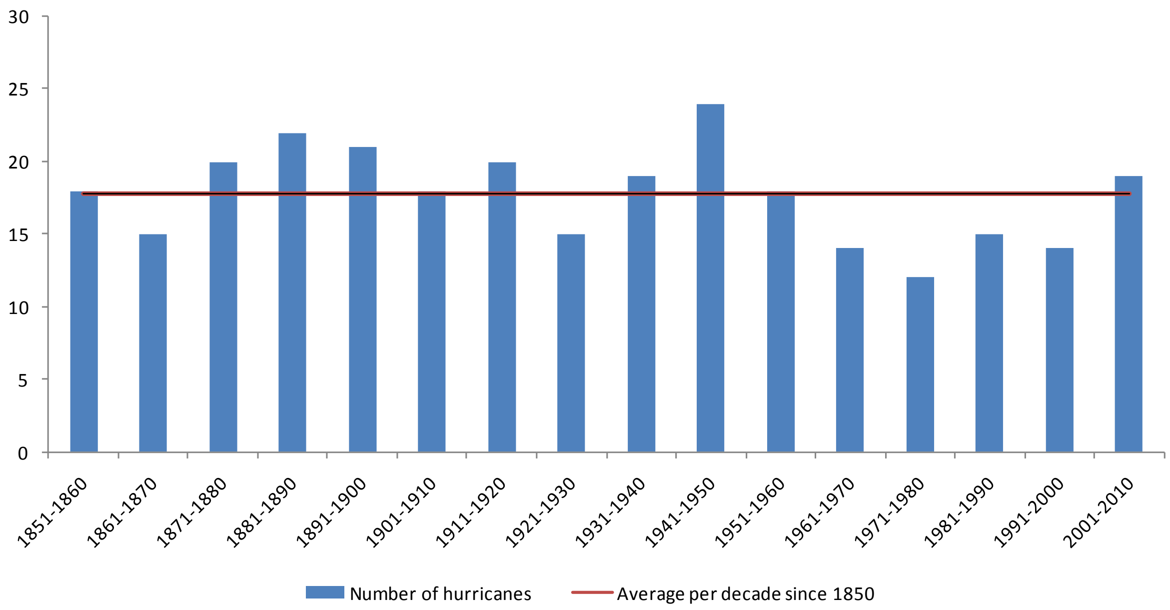

Figure 2 – Neighbours Identification: Illustration for Hurricane Fran (1996)

This map presents the result of the matching procedure performed to identify the degree of proximity of each county to the disaster area affected by Hurricane Fran in 1996. Each county inside the disaster area is matched with replacement with the 5 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.

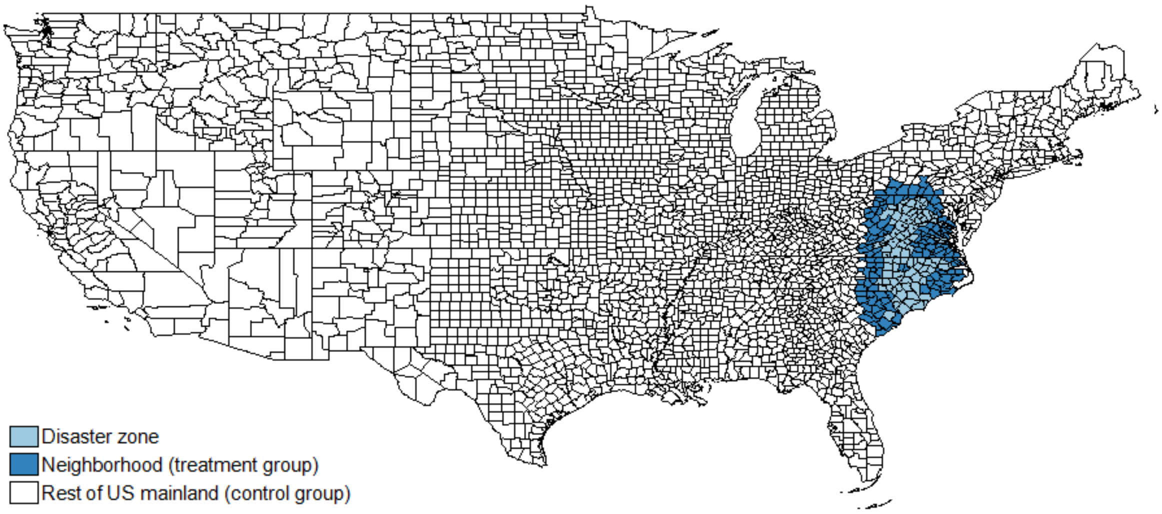

Figure 3 – Neighbours Identification: Illustration for Hurricane Floyd (1999)

This map presents the result of the matching procedure performed to identify the degree of proximity of each county to the disaster area affected by Hurricane Floyd in 1999. Each county inside the disaster area is matched with replacement with the 5 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.

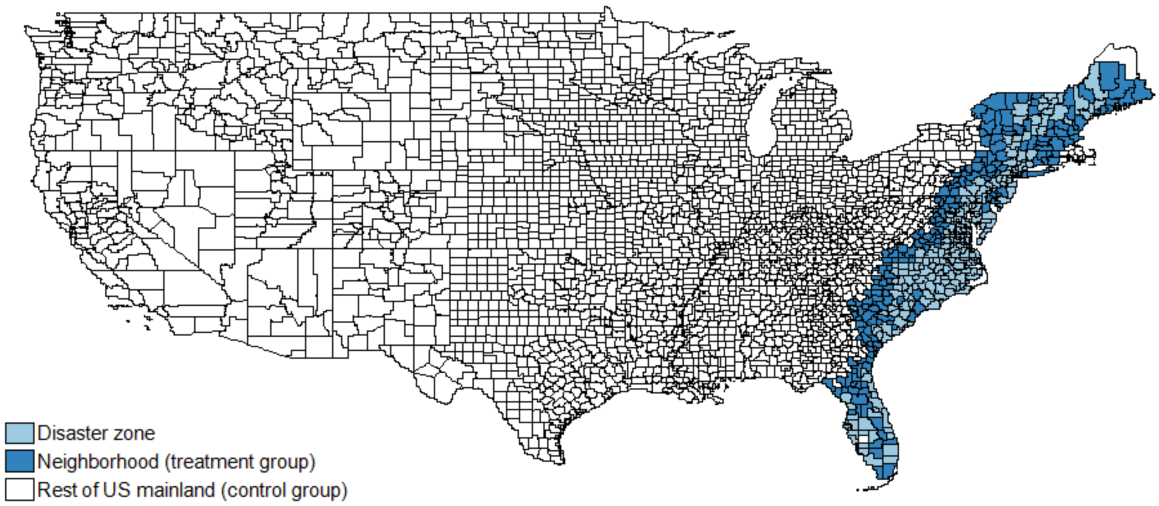

Figure 4 – Neighbours Identification: Illustration for Hurricane Allison (2001)

This map presents the result of the matching procedure performed to identify the degree of proximity of each county to the disaster area affected by Hurricane Allison in 2001. Each county inside the disaster area is matched with replacement with the 5 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.

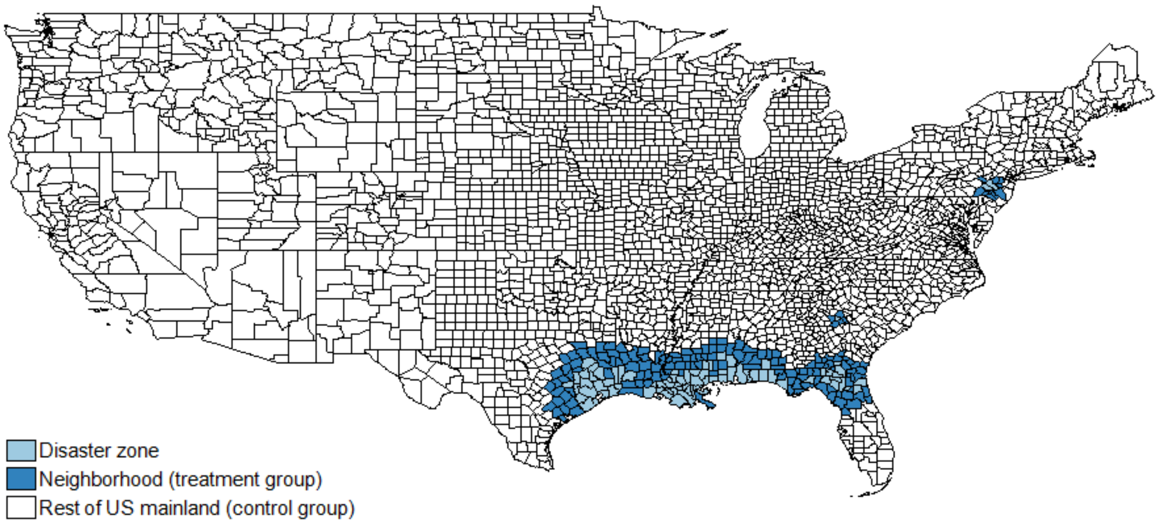

Figure 5 – Neighbours Identification : Illustration for Hurricane Katrina (2005)

This map presents the result of the matching procedure performed to identify the degree of proximity of each county to the disaster area affected by Hurricane Katrina in 2005. Each county inside the disaster area is matched with replacement with the 5 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.

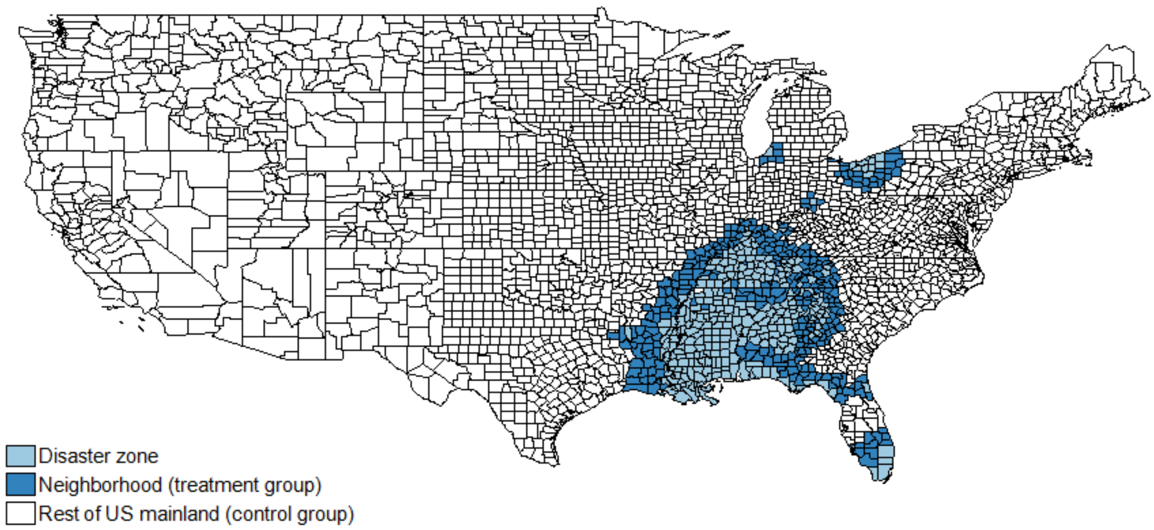

Figure 6 – Effects of Hurricane Proximity on Corporate Cash holdings over time

This graph presents the evolution of corporate cash holdings over time caused by the proximity of a hurricane occurred at quarter *q0*. Standard errors are corrected for clustering of the observations at the county level. ***, **, and * denote significance at the 1%, 5% and 10% levels.

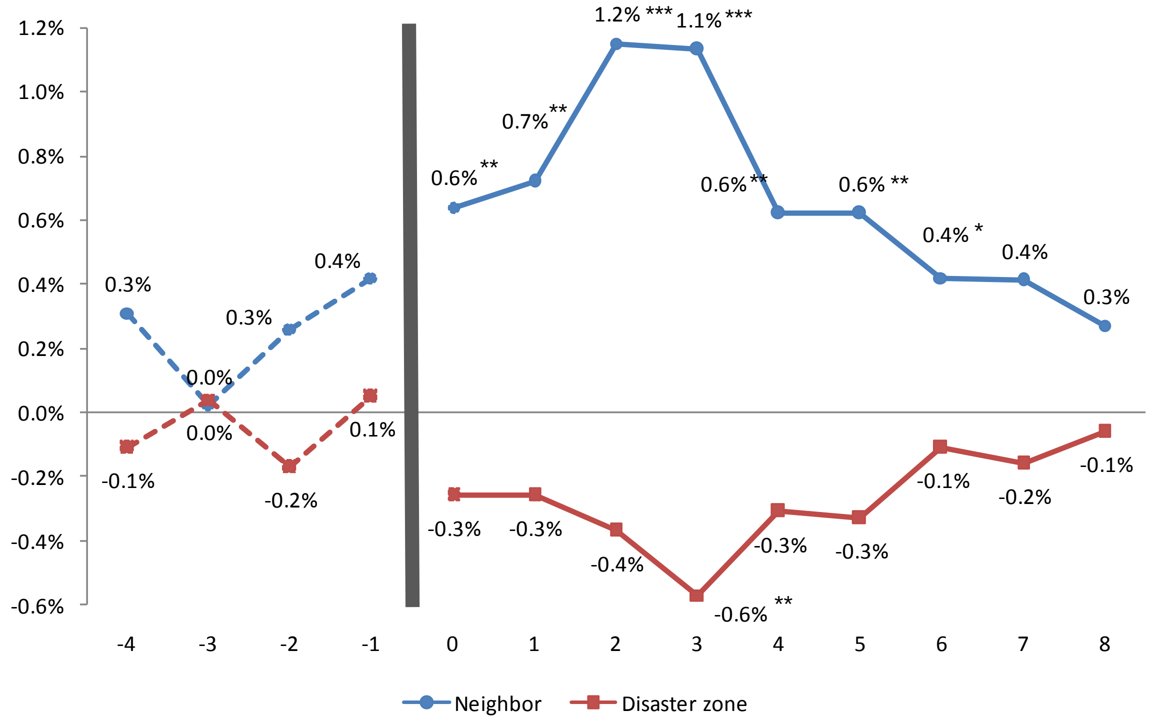

Figure 7 – Effects of Hurricane Proximity on Corporate Cash holdings over time

This graph presents the evolution of corporate cash holdings over time caused by the proximity of a hurricane occurred at quarter *q0*. The sample comprises 2,060 treated firm*s* 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 6 months before the hurricane landfall at quarter q-3 along 6 dimensions : size, age, market-to-book, financial leverage, capital expenditures and net working capital. *t*-statistics are reported between parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels.

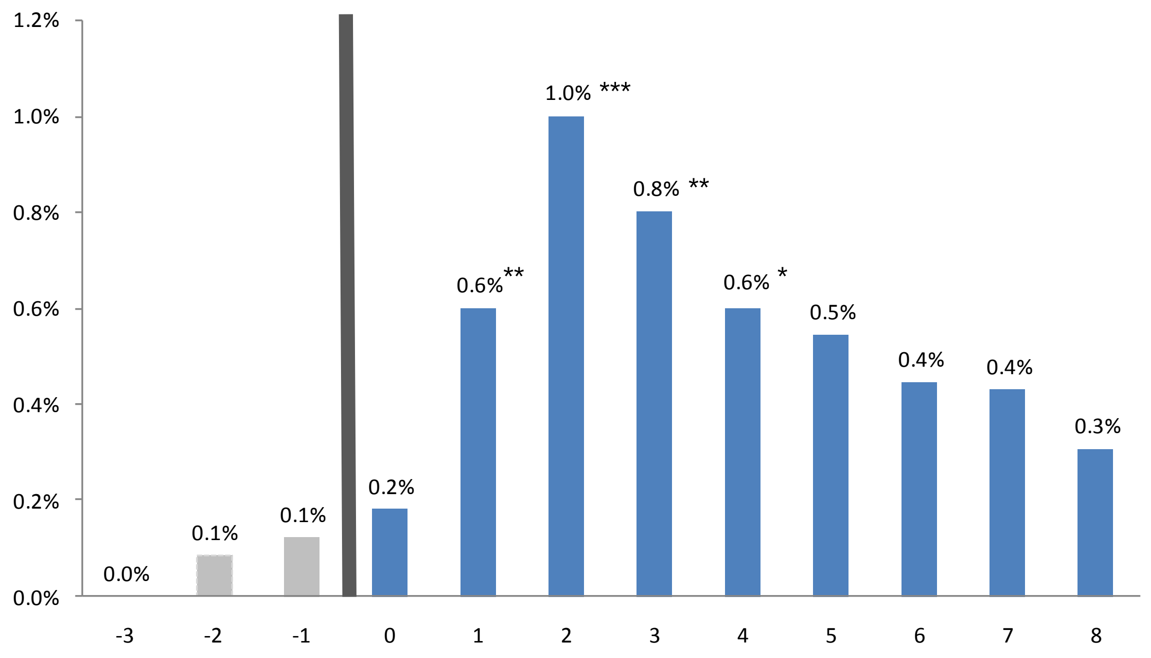

Figure 8 – Effects of Earthquakes outside the US on Corporate Cash holdings of US Firms

This graph presents the evolution of 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 firms whose headquarter is 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 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. 3 months before the earthquake occurrence) along 4 dimensions: size, age, market-to-book, and financial leverage. *t*-statistics are reported between parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels.