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Natural Disaster Risk and Corporate Leverage

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Abstract

Firms located in more disaster-prone counties adopt more conservative leverage policies than those in less disaster-prone counties. Compared to peers in the least disastrous areas, firms in the most disastrous areas are less levered by 3.6 percentage points, equivalent of foregoing $13.47 million. We argue that this systematic difference in leverage is attributed to elevated operating disruption, increased cost of capital, and tightened financial flexibility. Our findings indicate that firms incorporate natural disaster risk in financing decision, which is consistent with the trade-off theory of capital structure.

JEL classification: G32, L11, L25

Keywords: Natural Disaster; Capital Structure; Leverage; Bank loan; Debt Maturity

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1. Introduction

For several decades, both social and natural scientists ignored the interaction between social and ecological systems. On the one hand, mainstream ecology excluded humans from the study of nature, and on the other hand, social scientists excluded environment when studying social systems. In the 1970s and 1980s, several areas of research raced to cross this bridge by paying more attention to the socio-ecological systems (Folke et al., 2003). More recently, business practitioners and independent organizations started to recognize the impact of the ecological systems on corporate operations. For example, Basel II lists sources of business operating risk to include, among others, damage to physical assets due to natural disasters.[2] Further, in 2017, the Task Force on Climate-related Financial Disclosures (TCFD) issued a recommendation asking companies to start reporting risks associated with climate changes.[3] Despite the possible risks associated with local natural systems, researchers on corporate finance largely ignore the impact of these systems on corporate decision making.

Early economic studies have extensively studied the long-term effect of natural disasters on human life, physical assets, and local economies (e.g., Ellson et al., 1984; Xiao, 2011). More recently, researchers started to use natural disasters as a part of quasi-experimental empirical design. For instance, Belasen and Polachek (2008) find that the average workers' earnings increase by 4 percentage points in Florida counties after being hit by a hurricane. Imberman et al. (2012) examine the effect of the inflow of evacuees on existing students' academic performance in Houston and non-disaster areas in Louisiana after Hurricane Katrina. Bernstein et al. (2017) find

[2] According to Basel II, other sources of operating risk include: internal fraud, external fraud, employment practices and workplace safety, clients, products & business practices, business disruption and system failures, and execution, delivery & process management.
[3] The full report could be found on the following link: https://www.fsb-tcfd.org/publications/final-recommendations-report/

that houses exposed to sea level rise are selling at a 7 percent discount compared to non-exposed ones. However, very few papers examine the effect of natural disasters on corporate activities and decision making. Barrot and Sauvagnat (2016) show that if a firm's supplier is affected by a hurricane, its sales growth decreases by 2 to 3 percentage points. Dessaint and Matray (2017) show that firms located in the neighborhoods of disaster areas tend to increase cash holdings. However, to the best of our knowledge, this is the first empirical research that investigates the impact of local environmental risk on corporate financing decision.

In this paper, we investigate the impact of natural disaster risk associated with corporate location on corporate capital structure. We hypothesize that firms with high natural disaster risk tend to lower their leverage. Firms headquartered in areas with high probability of natural disasters are expected to have higher operating risk due to business disruptions, to experience more physical assets damage (deteriorated collateral value), and to seek higher levels of financial flexibility — which should lead these firms to employ more conservative debt policies (Lemmon et al., 2008 and Graham, 2000). Alternatively, if managers are able to reallocate firms' resources as natural disaster risk increases, they might be less concerned about elevated natural disaster risk — leading to a negligent effect of natural disasters on corporate leverage.

To measure natural disaster risk associated with corporate location, we obtain data for all natural disasters occurred in the U.S. during the period 1987-2013. The Federal Emergency Management Agency (FEMA) assesses the extent of damage caused by natural disasters jointly with federal, state, and tribal Preliminary Damage Assessment (PDA) teams and declares emergency in the affected areas. In this paper, our measure of natural disaster risk takes the duration of natural disaster events into consideration by counting the number of natural disaster days declared by the FEMA for each natural disaster event. Since FEMA records main disaster events, the duration of a disaster is expected to be highly correlated with its unobservable/difficult to measure economic impact. For each year, our main proxy for natural disaster risk is calculated as the total number of days of all natural disaster events in a firm's headquarter county.

We argue that natural disasters represent a source of idiosyncratic risk to a firm's operations. Alternatively, one would argue that technological advancements enabled us to better predict some natural disasters, and/or that some natural disasters repeatedly struck the same areas, making natural disasters highly predictable in these areas. The notion that technological advancements improved our prediction capabilities is indeed plausible when it comes to predicting the occurrence of natural disasters. However, it is virtually impossible to ex-ante predict the severity/economic impact of natural disasters — which is more relevant to a manager's perception of operating risk and as a result to a firm's capital structure decision. Although the occurrence of these incidents is sometimes predictable, their severity/economic impact comes as a surprise that local businesses and residents have to recognize in the aftermath of each disaster. If natural disasters severely disrupt a firm's daily operation, then it is plausible to contend that natural disaster risk should be incorporated in corporate financing decision.[4]

Our empirical results show that the average leverage of firms headquartered in areas with high probability of natural disasters is 3.6 percentage points lower than that of counterparts in areas with low probability of natural disasters. Our further tests of the dynamic effects of natural disaster risk on corporate leverage show that firms slowly adjust their capital structure over multiple years, which is consistent with the view of Flannery and Rangan (2006) and Harford et al. (2009). Results

[4] Firms can partially eliminate this risk through purchasing insurance against natural disasters. However, the role that insurance plays in this context might be minimal. According to the 2016 Annual Global Climate and Catastrophe Report, only 26 percent ($54 billion) of overall economic losses caused by natural disasters worldwide during 2016 were covered by insurance. This report could be found in the following link: http://thoughtleadership.aonbenfield.com/Documents/20170117-ab-if-annual-climate-catastrophe-report.pdf .

from tests of dynamic effects also refute the alternative hypothesis that the negative association between leverage and natural disaster risk is a result of a pre-existing condition.

In addition to testing the association between natural disaster risk and corporate financial leverage, we also investigate three channels through which elevated natural disaster risk could impact corporate debt policies. Specifically, high natural disaster risk can (1) cause firms to experience higher earnings volatility, (2) cause firms to receive unfavorable credit terms due to collateral asset value deterioration, and (3) cause managers to become more financially-conservative and to prefer financial flexibility. Our empirical findings are consistent with these three conjectures. First, our results show that natural disaster risk is positively associated with firm's earnings volatility. Second, investigating the association between natural disaster risk and cost of debt shows that lenders impose higher rates on disaster-prone firms. Specifically, when the number of local natural disasters increases by one standard deviation, the loan spread increases by 35 basis points. Our results also show that lenders include significantly greater number of loan covenants in contracts with firms located in high natural disaster risk areas. Lastly, our results show that firms with high natural disaster risk do (do not) lower their long-term (short-term) debt issuance — which is consistent with the idea that these firms favor higher degree of financial flexibility.

Corporate headquarters is usually close to corporate core business activities. Further, headquarters is the place where corporate decision makers reside and craft main corporate decisions (Davis and Henderson, 2008). However, since locations of a corporate headquarters and operations can be different, we conduct a robustness test using facility location data. Our difference-in-difference (DID) facility-based test shows that firms reduce their leverage in reaction to increasing natural disaster risk of their major facilities locations.

Further, one may argue that corporate headquarters location is not randomly determined and thus our findings are subject to sample selection bias. To address this concern, we use corporate headquarter relocation as a natural experiment to further confirm the association between natural disaster risk and financial leverage. We find that firms increase their leverage level after relocating headquarters to areas with lower natural disaster risk. Overall, our results indicate that firms adjust their leverage in response to changes in the level of regional natural disaster risk.

This paper contributes to several areas of the literature. First, this paper has a methodological contribution to the literature on the determinants of corporate debt policy. Measuring operating volatility has always been problematic for researchers on corporate leverage. For example, Titman and Wessels (1988) argue that possible indicators of operating risk such as a firm's stock beta or total volatility, are partially determined by the firm's debt ratio. To partially solve this simultaneous causality problem, empirical studies usually use some form of earnings volatility as a proxy for operating risk. These measures are not free of the endogeneity problem either. For example, Watts and Zimmerman (1986) and Dhaliwal and Reynolds (1994) show that high leverage leads firms to employ income-accelerating accounting methods. Consequently, reported earnings could be indirectly affected by the level of firm leverage. More recently, researchers have been trying to use various measures of operating volatility (for example; labor union strength (Chen et al., 2011), production flexibility (Reinartz and Schmid, 2016), and employment contract flexibility (Kuzmina, 2018)). To the best of our knowledge, this paper is the first to employ natural disaster risk as a measure of operating volatility. It is worth noting that although finding a negative association between operating risk and leverage is not surprising, understanding the impact of natural disasters on business operations and decision making is of critical importance due to the fact that natural disasters, unlike several other sources of risk, seem to be increasing in frequency and severity over time.[5]

Second, this paper contributes to the literature on the impact of corporate location on corporate decision making. The overwhelming majority of that literature focuses on the impact of social systems by using location to capture local culture, social interactions and networks, demand of local investors' clienteles, conditions of banks and stock markets, and level of information asymmetry. This paper contributes to this literature by studying the risks caused by the ecological systems associated with corporate location, and more importantly, the impact of these systems on corporate debt policies.

Third, this paper contributes to the literature that investigates the economic impact of natural disasters (Belasen and Polachek, 2008; Berkman et al., 2011; Kelly and Jiang, 2014; and Gourio, 2012). Lastly, this paper contributes to the recent empirical literature that investigates the effect of idiosyncratic shocks on corporate decision making and financial markets (Dessaint and Matray, 2017 and Barrot and Sauvagnat, 2016). We show that exogenous idiosyncratic shocks not only affect corporate short-term cash holdings but also seem to alter long-term corporate use of debt. In addition to the contribution to academic research, this paper also contributes to the ongoing debate regarding the role that climate-related risks play in financial planning and reporting (Eccles and Krzus, 2018).

The remainder of this paper proceeds as follows: Section 2 summarizes related literature and develops hypotheses. Section 3 presents data and sample construction. Section 4 reports empirical results and discussion, and Section 5 summarizes concluding remarks.

[5] For example, The National Oceanic and Atmospheric Administration (NOAA) Geophysical Fluid Dynamics Lab's (GFDL) report on Hurricanes and Global Warming conclude that frequency and intensity of natural disasters increased in the last few decades, possibly due to global warming that resulted from human activity.

2. Literature Review and Hypotheses Development.

Research in financial economics recognizes the importance of corporate geographical location. Location has been used to capture different aspects such as proximity, investors' clienteles, and local culture and other non-economic factors. As a proxy for proximity, location has been shown to affect portfolio formation and returns of institutional as well as individual investors (Coval and Moskowitz, 1999, and Ivković and Weisbenner, 2005), analysts accuracy (Bae et al., 2008) and investors' informativeness (Massa and Simonov, 2006). Location has also been used to capture the clientele effect at which corporations alter their policies to cater for local investors. For example, Becker et al. (2011) show that firms cater to local seniors by designing a suitable payout policy. Similarly, Gao et al. (2008) show that headquarter location affects firms' capital structure. Location can also affect corporate decision making because of the location-specific non-economic factors. For example, Hilary and Hui (2009) show that higher level of religiosity reduces degree of firms' risk exposure.

The abovementioned research focuses on the impact of the social systems associated with corporate location on corporate policies — ignoring the impact of the ecological systems. Despite the relative attention that economists have paid to understanding the impact of nature on economic outcomes, financial economists paid very little attention to the impact of the location-specific ecological systems on corporate decision making.

2.1. Natural Disasters, Economic Development, and Corporate Decision Making

Studies on the impact of natural disasters on economic development received considerable attention. This importance stems in part from the fact that natural disasters have long been known to result in substantial and unexpected losses to physical capital, particularly due to the increasing value of physical assets and the increasing population in high-risk zones (Froot, 2001).[6] This importance has led several economists to investigate the economic impact of natural disasters. Particularly, while several papers show that natural disasters hinder economic development, others show that natural disasters benefit the economy (Albala-Bertrand, 1993; Skidmore and Toya, 2002; and Caselli and Malhotra, 2004).

More recently, few studies attempted to understand the effect of idiosyncratic shocks of natural disasters on corporate decision making and financial markets. For example, Born and Viscusi (2006) show, on a state-level, that natural disasters reduce total insurance premiums earned, reduce total number of writing insurance coverage, and increase insurance firms exits. Dessaint and Matray (2017) show that managers react to hurricanes in neighborhood areas by temporarily increasing their cash holdings, even though the real liquidity risk remains unchanged. Further, Barrot and Sauvagnat (2016) show that suppliers located in areas affected by natural disasters impose substantial output losses on their customers. They also show that these losses result in significant market value losses and spill over to other suppliers in the production network.[7]

2.2. Capital Structure and Operating Volatility – Endogeneity.

Since the ground breaking work of Modigliani and Miller (1958), corporate capital structure is probably one of the most studied areas in financial economics. However, researchers consistently claim to know very little about corporate capital structure — which stems in part from the fact that, with the overwhelming nature of empirical evidence, it is easy to provide empirical support to any theoretical idea (Frank and Goyal, 2009). These decades of theoretical and empirical work provide several frameworks to understand corporate use of debt. Among the most

[6] According to Froot, K.A., 2001. The market for catastrophe risk: a clinical examination. Journal of Financial Economics 60, 529-571., a single hurricane or earthquake could result in damages of $50 - $100 billion.
[7] Interestingly, Giroud et al., (2011) use unexpected snow as an instrument variable for a reduction in leverage.

pronounced frameworks are the trade-off theory (Kraus and Litzenberger, 1973; Stulz, 1990; and Morellec, 2004), the pecking order theory (Myers, 1984; Myers and Majluf, 1984), and the market timing theory (Baker and Wurgler, 2002).[8]

Extant theoretical and empirical literature recognizes the importance of operating risk in determining corporate debt policy. For example, Marsh (1982) states that "*it seems reasonable to expect companies with high operating risk to use less debt.*" Further, Flath and Knoeber (1980) state that "*Cross-sectional variation in capital structure was best explained by differences in operating risk*." Despite its theoretical importance in predicting leverage, measuring operating risk has always been problematic due to the endogeneity (simultaneous causality) problem. Titman and Wessels (1988) argue that possible indicators of operating risk such as a firm's stock beta or total volatility, are partially determined by the firm's debt ratio. The use of exogenous sources of operating risk is then expected to have special merits in the empirical tests of the determinants of capital structure (Chen et al., 2011, Reinartz and Schmid, 2016, and Kuzmina, 2018).

More recently, Basel II defines operating risk as "*the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events.*" In addition, Basel II provides a comprehensive list of sources of operating risk. This list includes, among others, damage to physical assets, which is defined as the "*Losses arising from loss or damage to physical assets from natural disaster or other events*." Probability of natural disasters is then a major source of operating risk that is apparently exogenous to corporate capital structure policy. In this paper, we utilize the availability of a comprehensive natural disasters data to investigate the impact of these exogenous idiosyncratic shocks on corporate use of debt.

[8] A comprehensive review of this literature could be found in Frank, M.Z., Goyal, V.K., 2009. Capital structure decisions: which factors are reliably important? Financial Management 38, 1-37..

Based on the above discussion, natural disaster risk, as a source of operating risk, is expected to have a negative association with corporate use of debt. This assumption leads to our first hypothesis:

H1: *Firms headquartered in areas with high natural disaster risk are expected to have lower leverage ratios*.

Elevated natural disaster risk could affect corporate leverage through several channels. Investigating these channels is important to fully understand the mechanism through which natural disasters affect leverage. First, natural disasters can affect leverage through its possible impact on firm's earnings volatility (Basel II). According to Strebulaev (2007), both the pecking order and trade-off theories of capital structure predict that the higher the volatility the lower the optimal amount of borrowing.[9] Natural disasters are expected to affect corporate regular operations, supply chain and deliveries, resulting in elevated earnings volatility, specifically during the disaster year. This leads to our second hypothesis:

H2: *There is a positive association between natural disaster risk and firm's earnings volatility.*

Second, natural disasters can impact corporate debt policy through their expected impact on firms' collateral asset value. Rajan and Zingales (1995) argue that high value of collateral assets would lead to reducing lenders' agency costs of debt, increasing asset value during liquidation, boosting lenders willingness to supply loans, and consequently, increasing firm leverage. Physical

[9] The association between volatility and corporate use of debt is also documented by Bradley, M., Jarrell, G.A., Kim, E., 1984. On the existence of an optimal capital structure: Theory and evidence. The Journal of Finance 39, 857-878., Graham, J.R., 2000. How big are the tax benefits of debt? The Journal of Finance 55, 1901-1941., and Lemmon, M.L., Roberts, M.R., Zender, J.F., 2008. Back to the beginning: persistence and the cross-section of corporate capital structure. Ibid. 63, 1575-1608.. However, Myers, S.C., 1977. Determinants of corporate borrowing. Journal of Financial Economics 5, 147-175. provides an opposite conclusion. Specifically, he argues that firms with high business risk may have a lower agency cost of debt, and thus optimally have higher debt on their capital structure. The empirical results of Kim, W.S., Sorensen, E.H., 1986. Evidence on the impact of the agency costs of debt on corporate debt policy. Journal of Financial and Quantitative Analysis 21, 131-144. lend strong support to this intuition.

asset damage associated with natural disasters is then expected to reduce collateral value, leading firms to become less levered. What makes this problem even worse is that the insurance industry, which is supposed to provide coverage for physical asset damage, is facing multiple hurdles doing so in high disaster areas. Born and Viscusi (2006) show that high natural disaster areas experience lack of proper insurance due to insurers' exits, bankruptcies, and even decisions not to renew some insurance policies in such areas. This channel, however, predicts that natural disaster risk would affect not only corporate leverage policy but also corporate cost of debt. Specifically, in order to account for the risk of physical asset damage, lenders are expected to impose higher interest rates on disaster risk-prone firms. This argument is consistent with Garmaise and Moskowitz (2009) who argue that bank financing of catastrophe-susceptible assets is likely to be inefficient. This conjecture leads to our third hypothesis,

H3: *Firms headquartered in areas with high risk of natural disasters have higher cost of debt as compared to firms headquartered in areas with low risk of natural disasters.*

Third, natural disaster risk could impact corporate leverage through its possible impact on managers' financial preferences. The probability of natural disasters could lead managers, as a precaution, to use less debt. Graham (2000) argues that firms often claim that they use debt conservatively to preserve financial flexibility and to be able to absorb economic bumps. Gorbenko and Strebulaev (2010) also show that temporary shocks increase the importance of financial flexibility and may provide an explanation to the empirically observed financial conservatism and the low leverage phenomena. Firms headquartered in areas with high probability of natural disasters, because of the increased risk of those bumps, are then expected to favor higher degrees of financial flexibility — leading these firms to become less likely to issue long-term debt. This assumption is consistent with Goyal et al. (2002) who provide evidence that firms choose shorter (longer) maturity borrowing when financial flexibility becomes more (less) valuable. As a result, firms headquartered in high natural disaster areas, that are expected to reduce debt while retaining flexibility in capital structure, might do so by cutting long-term instead of short-term debt. This leads to our last hypothesis:

H4: *Firms headquartered in high natural disaster areas are expected to apply higher cuts to their long-term debt as compared to short-term debt.*

In addition to the firm-level channels discussed above, natural disasters could indirectly affect corporate use of debt due to their economic impact. Vast literature links natural disasters and economic contractions. Specifically, Gourio (2009) argues that an increase in the perceived probability of natural disasters leads to a collapse of investment and a recession. According to Hackbarth et al. (2006), the state of the economy (expansion vs. contraction) affects both benefits and costs of corporate use of debt. In other words, the possible recession following natural disasters – especially severe ones – affects level of cash flows, probability of default, and costs in the case of default — factors that together determine the level of corporate leverage.

In summary, we hypothesize that elevated natural disaster risk would increase earnings volatility due to business disruptions, diminish value of firms' collateral assets due to physical assets damage, increase managers' preference for financial flexibility, and, at a macro-level, hinder economic development. As a result, we predict a negative association between the probability of natural disasters and corporate use of debt.

3. Data and Sample Construction

3.1. Natural Disaster Risk

We acquired natural disasters data from the Federal Emergency Management Agency (FEMA) database.[10] The FEMA Disaster Declarations file published by OpenFEMA is a summarized dataset describing all federally declared natural disasters since 1953, and features all three disaster declaration types: major disaster, emergency, and fire management assistance with corresponding geographic areas (states and counties). The FEMA reports several forms of incidents (e.g., severe storm, fire, flood, hurricane, snow, tornado, earthquake, and other forms of incidences) updated on a quarterly basis.[11] During our sample period of 1987-2013, severe storm, fire, flood, and hurricane were ranked as the top four federally declared major disaster-types based on number of occurrences. For instance, there were 753 severe storms, 596 fires, 219 floods, and 216 hurricanes over the sample period. In this paper, we limit our focus to natural disaster exposure calculated as the total number of disaster days for all incidents for each county.[12] To conduct our facility-based robustness check, we use data from the Toxic Release Inventory (TRI) program, a publicly available dataset compiled by the U.S. Environmental Protection Agency (EPA). The TRI contains information on disposal and other releases of over 650 toxic chemicals from more than 50,000 U.S. industrial facilities (including facility's detailed physical address) that have reported at least once since the TRI was launched in 1987.

We acquired financial information from the Compustat database. In order to merge natural disasters data with Compustat data, we mapped the zip codes of COMPUSTAT firms to the Federal

[10] The official FEMA Disaster Declarations summary data is available at https://catalog.data.gov/dataset/fema-disaster-declaration-summary-api/resource/76cdf0f2-b92f-4c6c-b45e-c0229be3588d [Accessed on 01/07/2017]. "FEMA and the Federal Government cannot vouch for the data or analyses derived from these data after the data have been retrieved from the Agency's website(s) and/or Data.gov.

[11] We provide additional details about different types of incidences in Appendix A.

[12] The days of disaster is calculated as the difference in the incident between the beginning date and the ending date.

Information Processing Standards (FIPS) of counties in the FEMA database. In this mapping process, we excluded firms in the financial (Standard Industrial Classification (SIC) codes 6000-6999) and utility (4900-4999) industries, and counties in Alaska (State FIPS code 02), Hawaii (State FIPS code 15), and Puerto Rico (State FIPS code 72). The final sample consists of 101,051 firm-year observations corresponding to 33,354 unique county-level natural disasters during the period 1987-2013. County-level data is graphically portrayed in Figure 1.

[Please insert Figure 1 here]

Figure 1 presents maps of county-level natural disaster areas as well as historical average financial leverages of firms in each county. During the period 1987-2013, an average natural disaster lasted 18 days and affected 16 counties. For instance, Hurricane Isaac, that was declared as a federal disaster on Aug 29, 2012, created damage across 112 counties in 3 different states (Alabama, Mississippi, and Louisiana) for 15 calendar days, resulting in an approximate economic damage of $2.9 billion.[13] Figure 1.a shows that 834 counties out of 3,091 counties (26.98%) are classified as high natural disaster risk counties in terms of the cumulative number of incidents. Each of those 834 counties had more than 47 natural disaster declarations (the value of the 75th percentile) over the sample period. By comparing panels a and b in Figure 1, one can observe a pattern that firms headquartered in counties that experienced natural disasters tend to subscribe less debt compared to firms headquartered in counties with less natural disasters incidences.

3.2. Bank Loan

In order to investigate the association between natural disaster risk and corporate cost of debt, we use corporate bank loan data. Bank loan data is obtained from the LPC DealScan database, which contains historical bank loan data from SEC filings and banks self-reporting. The LPC

[13] The figure is CPI-adjusted estimated cost reported by National Centers for Environmental Information (NOAA). The data is available on https://www.ncdc.noaa.gov/billions/events [Accessed on 1-17-2017]

DealScan database includes detailed deal terms and conditions on loans, such as interest rates, loan size, maturities, covenants, performance, pricing, and loan security status.

To examine the influence of natural disasters on the pricing of bank loans, we control for other factors that have been shown in the literature to impact price and non-price terms of bank loans. Further, we control for two macro-economic variables that capture business-cycle effects and that might affect loan terms; *CreditSpread*, defined as the difference between the yields on Baa-rated and AAA-rated corporate bonds, and *TermSpread*, defined as the difference between the 10-year Treasury yield and the 1-year Treasury yield one month before the loan date. *CreditSpread* and *TermSpread* data are obtained from the Federal Reserve database. After merging the bank loans database with Compustat, we have 23,387 bank loan-year observations for the period of 1987-2013. Our measures of natural disaster risk, leverage, and control variables are described in Table 1.

[Please insert Table 1 here]

Our measures of natural disaster risk are constructed by calculating the number of disaster days in each county during a specified period of time. Measures of natural disaster risk that focus only on one year (*#Disa* and *Disaday*) have zero medians. However, long-term cumulative disasters measures (*#Disa5* and *Disaday5*) have much larger variation and less zero values.[14]

Measuring financial leverage represents another area of disagreement in the empirical corporate finance literature. While Myers (1977) and survey responses in Graham and Harvey (2001) favor the backward-looking book leverage, Welch (2004) for example favors the forward-

[14] In addition to our baseline cumulative disaster measures, we also construct two alternative disaster risk measures. (1) time-weighted disaster measures (*Wdisaday*) at which more recent disasters receive higher weights than less recent ones. This alternative measure accounts for the possibility that managers' perceptions about natural disaster risk might be heavily affected by more recent incidents (i.e., availability heuristic). And (2) a measure based on number of events (*#Disa*). Since this measure counts the number of disaster events instead of days, it is less sensitive to the severity associated with prolonged incidents. Our results using these alternative measures are quantitatively and qualitatively similar to our baseline results and are available upon request.

looking market leverage. In this paper, we report results using both measures of capital structure. *Book Leverage* is the ratio of the summation of debt in current liabilities and long-term debt to firm's total assets, while *Market Leverage* is the ratio of total debt to the summation of total debt and market value of equity. Firms in our sample have a median *Book Leverage* (*Market Leverage*) of 17% (10%). Further, median leverage is below its mean and there is a significant variation in leverage with the 25 percentile around 0, and the 75 percentile around 26-34%, depending on the used measure. These statistics are similar to those of Frank and Goyal (2009). Mean returns on assets (*ROA*) in our sample is -3%. This is consistent with the notion that an increasing number of public firms achieve net losses.

4. Empirical Results and Discussion

4.1. Natural Disaster Risk and Capital Structure

4.1.1. Univariate Analysis

We start our analysis by comparing mean leverage of firms headquartered in areas with high probability of natural disasters and their counterparts headquartered in areas with low probability. This comparison is reported in Table 2.

[Please insert Table 2 here]

Table 2 reports mean leverage for three groups of firms ranked based on the probability of natural disasters. For the sake of completeness, we report results using three measures of natural disasters probability; *Disaday*, *Disaday3*, and *Disaday5*, which are the cumulative number of natural disasters days in a firm's county during the previous year, 3 years, and 5 years, respectively. It is well accepted in ecology that the frequency is an essential element to understand -and hence to form an accurate assessment of risks associated with- natural disasters (O'Brien et al., 2006). Consequently, corporate managers are not expected to alter their use of debt due to an occasional natural disaster that hits their area. Instead, managers' assessment of natural disaster risk in their areas is going to be crafted by disaster incidences over a long period of time. As a result, *Disaday5* is expected to better capture actual managerial assessment of natural disaster risk. This idea is also consistent with Lucas and Rapping (1969), who claim that when people perceive a shock as having a temporary effect, they do not change their long-term perception of the economic variables that are affected by the shock.

Panel A of Table 2 reports average book leverage. Using *Disaday5* to proxy for natural disaster risk, these statistics show that firms that are highly susceptible to natural disasters (*High Disaster*) have less *Book Leverage* than firms that are less susceptible to natural disasters (*Low Disaster*). Specifically, *High Disaster* firms have an average *Book Leverage* of 20.2% as compared to 23.8% for the *Low Disaster* firms. The difference between the leverage of these two groups is statistically significant at the 1 percent level. Compared to peers in the least disastrous areas, firms in the most disastrous areas are less levered by 3.6 percentage points, equivalent to $13.47 million.[15] Similar results, however weaker, are reported when we use *Disaday* to proxy for natural disaster risk. We also find similar results with *Market Leverage* (Panel B of Table 2). Using *Disaday5, High Disaster* firms have an average *Market Leverage* of 14.7% as compared to 18.2% for the *Low Disaster* firms. The difference between the *Market Leverage* of these two groups is statistically significant at the 1 percent level.

Results of the univariate test lend primary support to our first hypothesis. Firms headquartered in areas with high natural disaster risk seem to have less debt in their capital structure. This result is not sensitive to the use of the backward-looking book leverage or the

[15] The economic magnitude of the leverage difference, $13.47 million, is calculated as firms' average total assets x average book leverage x difference in book leverage between high and low natural disaster risk firms, which equals to 1,700.9 x 0.22 x 0.036.

forward-looking market leverage. In order to formally test our first hypothesis on the association between natural disaster risk and corporate use of debt, we next control for the main determinants of capital structure.

4.1.2. Regression Models

After decades of theoretical and empirical research on the determinants of corporate use of debt, there is a little consensus on what variables matter the most (Frank and Goyal, 2009). Our model of the determinants of capital structure is based on the four-factor model of Rajan and Zingales (1995). Specifically, we control for typical firm characteristics such firm size, cash, return on assets, a ratio of market to book, asset tangibility, product market concentration, and an indicator for dividend payment used in prior capital structure research (e.g., Klasa et al., 2016.) We also control for within-industry competition (Herfindahl-Hirschman index (*HHI*)) following the literature of the industrial organization theory (Tirole, 1988). *Dividends* is a binary variable that takes the value of "1" if the firm pays out dividends in a fiscal year and the value of "0" otherwise.[16] Specifically, we estimate the following model of the determinants of corporate use of debt:

$$\begin{aligned} Leverage_{i,t} = \beta_0 + \beta_1 Disaster_{i,t-1} + \beta_2 Ln(Assets)_{i,t-1} + \beta_3 Cash_{i,t-1} \\ + \beta_4 ROA_{i,t-1} + \beta_5 MB_{i,t-1} + \beta_6 Tangibility_{i,t-1} + \beta_7 HHI_{i,t-1} \\ + \beta_8 Dividends_{i,t-1} + \varepsilon_{i,t} \end{aligned} \tag{1}$$

where the dependent variable, *Leverage*, is measured by either *Book leverage* or *Market Leverage*. *Disaster* is our measure of natural disaster risk. We use the natural logarithm of our three measures of natural disaster risk; *Disaday*, *Disaday3*, and *Disaday5.* We include firm fixed effects to control for time-invariant unobservable firm characteristics. We also control for year times industry fixed effects, that controls for time-varying unobservable industry characteristics

[16] A detailed variable definition associated with COMPUSTAT item information is provided in Appendix B.

(e.g., investment opportunities). Lastly, our standard errors are clustered at the county level because financing decision might be interdependent among firms within county after being hit by natural disasters.[17]

[Please insert Table 3 here]

Table 3 presents results of our OLS regression for the determinants of firm leverage. The dependent variable in models (1), (2), and (3) is *Book Leverage*, while the dependent variable in models (4), (5), and (6) is *Market Leverage*. Consistent with our first hypothesis regarding the association between natural disaster risk and financial leverage, coefficient estimates of natural disaster variables are negative and statistically significant. Specifically, disaster coefficients in specifications (2) and (3) – that use *Book Leverage* to proxy for corporate capital structure and *ln(Disaday3)* and *ln(Disaday5)* to proxy for natural disasters – are statistically significant at the 10 percent (1 percent) levels. Similar results are reported for models (4) and (5) that use *Market Leverage*. The negative association between leverage and disasters risk, which presumably captures operating risk of physical asset damage, is consistent with our first hypothesis, and with the assumption of the trade-off theory of capital structure (Strebulaev, 2007). The statistical significance of disaster variables weakens (disappears) when using *ln(Disaday3)* (*ln(Disaday)*). This observation is consistent with the intuition of Lucas and Rapping (1969) who argue that temporary shocks do not alter long-term perceptions of economic variables. These results imply that natural disasters risk has slowly been incorporated in financing decision.[18]

We report positive association between firm size (*ln(Assets)*) and leverage. Larger firms - that are usually more diversified, are less prone to default, and have less volatility - have more debt

[17] Further, we test the sensitivity of our results to the use of the firm and year fixed effects and/or clustering standard errors at the firm level. Results of these alternative specifications are similar to our baseline models and are available upon request.

in their capital structure. Our results show a statistically significant negative association between leverage and firm profitability (*ROA*). More profitable firms seem to retain more earnings, resulting in a lower debt in their capital structure over time. Further, coefficient estimates of collateral asset value (*Tangibility*) are significantly positive. Firms with larger proportions of fixed assets seem to enjoy a more favorable debt supply, leading to a higher use of leverage. These result are consistent with the assumptions of the trade-off theory of capital structure, and with the findings of Rajan and Zingales (1995), and Frank and Goyal (2009).

We find a mixed evidence when it comes to the association between leverage and growth, measured by market-to-book ratio. We report a statistically significant positive (negative) association between *MB* and *Book Leverage* (*Market Leverage*). The positive association between growth and leverage is consistent with the assumptions of the pecking order theory, whereas the negative association between leverage and growth is consistent with the assumptions of the trade-off theory. These results are consistent with the empirical findings of Frank and Goyal (2009) who argue that the association between leverage and growth is not reliable. This result is possibly symptomatic of the difference in focus between book- and market- leverage measures. Indeed, Barclay et al. (2001) argue that there is no reason for these two measures to match. Our results also show a statistically significant association between *Dividend* and leverage. Firms that pay dividends seem to have less debt in their capital structure. This finding is consistent with Frank and Goyal (2009). We, however, couldn’t find statistically significant association between *HHI* and leverage.

An alternative hypothesis - to the causality explanation of our results - is the pre-existence of low leverage in firms in affected areas due to an omitted variable(s) not related to natural disaster risk. In order to investigate the pre-existing condition hypothesis and to better test the causality between natural disaster risk and corporate leverage, we examine the dynamic effects of natural disaster risk on corporate leverage. Specifically, we add to our baseline model, a lead, a contemporaneous, as well as several lagged values of disaster risk. Our dynamic regression model is as follows:

$$\begin{aligned} Leverage_{i,t} = \beta_0 + (\beta_1 - \beta_{11}) Disaster_{i,t-9,t+1} + \beta_{12} Ln(Assets)_{i,t-1} \\ + \beta_{13} Cash_{i,t-1} + \beta_{14} ROA_{i,t-1} + \beta_{15} MB_{i,t-1} \\ + \beta_{16} Tangibility_{i,t-1} + \beta_{17} HHI_{i,t-1} + \beta_{18} Dividends_{i,t-1} + \varepsilon_{i,t} \end{aligned} \quad ((2)$$

where $Disaster_{i,t-9,t+1}$ is a series of natural log-transformed disaster risk variables starting with a nine years lagged disaster risk, $Disaday_{t-9}$, and ending with disaster risk measured one year into the future, $Disaday_{t+1}$. We include the same set of control variables used in our baseline model. Using this specification, we can observe whether changes in managerial perceptions of disaster risk caused by the occurrence of disasters lead to leverage alteration (hence confirming the causality hypothesis), or a pre-existing lower leverage of the affected firms drive the observed negative association (hence confirming the pre-existing condition alternative hypothesis) (e.g., Simintzi et al., 2014 and Klasa et al., 2016). Results of this test are reported in Table 4.

[Please insert Table 4 here]

The coefficients on the lead disaster risk variable ($ln(Disaday)_{t+1}$) in the models presented in Table 4 allow us to assess whether any leverage effects can be found prior to the occurrence of natural disasters. If the coefficient of $ln(Disaday)_{t+1}$ is statistically significant, it could be symptomatic of a pre-disaster trends in corporate use of debt. Using both *Book Leverage* and *Market Leverage* as measures of debt, we find that the estimated coefficients on $ln(Disaday)_{t+1}$ are statistically insignificant across all specifications. This refutes any support for the pre-existence condition alternative hypothesis. Moreover, coefficients on the lagged variables $ln(Disaday)_{t-9}$ - $ln(Disaday)_{t-2}$ are mostly significant across specifications. These findings support our causal interpretation of the negative association between natural disaster risk and corporate use of debt. It is also worth noting that there seems to be a delayed impact of natural disaster risk on corporate leverage. This delay is consistent with findings of Flannery and Rangan (2006) who show that typical firms adjust their leverage by 30% per annum toward their target capital structure, which implies a slow adjustment in leverage policies.

In the following sections, we investigate the three channels through which elevated natural disaster risk could impact corporate capital structure. Specifically, as discussed earlier, we test the association between natural disaster risk and earnings volatility, cost of debt, and debt maturity, respectively.

4.2. Natural Disaster Risk and Earnings Volatility,

The idea that natural disaster risk presents an exogenous source of operating volatility is core to our arguments and to the interpretation of our earlier results. Basel II suggests that corporate policies should reflect business operating risk associated with natural disasters. To further investigate the association between natural disaster risk and the degree of firm's operating risk, we estimate the following model of the determinants of corporate earnings volatility:

$$\begin{aligned} Earn\_Vol_{i,t} = \beta_0 + \beta_1 Disaster_{i,t-1} + \beta_2 Size_{i,t-1} + \beta_3 Profitability_{i,t-1} \\ + \beta_4 Growth_{i,t-1} + \beta_5 Tangibility_{i,t-1} + \beta_6 Leverage_{i,t-1} + \beta_7 HHI_{i,t-1} \\ + \varepsilon_{i,t} \end{aligned} \quad (3)$$

where $Earn\_Vol$ is earnings volatility. We use two proxies for earnings volatility; *Std.(ROA)*$_t$ is the standard deviation of quarterly returns on assets, *Std.(Margin)*$_t$, is the standard deviation of *Margin*, where *Margin*$_t$ is the average quarterly earnings before interest and tax divided by sales at year *t*. Results of this test are reported in Table 5.

[Please insert Table 5 here]

Coefficient estimates of the natural disaster risk variable (*Ln(Disaday)*) lend further support to the idea that natural disaster risk is a source of operating risk. Results reported in Table 5 show a significant positive association between *Ln(Disaday)* and earnings volatility measured using both $Std.(ROA)_t$ and $Std.(Margin)_t$. This positive association is robust to controlling for firm size, profitability, growth, and other determinants of firm's operating volatility. It is worthwhile to note that the positive association between disaster risk and operating volatility only appears in the year when the headquarters are struck by natural disasters - but not in the pre- and/or the post-disasters years. This result is intuitively appealing. Unlike manager's assessment of risk (and how they adjust their leverage accordingly) which is expected to be affected by long-term natural disaster risk, earnings volatility is expected to reflect contemporaneous disaster events. These results are consistent with our second hypothesis and with Basel II. Firms headquartered in areas with high natural disaster risk experience higher operating risk. According to the trade-off theory of capital structure, this elevated operating risk is expected to be translated into less debt in firms' capital structure.

4.3. *Natural Disaster Risk and Cost of Debt*

Natural disaster risk could also affect capital structure through its possible impact on the supply side of the debt market. Physical asset damage and the deterioration in collateral asset value associated with natural disasters are expected to impact lending conditions to the affected firms. According to Rajan and Zingales (1995), firms with high collateral asset value face more lenient credit markets, leading them to be more levered. This argument would predict a positive association between natural disaster risk and firm's cost of debt. In that regard, Garmaise and Moskowitz (2009) argue that, although financial markets play crucial roles in managing disasters risk, "Little is known, however, about how well financial markets perform these functions". Our third hypothesis assumes that financial markets would adjust their lending terms to reflect operating risks associated with natural disasters. This argument is consistent with Graham (2000) who argues that firms with valuable collateral assets are expected to have low borrowing costs. In order to formally test this hypothesis, we follow Francis et al. (2012) by estimating the following model of the determinants of firm's bank loan pricing:

$$\begin{aligned} Loan\_Price_{i,t} = {} & \beta_0 + \beta_1 Disaster_{i,t-1} + \beta_2 Size_{i,t-1} + \beta_3 Profitability_{i,t-1} \\ & + \beta_4 Earn\_Vol_{i,t-1} + \beta_5 Leverage_{i,t-1} + \beta_6 Tangibility_{i,t-1} \\ & + \beta_7 Growth_{i,t-1} + \beta_8 ModifiedZ_{i,t-1} + \beta_9 HHI_{i,t-1} \\ & + \beta_{10} ln(1 + ForeignBank)_{i,t} + \beta_{11} Maturity_{i,t} + \beta_{12} LoanSize_{i,t} \\ & + \beta_{13} PriorRelation_{i,t} + \beta_{14} InvestmentGrade_{i,t} \\ & + \beta_{15} TermSpread_{i,t} + \beta_{16} CreditSpread_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{4}$$

where the dependent variable, $Loan\_Price_{i,t}$, is *Ln(LoanSpread)* which is the natural logarithm of the all-in spread drawn defined as the amount a borrower pays in basis points over LIBOR or LIBOR-equivalent for each dollar drawn down. All control variables are defined in Appendix B. Results of this test are reported in Table 6.

[Please insert Table 6 here]

Coefficient estimates reported in models (1) and (2) of Table 6 are consistent with our third hypothesis that firms with high natural disaster risk would acquire bank loans at much higher spreads. Specifically, coefficient estimate of *Ln(Disaday)*$_t$ (*Ln(Disaday)*$_t$) is positive and statistically significant at the 10 (1) percent level. This positive association between natural disaster risk and bank loan pricing is robust to controlling for major determinants of bank loan pricing and to adding firm, year, loan type, and loan purpose fixed effects.

Prior literature also highlights the importance of non-price terms on loan contracts (Rajan and Winton, 1995; and Demiroglu and James, 2010.) Consequently, we investigate the impact of natural disaster risk on the intensity of banks' use of non-price terms. Results of these tests are reported in models (3) - (6) of Table 6. We use two proxies for non-price loan terms; *Ln(GenCov)* and *Ln(FinCov)*, which are the natural logarithm of the number of general covenants and financial covenants in a loan contract, respectively. Coefficient estimates of $Ln(Disaday)_t$ in models (3) and (4) ((5) and (6)) are positive and statistically significant at the 1 (5) percent level, suggesting that natural disasters increase banks' use of loan covenants (both financial and non-financial) — arguably to better control for natural disaster risks.

This empirical evidence is consistent with the role that collateral asset value is assumed to play in shaping the supply side of the credit market. Banks seem to ex-ante charge natural disaster-susceptible firms for their elevated chances of physical asset damage.

4.4. Natural Disaster Risk and Debt Maturity.

The third channel through which natural disaster risk could impact corporate capital structure is through its effect on managers' preference for financial flexibility. Goyal et al. (2002) show that firms favor shorter (longer) maturity debt when flexibility becomes more (less) valuable. Consequently, our fourth hypothesis assumes that the expected cuts in corporate debt might be concentrated on long-term debt to sustain financial flexibility. In this section, we test the impact of natural disaster risk on firm's choice of debt maturity. Following Klasa et al. (2016) and Simintzi et al. (2014), we examine the choice of debt maturity relative to the timing of the occurrences of natural disasters. Results of this test are reported in Table 7.

[Please insert Table 7 here]

Specifications (1) and (2) in Table 7 report results for the association between natural disaster risk and long-term debt issuance. We find that the coefficients on $Ln(Disaday)_{t-1}$, $Ln(Disaday)_t$, and $Ln(Disaday)_{t+1}$ are not significantly different from zero while the coefficient on $Ln(Disaday)_{t-2}$ is negative and statistically significant. This result shows that firms located in area with high natural disaster risk are more likely to decrease their long-term debt issuance only after the occurrences of natural disasters, but not before. This pattern is not observed with short-term debt issuance. Specifications (3) and (4) in Table 7 report results for the association between natural disaster and short-term debt issuance. These results indicate that natural disaster risk does not affect short-term financing activities measured by the amount of net short-term debt issuance. This result is consistent with our fourth hypothesis and with the notion that conservative managers – affected by elevated natural disaster risk – might apply alterations to their capital structure by cutting long-term debt instead of short-term debt.

The collective evidence presented so far is consistent with Basel II which claims that natural disaster risk constitutes a form of operating risk. Our results indicate that this source of operating risk could be an omitted variable in the empirical research of the determinants of corporate leverage.

4.5. Further Test: Impact of Headquarter Relocation

Our hypotheses assume that firms adjust their capital structure to reflect their perception of risks associated with natural disasters. However, corporate headquarters location is not always randomly chosen. Therefore, headquarters relocation provides a natural experiment to further test how firms change their leverage in reaction to changes in the perceived natural disaster risk. This context would enable us to isolate the impact of location from other possible confounding variables. This section presents results from quasi difference-in-differences (DID) approach. We identify firms' headquarters from their business addresses and compare changes in leverage before and after headquarters' relocation.[19] In particular, we have two groups of firms; the first group consists of firms that headquarters got relocated to areas with less exposure to natural disasters and

[19] We obtain corporate headquarters' address from a firm's 10-K filings on the SEC (1995~2010). To ensure a change in corporate headquarters' address is a physical relocation, we measure distance from the old address to the new address. We initially identified 1,729 headquarters relocations. The median value of distance for relocation is 970.47 miles.

the other group consists of firms that headquarters got relocated to areas with no change in natural disaster risk (i.e., we exclude firms being relocated from areas with low disaster risk to areas with high disaster risk). *Post* is a binary variable that takes the value of 1 (0) for years after (before) headquarters relocation. *Decrease* is a binary variable that takes the value of 1 if a firm's headquarters is relocated to an area with less exposure to natural disaster and zero otherwise. The variable of our primary interest is *Post* x *Decrease.* Results of this test are reported in Table 8.

[Please insert Table 8 here]

The sign of the coefficient on *Post* x *Decrease* allows us to estimate firms' changes in leverage after their headquarters relocation. To avoid potential confounding effects, we limit our analysis to a 5-year window before and after headquarters relocation. Using *Book Leverage* in model (1), the coefficient on *Post* x *Decrease* is positive and statistically significant at the 5 percent level. The coefficient of *Post* x *Decrease* in model (2) that uses *Market Leverage* is still positive, but statistically insignificant. These results indicates that firms increase their leverage after relocating to areas with less natural disaster risk.

4.6. Further Test: Facility-Based Analysis.

Our previous tests use information for corporate headquarters. Headquarters location plays a significant role in shaping corporate decision making, as it is usually close to firm's core activities and is the place where corporate executives and main decision makers are always resided (Davis and Henderson, 2008). However, in some cases, corporate main operating facilities might be located far from corporate headquarters. To ensure that our baseline results are robust to these incidences, we also test the association between natural disaster risk and corporate leverage using a facility-level data. Specifically, we used Toxic Release Inventory (TRI) waste data to identify firms' major operating facilities. We identify a firm's major operating facility using *WasteRate*, which is the ratio of individual facility's waste production to firm's total waste production. Despite the sample size limitation of this dataset, it has several benefits to our investigation. For example, using waste-producing facilities would ensure that we are dealing with operating locations instead of pass-through or administrative entities. Further, the use of *WasteRate* data enables us to identify firm's major operating facility — which is expected to have a substantial impact on manager's risk perception.

We use a difference-in-differences (DID) estimate in our facility-based test. Specifically, our *Treatment* group consists of facilities that (1) account for 60% or more of a firm's entire production, and (2) got struck by a major natural disaster.[20] We use multiple definitions of *MajorShock*, as incidents when a facility experience more than 9, 38, or 75 days of natural disasters in a given year.[21] Consequently, our *Control* group consists of firms that do not satisfy these two conditions. Results of the facility-based test are reported in Table 9.

[Please insert Table 9 here]

Table 9 reports results for the facility-based DID test. *PostShock* is an interaction binary variable that takes the value of "1" in post-major-natural-disaster years for facilities with a greater than 60% *WasteRate*. Results of this facility-based test are consistent with those of the headquarters-based tests. Coefficient estimates of the DID variable, *PostShock*, are negative in the models of the determinants of corporate leverage. This result is consistent for models that use *Book*

[20] Facilities produce more than 60% of the entire production are in the top decile groups in the distribution of facility size.
[21] These definitions are based on percentiles of facility-level number of disaster days, where the 75th, 90th, and 95th percentiles of natural disaster days are 9, 38, and 75 days, respectively. Please see Table 9 for complete variable description.

Leverage (models (1)-(3)), and for those that use *Market Leverage* (models (4)-(6)). Similar to our base-line results, coefficients of $PostShock_{t-2}$ variable are statistically significant indicating a delay in the association between natural disasters occurrence and corporate leverage. The most significant results are reported for disaster days in the 95th percentile (when shocks are defined as incidences with more than 75 days of natural disasters in a year). Specifically, coefficient estimates of $PostShock_{t-2}$ at models (3) and (6) in Table 9 are -0.03 and -0.02, respectively, and are statistically significant. This result is intuitively appealing and is consistent with the notion that managers revise their perception about operating risks and consequently their leverage decisions in reaction to severe and prolonged natural disasters.

5. Conclusion

This paper aims at investigating the impact of natural disasters, as exogenous idiosyncratic shocks to operating risk, on corporate leverage policy. We argue that firms headquartered in areas with high probability of natural disasters are expected to have higher earnings volatility due to business disruptions, experience more physical assets damage (deteriorated collateral value), and seek higher levels of financial flexibility. Consequently, we expect firms headquartered in high natural disasters susceptible areas to sparingly use debt in their capital structure. This paper also investigates several channels through which natural disaster risk could impact corporate capital structure. Our results show that firms headquartered in areas with high natural disaster risk experience higher earnings volatility, receive less favorable lending terms, and prefer short-term over long-term borrowing. This paper contributes to the empirical literature on the determinants of capital structure that largely ignores operating risk resulting from exogenous idiosyncratic shocks. This paper also contributes to the literature that investigates the economic and corporate impact of natural disasters. Our empirical results imply that business disruption risks and earnings volatility associated with natural disasters seem to lead firms in the affected areas to adopt more conservative leverage policies. The negative association between operating volatility associated with natural disaster risk and corporate use of debt is consistent with the trade-off theory of capital structure.

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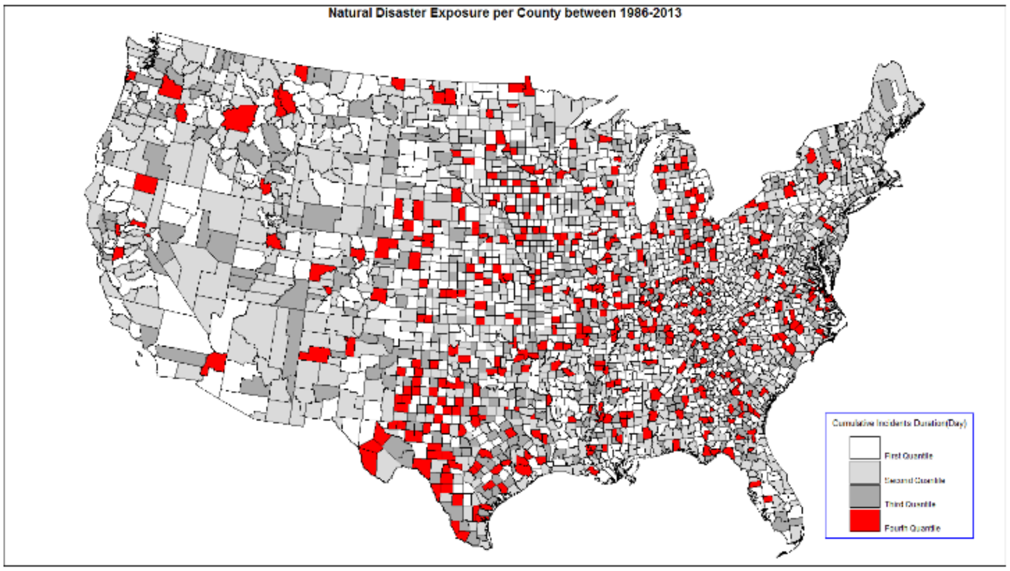
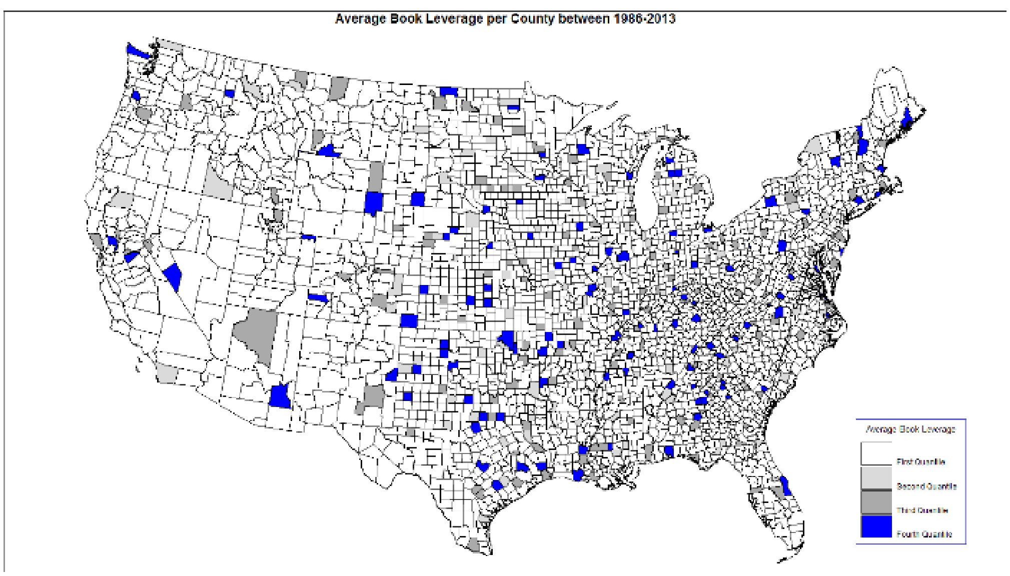
Figure 1. Natural Disaster Exposure and Average Financial Leverages

This figure exhibits natural disaster exposure as well as average book leverage of firms located in U.S. counties over the period 1987-2013. Panel A. shows natural disaster exposure measured as the cumulative number of incidents per county over the entire sample period. Colored counties are those with high natural disaster exposure. Panel B. shows a quartile ranking of U.S. counties based on average book leverage of firms headquartered in these counties.

Panel A. U.S. counties natural disaster exposure



Panel B. County-level average book leverage



Appendix A. Natural Disasters

Appendix A reports the full sample descriptive statistics on natural disaster occurred in the U.S. for the period from 1987 to 2013. Panel A reports the days of disasters and the numbers of counties affected by disasters for each sample year. Panel B reports types of federal natural disasters between 1987 and 2013.

Panel A. Historic Federal Disasters between 1987 and 2013

		Number of disaster days				Number of disaster counties			
	N	Mean	Median	Min	Max	Mean	Median	Min	Max
1987	17	11	10	1	51	7	8	1	16
1988	7	12	6	1	52	7	4	1	24
1989	28	16	3	1	63	13	8	1	87
1990	32	25	19	1	69	19	15	1	64
1991	38	18	16	1	59	16	11	1	73
1992	40	15	5	1	126	8	5	1	35
1993	49	36	5	1	193	34	21	1	149
1994	33	39	18	2	318	19	13	1	71
1995	29	23	10	2	127	20	15	1	60
1996	78	20	10	1	210	19	10	1	120
1997	40	33	22	1	159	23	13	1	101
1998	65	26	13	1	259	21	11	1	254
1999	82	15	6	1	141	15	7	1	227
2000	87	17	7	1	130	10	2	1	94
2001	78	20	14	1	162	14	6	1	66
2002	110	16	10	1	106	9	1	1	78
2003	106	18	9	1	167	12	3	1	75
2004	106	17	10	2	81	16	5	1	88
2005	142	19	14	1	68	33	11	1	254
2006	93	15	9	1	169	10	2	1	254
2007	114	13	8	1	163	14	6	1	113
2008	128	16	7	1	172	17	6	1	229
2009	99	13	7	1	151	12	5	1	113
2010	98	19	8	1	140	16	8	1	83
2011	219	18	7	1	157	11	3	1	122
2012	85	11	10	1	70	14	3	1	98
2013	57	11	8	1	69	12	8	1	49
Total	2,060	18	9	1	318	16	6	1	254

Panel B. Types of Federal Natural Disasters between 1987 and 2013

	N	Mean	Median	Min	Max	Mean	Median	Min	Max
Severe Storm	753	18	10	1	159	18	10	1	254
Fire	596	15	7	1	210	4	1	1	254
Flood	219	33	20	1	193	17	10	1	101
Hurricane	216	18	13	1	68	34	21	1	254
Snow	128	6	4	1	41	22	13	1	120
Tornado	55	7	2	1	45	11	6	1	68
Severe Ice Strom	45	13	8	2	91	35	26	2	113
Coastal Storm	17	17	16	2	34	24	11	1	66
Earthquake	16	58	39	1	318	5	3	1	24
Freezing	9	50	16	3	167	20	11	8	49
Tsunami	3	1	1	1	1	3	3	3	3
Dam/Levee	1	40	40	40	40	1	1	1	1
Drought	1	78	78	78	78	149	149	149	149
Mud/Lands	1	259	259	259	259	1	1	1	1

Appendix B. Definitions of Variables

Variables	Definitions
Measures of Natural Disasters	
Disaday	Total days of natural disasters in a county per year. For a single natural disaster event, *Disaday* is the duration of the disaster (the difference between start-date and end-date).
Disaday3	Cumulative number of natural disasters days in a county over the prior 3 years.
Disaday5	Cumulative number of natural disasters days in a county over the prior 5 years.
# Disa	Total number (count) of natural disaster events in a county per year.
#Disa3	Total number (count) of natural disaster events in a county over the prior 3 years.
#Disa5	Total number (count) of natural disaster events in a county over the prior 5 years.
Capital Structure measures and determinants	
Book Leverage	Debt in current liabilities plus long-term debt divided by assets [(DLC+DLTT)/AT].
Market Leverage	Ratio of total debt to total debt plus market value of equity [(DLC+DLTT)/(PRCC_F*CSHO +DLC+DLTT)]
Assets ($ Mil.)	Book value of a firm's assets [AT].
Ln(Assets)	Natural logarithm of total assets [AT].
LT Debt Issue	Ratio of difference between Long-term debt issues and Long-term debt reduction to assets [(DLTIS-DLTR)/AT]
ST Debt Issue	Ratio of change in short-term debt to assets [DLCCH/AT]
Tangibility	Ratio of fixed assets to book assets [PPNET/AT].
Cash	Ratio of cash to book assets [CASH/AT].
ROA	Ratio of earnings before interests and taxes to assets [EBIT/AT].
MB	Ratio of market value of equity to book value of equity [(PRCC_F*CSHO)/(AT-LT)]
HHI	$\sum_{i=1}^{N} \text{sales}_{ijt}^{2}$ where sales_{ijt} is the market share of firm i industry j in year t. Market shares are computed based on firms' sales [sale] from COMPUSTAT.
Dividend	Indicator variable that equals one if the firm pays out dividend in the fiscal year.
Bank Loan Variables	
LoanSize($ Mil)	Total amount of facility. Loan amount is measured in millions of dollars
LoanSpread(Bp)	Loan spread is measured as all-in spread drawn in the Dealscan database. All-in spread drawn is defined as the amount the borrower pays in basis points over LIBOR or LIBOR equivalent for each dollar drawn down. (For loans not based on LIBOR, LPC converts the spread into LIBOR terms by adding or subtracting a differential which is adjusted periodically.) This measure adds the borrowing spread of the loan over LIBOR with any annual fee paid to the bank group.

Appendix B – Continued.

Ln(LoanSpread)	Natural logarithm of *LoanSpread.*
Ln(LoanMaturity)	Natural logarithm of loan maturity.
Ln(DealSize)	Natural logarithm of loan maturity.
$PriorRelation_t$	Indicator variable that equals one if the loan is relationship loan and zero otherwise. A given loan is classified as a relationship loan if any of the lead leaners retained in the give loan facility were retained as the lead lenders in any loan taken by the same borrower.
$Ln(1+ ForeignBanks)_t$	Natural logarithm of an indicator variable that equals one if the issuers are foreign banks and zero otherwise.
Modified Z_{t-1}	Altman's (1968) Z-score = (1.2*working capital+1.4*retained earnings+ 3.3*EBIT+0.999*sales)/total assets.
$InvestmentGrade_t$	Indicator variable that equals one if a firm's credit rating by S&P is below than BBB rate and 0 otherwise.
TermSpread	The difference in the rate on between the 10-year and the 2-year Treasury bonds
CreditSpread	The difference in the rate on between the AAA-rated and BAA-rated corporate bond
Loan type	Binary variable for loan types, including term loan, revolver greater than one year, revolver less than 1 year, and 364-day facility.
Loan purpose	Binary variable for loan purposes, including corporate purposes, debt repayment, working capital, takeover, etc.
Ln(GenCov)	Natural logarithm of the number of general covenants.
Ln(FinCov)	Natural logarithm of the number of financial covenants.

Table 1
Descriptive Statistics

Variable	N	Mean	Median	Std. Dev	25th Pctl	75th Pctl
#Disa	101,051	0.55	0.00	0.89	0.00	1.00
Disaday	101,051	16.65	0.00	43.40	0.00	12.00
Ln(Disaday)	101,051	1.16	0.00	1.68	0.00	2.56
#Disa3	101,051	1.62	1.00	1.72	0.00	2.00
Disaday3	101,051	49.34	17.00	83.95	0.00	61.00
Ln(Disaday3)	101,051	2.53	2.89	1.92	0.00	4.13
#Disa5	101,051	2.59	2.00	2.36	1.00	4.00
Disaday5	101,051	80.37	38.00	117.35	7.00	94.00
In(Disaday5)	101,051	3.25	3.66	1.84	2.08	4.55
Book Leverage	101,051	0.22	0.17	0.21	0.02	0.34
Market Leverage	101,051	0.16	0.10	0.17	0.01	0.26
LT Debt Issue	95,548	0.01	0.00	0.10	-0.02	0.02
ST Debt Issue	50,572	0.01	0.00	0.10	0.00	0.00
Assets	101,051	1700.90	111.35	9840.76	25.40	566.50
Ln(Assets)	101,051	4.82	4.71	2.24	3.23	6.34
Cash	101,051	0.20	0.10	0.24	0.03	0.30
ROA	101,051	-0.03	0.06	0.35	-0.04	0.12
MB	101,051	3.82	2.08	5.77	1.20	3.80
Tangibility	101,051	0.27	0.20	0.23	0.08	0.39
HHI	101,051	0.07	0.05	0.07	0.04	0.08
Dividend	101,051	0.01	0.00	0.03	0.00	0.01
Loan Spread (bp)	23,387	188.38	175.00	132.92	87.50	250.00
Ln(LoanSpread)	23,387	4.96	5.16	0.81	4.47	5.52

Notes: This table reports descriptive statistics for measures of disasters risk, leverage, and control variables. Our sample consists of 101,051 firm-year observations covering the period 1987-2013. *#Disa* is the total number of natural disaster events in a county per year. *#Disa3*, and *#Disa5* is the cumulative number of natural disaster events in a county over the prior 3 years, 5 years period, respectively. *Disaday* is the total number of natural disaster days in a county per year. *Disaday3*, and *Disaday5* is the cumulative number of natural disaster days in a county over the prior 3 years, 5 years period, respectively. We also report statistics for natural logarithms of *Disaday* measures. *Book Leverage* is debts in current liabilities plus long-term debt divided by total assets. *Market Leverage* is the ratio of total debt to total debt plus market value of equity. *LT (ST) Debt Issue* is long-term (short-term) debt issuance. *Ln(Assets)* is the natural logarithm of total asset. *Cash* is cash divided by total assets. *ROA* is earnings before interests and taxes divided by total assets. *MB* is the market value of assets divided by book value of assets. *Tangibility* is the ratio of fixed assets to total assets. *HHI* is the Herfindahl-Hirschman concentration index based on sales of the first two digit of the SIC code. *Dividend* is a binary variable that equals one if the firm pays out dividend in the fiscal year. *Ln(LoanSpread)* is the natural logarithm of the All-in spread drawn that is defined as the amount the borrower pays in basis points over LIBOR or LIBOR equivalent for each dollar drawn down. Appendix B provides detailed descriptions of all variables.

Table 2
Univariate Analysis

	Disaday5	*Disaday3*	*Disaday*
No. of Obs.	101,051	101,051	101,051
Panel A. Book Leverage			
Low Disaster (Tercile 1)	0.238	0.232	0.222
Mid Disaster (Tercile 2)	0.211	0.213	0.211
High Disaster (Tercile 3)	0.202	0.205	0.208
Diff. [3]-[1]	-0.036***	-0.028***	-0.014***
	(-22.59)	(-17.28)	(-9.78)
Panel B. Market Leverage			
Low Disaster (Tercile 1)	0.182	0.177	0.167
Mid Disaster (Tercile 2)	0.155	0.157	0.160
High Disaster (Tercile 3)	0.147	0.150	0.152
Diff. [3]-[1]	-0.036***	-0.027***	-0.015***
	(-26.87)	(-20.72)	(-13.14)

Notes: This table provides comparisons of firm leverage across natural disaster terciles. We create separate tercile groups of firms based on three different measures of natural disaster risk; Disaday5, Disaday3, and Disaday. *Disaday* is the total number of natural disaster days in a county per year. *Disaday3*, and *Disaday5* is the cumulative number of natural disaster days in a specific county over the prior 3 years, 5 years period, respectively. Based on natural disaster risk, firms are classified into *Low Disaster*, *Mid Disaster*, or *High Disaster*. Panel A reports average (mean) *Book Leverage* of firms in the three disasters terciles along with the mean difference of book leverage between *High Disaster* and *Low Disaster* firms. Panel B reports average (mean) *Market Leverage* of firms in the three disasters terciles along with the mean difference of market leverage between *High Disaster* and *Low Disaster* firms. *T*-statistics are reported in parentheses. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 3
Baseline Regression: Determinants of Corporate Capital Structure

	Book Leverage$_t$			*Market Leverage$_t$*		
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Disaday)$_{t-1}$	0.0002			0.0002		
	(0.45)			(0.67)		
Ln(Disaday3)$_{t-1}$		-0.0007*			-0.0004	
		(-1.88)			(-1.41)	
In(Disaday5)$_{t-1}$			-0.0017***			-0.0011**
			(-3.25)			(-2.52)
Ln(Assets)$_{t-1}$	0.0314***	0.0314***	0.0314***	0.0358***	0.0358***	0.0359***
	(15.43)	(15.41)	(15.40)	(18.65)	(18.63)	(18.60)
Cash$_{t-1}$	-0.1698***	-0.1698***	-0.1698***	-0.1235***	-0.1235***	-0.1235***
	(-20.61)	(-20.57)	(-20.51)	(-16.67)	(-16.64)	(-16.60)
ROA$_{t-1}$	-0.0593***	-0.0593***	-0.0593***	-0.0420***	-0.0419***	-0.0420***
	(-13.65)	(-13.62)	(-13.63)	(-14.66)	(-14.64)	(-14.64)
MB$_{t-1}$	0.0030***	0.0030***	0.0030***	-0.0006***	-0.0006***	-0.0006***
	(14.43)	(14.43)	(14.45)	(-5.33)	(-5.35)	(-5.36)
Tangiblity$_{t-1}$	0.0784***	0.0785***	0.0784***	0.0699***	0.0699***	0.0699***
	(7.92)	(7.93)	(7.94)	(8.96)	(8.96)	(8.96)
HHI$_{t-1}$	-0.0091	-0.0093	-0.0092	0.0232	0.0231	0.0232
	(-0.24)	(-0.25)	(-0.24)	(0.71)	(0.71)	(0.71)
Dividend$_{t-1}$	-0.1262***	-0.1262***	-0.1256***	-0.1241***	-0.1241***	-0.1237***
	(-5.47)	(-5.47)	(-5.44)	(-8.16)	(-8.15)	(-8.12)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year x Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
County Clustering	Yes	Yes	Yes	Yes	Yes	Yes
Observations	101,051	101,051	101,051	101,051	101,051	101,051
Adj. R-squared	0.615	0.615	0.615	0.675	0.675	0.675

Notes: This table reports estimates from the OLS regressions where financial leverage (book leverage or market leverage) is the dependent variable. *Book Leverage* is the total debt over book asset ratio. *Market Leverage* is total debt over total debt plus the market value of equity. *Disaday* is the number of days between disaster-begin-date and disaster-close-out-date for a specific incident per county in a given year. *Ln(Disaday)*, *Ln(Disaday3)* and *Ln(Disady5)* are the natural logarithm of *Disaday*, *Disaday3 and Disaday5* that are cumulative days of incidences per county over the prior 1- , 3- and 5-year, respectively. All other independent variables are defined in Appendix B. All models include firm and year x industry fixed effects. *T*-statistics are computed using standard errors corrected for clustering at the county level and reported in parentheses. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4
Dynamic Effects: Determinants of Corporate Capital Structure

	Book Leveraget			Market Leveraget		
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Disaday)$_{t+1}$		0.0003	0.0000		0.0004	0.0002
		(1.03)	(0.00)		(1.43)	(0.53)
Ln(Disaday)$_{t}$	-0.0000	-0.0001	-0.0005	0.0003	0.0002	-0.0000
	(-0.13)	(-0.33)	(-1.24)	(0.85)	(0.78)	(-0.04)
Ln(Disaday)$_{t-1}$		0.0002	-0.0003		0.0002	-0.0001
		(0.54)	(-0.66)		(0.79)	(-0.20)
Ln(Disaday)$_{t-2}$		-0.0006**	-0.0010***		-0.0001	-0.0004
		(-2.01)	(-2.93)		(-0.57)	(-1.64)
Ln(Disaday)$_{t-3}$			-0.0011***			-0.0006*
			(-2.71)			(-1.94)
Ln(Disaday)$_{t-4}$			-0.0010**			-0.0008**
			(-2.19)			(-2.21)
Ln(Disaday)$_{t-5}$			-0.0012***			-0.0009***
			(-3.01)			(-2.62)
Ln(Disaday)$_{t-6}$			-0.0013***			-0.0011***
			(-3.25)			(-3.53)
Ln(Disaday)$_{t-7}$			-0.0009**			-0.0006*
			(-2.31)			(-1.92)
Ln(Disaday)$_{t-8}$			-0.0007*			-0.0002
			(-1.92)			(-0.59)
Ln(Disaday)$_{t-9}$			-0.0003			0.0004
			(-0.61)			(1.16)
Ln(Assets)$_{t}$	0.0314***	0.0313***	0.0314***	0.0358***	0.0358***	0.0359***
	(15.43)	(15.43)	(15.38)	(18.65)	(18.67)	(18.67)
Cash$_{t}$	-0.1698***	-0.1698***	-0.1699***	-0.1235***	-0.1235***	-0.1236***
	(-20.60)	(-20.61)	(-20.48)	(-16.66)	(-16.67)	(-16.57)
ROA$_{t}$	-0.0593***	-0.0593***	-0.0593***	-0.0419***	-0.0419***	-0.0420***
	(-13.65)	(-13.63)	(-13.61)	(-14.68)	(-14.68)	(-14.67)
MB$_{t}$	0.0030***	0.0030***	0.0030***	-0.0006***	-0.0006***	-0.0006***
	(14.42)	(14.45)	(14.50)	(-5.34)	(-5.34)	(-5.34)
Tangiblity$_{t}$	0.0784***	0.0785***	0.0781***	0.0699***	0.0700***	0.0697***
	(7.93)	(7.93)	(7.93)	(8.96)	(8.96)	(8.96)
HHI$_{t}$	-0.0092	-0.0089	-0.0067	0.0233	0.0234	0.0248
	(-0.24)	(-0.24)	(-0.18)	(0.71)	(0.72)	(0.76)
Dividend$_{t}$	-0.1262***	-0.1261***	-0.1257***	-0.1242***	-0.1241***	-0.1239***
	(-5.47)	(-5.46)	(-5.47)	(-8.16)	(-8.16)	(-8.13)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year x Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
County Clustering	Yes	Yes	Yes	Yes	Yes	Yes
Observations	101,051	101,051	101,051	101,051	101,051	101,051
Adj. R-squared	0.615	0.615	0.615	0.675	0.675	0.675

Notes: This table reports estimates from the OLS regressions where financial leverage (book leverage or market leverage) is the dependent variable. *Book Leverage* is the total debt over book asset ratio. *Market Leverage* is total debt over total debt plus the market value of equity. *Ln(Disaday)*$_{t+N}$ is the natural logarithm of the number of days between disaster-begin-date and disaster-close-out-date for a specific incidence per county in a given year. All other independent variables are defined in Appendix B. All models include firm and year x industry fixed effects. *T*-statistics are computed using standard errors corrected for clustering at the county level and reported in parentheses. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5
Natural Disaster Risk and Earnings Volatility

	Std. (ROA)$_t$		*Std. (Margin)$_t$*	
	(1)	(2)	(3)	(4)
Ln(Disaday)$_{t+1}$		-0.0000		0.0011
		(-0.22)		(1.16)
Ln(Disaday)$_t$	0.0002**	0.0002**	0.0018*	0.0016*
	(2.02)	(2.06)	(1.68)	(1.65)
Ln(Disaday)$_{t-1}$		0.0000		0.0001
		(0.14)		(0.12)
Ln(Disaday)$_{t-2}$		0.0001		0.0007
		(0.56)		(0.52)
Ln(Assets)$_t$	-0.0009	-0.0009	-0.0189***	-0.0189***
	(-1.35)	(-1.35)	(-8.00)	(-7.99)
Cash$_t$	-0.0307***	-0.0307***	0.5836***	0.5835***
	(-9.61)	(-9.60)	(19.62)	(19.61)
ROA$_t$	-0.0448***	-0.0448***	-0.8977***	-0.8977***
	(-14.69)	(-14.69)	(-38.11)	(-38.12)
MB$_t$	0.0002**	0.0002**	0.0033***	0.0033***
	(2.23)	(2.23)	(3.84)	(3.82)
Tangibility$_t$	-0.0204***	-0.0204***	-0.0332	-0.0330
	(-5.27)	(-5.27)	(-1.33)	(-1.32)
Leverage$_t$	-0.0080***	-0.0080***	0.0966***	0.0967***
	(-3.54)	(-3.53)	(4.83)	(4.82)
HHI$_t$	0.0084	0.0084	0.1078**	0.1078**
	(1.16)	(1.16)	(2.40)	(2.40)
Dividend$_t$	0.0110	0.0110	0.0857	0.0861
	(1.10)	(1.10)	(0.75)	(0.75)
Firm FE	Yes	Yes	Yes	Yes
Year x Industry FE	Yes	Yes	Yes	Yes
County Clustering	Yes	Yes	Yes	Yes
Observations	88,901	88,901	87,035	87,035
Adj. R-squared	0.251	0.251	0.349	0.349

Notes: This table reports estimates from the OLS regressions where a firm's earning volatility is the dependent variable. Earnings volatility is measures as *Std.(ROA)$_t$*, which is the standard deviation of quarterly *ROAs and Std.(Margin)$_t$*, which is the standard deviation of quarterly operating margin measured as EBIT divided by sales. *Disaday* is the total number of natural disaster days in a county per year. All other independent variables are defined in Appendix B. All models include firm and year x industry fixed effects. *T*-statistics are computed using standard errors corrected for clustering at the county level and reported in parentheses. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 6
Natural Disaster Risk and Bank Loan

	$Ln(LoanSpread)_t$		$Ln(GenCov)$		$Ln(FinCov)$	
	(1)	(2)	(3)	(4)	(5)	(6)
$Ln(Disaday)_{t+1}$		0.0013		-0.0022		-0.0006
		(0.43)		(-1.27)		(-0.30)
$Ln(Disaday)_t$	0.0025	0.0035^{*}	0.0055^{***}	0.0060^{***}	0.0049^{**}	0.0053^{**}
	(1.33)	(1.85)	(2.76)	(2.83)	(2.56)	(2.70)
$In(Disaday)_{t-1}$		0.0037^{*}		-0.0013		0.0002
		(1.76)		(-0.35)		(0.05)
$In(Disaday)_{t-2}$		0.0063^{***}		0.0039^{*}		0.0026
		(6.03)		(1.70)		(1.41)
$Ln(Assets)_t$	-0.1432^{***}	-0.1435^{***}	-0.0627^{***}	-0.0629^{***}	-0.0482^{***}	-0.0484^{***}
	(-10.77)	(-10.87)	(-4.38)	(-4.42)	(-5.58)	(-5.64)
ROA_t	-1.2462^{***}	-1.2472^{***}	-0.1278^{**}	-0.1273^{**}	0.1861^{**}	0.1861^{**}
	(-13.90)	(-13.80)	(-2.61)	(-2.58)	(2.72)	(2.69)
Book Levereage$_t$	0.4335^{***}	0.4347^{***}	0.0537	0.0545	-0.0632^{***}	-0.0626^{***}
	(7.90)	(7.91)	(1.63)	(1.66)	(-3.09)	(-3.04)
$Tangiblity_t$	-0.2921^{***}	-0.2939^{***}	0.0769	0.0773	0.0977^{**}	0.0977^{**}
	(-4.07)	(-4.13)	(1.56)	(1.58)	(2.18)	(2.17)
MB_t	-0.0036^{***}	-0.0037^{***}	-0.0025	-0.0025	-0.0012	-0.0012
	(-2.97)	(-3.04)	(-1.24)	(-1.25)	(-0.83)	(-0.84)
Modified Z_t	-0.0228^{***}	-0.0225^{***}	-0.0111	-0.0111	-0.0029	-0.0029
	(-3.35)	(-3.39)	(-1.53)	(-1.54)	(-0.38)	(-0.38)
HHI_t	0.4171^{***}	0.4228^{***}	0.3272	0.3255	-0.2119	-0.2119
	(6.80)	(6.69)	(1.49)	(1.49)	(-1.04)	(-1.04)
$Ln(1+ ForeignBanks)_t$	-0.0559^{***}	-0.0562^{***}	0.1106^{***}	0.1104^{***}	0.0927^{***}	0.0926^{***}
	(-7.17)	(-7.20)	(8.58)	(8.57)	(10.62)	(10.66)
$Ln(LoanMaturity)_t$	0.0120	0.0122	-0.0158	-0.0156	-0.0103	-0.0102
	(0.55)	(0.56)	(-0.80)	(-0.80)	(-0.59)	(-0.59)
$Ln(DealSize)_t$	0.0139	0.0140	0.1569^{***}	0.1570^{***}	0.0742^{***}	0.0743^{***}
	(1.23)	(1.24)	(11.82)	(11.84)	(9.06)	(9.08)
$PriorRelation_t$	0.0033	0.0032	-0.0255	-0.0254	-0.0189	-0.0189
	(0.25)	(0.24)	(-1.37)	(-1.37)	(-1.14)	(-1.14)
$InvestmentGrade_t$	-0.4622^{***}	-0.4607^{***}	-0.0030	-0.0025	-0.0279	-0.0275
	(-12.87)	(-12.67)	(-0.12)	(-0.10)	(-0.89)	(-0.86)
$TermSpread_t$	0.0917^{***}	0.0913^{***}	-0.0060	-0.0062	0.0220	0.0219
	(7.45)	(7.50)	(-0.33)	(-0.34)	(1.54)	(1.52)
$CreditSpread_t$	0.2161^{***}	0.2170^{***}	0.1010	0.1017	0.0482	0.0487
	(10.92)	(10.97)	(1.62)	(1.63)	(0.91)	(0.91)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year x Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25,130	25,130	34,162	34,162	34,162	34,162
Adj. R-squared	0.763	0.763	0.552	0.552	0.546	0.546

Notes: This table reports estimates from the OLS regressions of the determinants of corporate cost of debt. The dependent variable in model (1) is *Ln(LoanSpread)*, which is the natural logarithm of the All-in spread drawn that is defined as the amount the borrower pays in basis points over LIBOR or LIBOR equivalent for each dollar drawn down. The dependent variable in model (2), (3) is *Ln(GenCov) and Ln(FinCov)*, which is the natural logarithm of the number of general covenants and financial covenants in a loan contract, respectively. Ln(*Disaday)* is the natural logarithm of the number of natural disaster days in a county per year. All other independent variables are defined in Appendix B. All models include firm, year x industry, loan type and loan purpose fixed effects. *T*-statistics are computed using standard errors corrected for clustering at the county level and reported in parentheses. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 7
Natural Disaster Risk and Debt Maturity

	LT Debt Issue$_t$		*ST Debt Issue$_t$*	
	(1)	(2)	(3)	(4)
Ln(Disaday)$_{t+1}$		0.0003		-0.0002
		(1.33)		(-0.54)
Ln(Disaday)$_t$	-0.0001	-0.0002	-0.0001	-0.0001
	(-0.44)	(-0.67)	(-0.32)	(-0.33)
Ln(Disaday)$_{t-1}$		-0.0001		-0.0003
		(-0.28)		(-0.97)
Ln(Disaday)$_{t-2}$		-0.0005**		-0.0000
		(-2.10)		(-0.04)
Ln(Assets)$_{t-1}$	-0.0099***	-0.0099***	-0.0093***	-0.0093***
	(-14.03)	(-14.04)	(-7.03)	(-7.04)
Cash$_t$	-0.0055	-0.0055	0.0003	0.0003
	(-1.37)	(-1.37)	(0.06)	(0.06)
ROA$_t$	-0.0026	-0.0025	-0.0226***	-0.0226***
	(-1.07)	(-1.05)	(-3.82)	(-3.82)
MB$_t$	0.0002*	0.0002*	0.0001	0.0001
	(1.76)	(1.75)	(0.45)	(0.45)
Tangibility$_t$	0.0079	0.0080	0.0266***	0.0266***
	(1.57)	(1.58)	(3.21)	(3.21)
HHI$_t$	-0.0128	-0.0126	0.0549*	0.0548*
	(-0.81)	(-0.80)	(1.96)	(1.96)
Dividend$_t$	0.0792***	0.0793***	0.0180	0.0180
	(4.66)	(4.67)	(0.73)	(0.73)
Firm FE	Yes	Yes	Yes	Yes
Year x Industry FE	Yes	Yes	Yes	Yes
County Clustering	Yes	Yes	Yes	Yes
Observations	95,548	95,548	50,572	50,572
Adj. R-squared	0.097	0.097	0.151	0.151

Notes: This table reports estimates from the OLS regressions where net long-term debt issuance (*LT Debt Issue*) and net short-term debt issuance (*ST Debt Issue*) are the dependent variables. Following Lemmon and Roberts (2010) we define LT debt issuance and ST debt issuance as follows: ratio of difference between Long-term debt issues and Long-term debt reduction to start-of-period assets [(DLTIS)-(DLTR)/AT] and ratio of change in current debt to start-of-period assets [DLCCH/AT], respectively. *Disaday* is the total number of natural disaster days in a county per year. All other independent variables are defined in Appendix B. All models include firm, and year x industry fixed effects. *T*-statistics are computed using standard errors corrected for clustering at the county level and reported in parentheses. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 8
Headquarters Relocation

	Book Leverage$_t$	*Market Leverage$_t$*
	(1)	(2)
Post$_t$	-0.031**	-0.011
	(-2.27)	(-1.45)
Decrease$_t$	-0.044	-0.007
	(-1.45)	(-0.43)
Post$_t$ x Decrease$_t$	0.031**	0.012
	(2.00)	(1.13)
Ln(Assets)$_t$	0.021***	0.031***
	(2.93)	(6.61)
Cash$_t$	-0.107***	-0.061***
	(-3.65)	(-4.12)
ROA$_t$	-0.049***	-0.018***
	(-3.59)	(-2.92)
MB$_t$	0.002***	-0.000
	(2.89)	(-0.97)
Tangibility$_t$	0.108**	0.122***
	(2.27)	(3.41)
HHI$_t$	-0.102	-0.063
	(-0.92)	(-0.91)
Dividend$_t$	-0.247**	-0.154***
	(-2.33)	(-3.15)
Firm FE	Yes	Yes
Year x Industry FE	Yes	Yes
County Clustering	Yes	Yes
Observations	5,542	5,542
Adj. R-squared	0.549	0.693

Notes: This table reports estimates from the difference-in-differences (DID) regressions where *Book (Market) Leverage* is the dependent variable. *Post* is a binary variable equals to one (zero) for years after (before) a firm's headquarter is relocated. *Decrease* is a binary variable equals to one if a firm's headquarter is less exposed to natural disaster after relocation, and 0 otherwise. All other independent variables are defined in Appendix B. All models include firm and year x industry fixed effects. *T*-statistics are computed using standard errors corrected for clustering at the county level and reported in parentheses. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 9
Natural Disaster Risk and Capital Structure: Facility-Based Analysis

	Book Leverage$_t$			*Market Leverage$_t$*		
	(1)	(2)	(3)	(4)	(5)	(6)
	>9 days	>38 days	>75 days	>9 days	>38 days	>75 days
PostShock$_{t+1}$	0.0055	0.0024	0.0123	0.0060	0.0011	0.0079
	(0.92)	(0.25)	(1.39)	(1.01)	(0.12)	(0.89)
PostShock$_t$	-0.0032	0.0024	0.0092	-0.0068	-0.0006	0.0048
	(-0.56)	(0.43)	(1.24)	(-1.34)	(-0.12)	(0.69)
PostShock$_{t-1}$	0.0069	0.0043	0.0009	0.0080	0.0087	0.0090
	(1.30)	(0.78)	(0.13)	(1.40)	(1.37)	(1.37)
PostShock$_{t-2}$	-0.0107	-0.0144*	-0.0297***	-0.0047	-0.0103	-0.0219**
	(-1.45)	(-1.66)	(-2.77)	(-0.78)	(-1.41)	(-2.02)
Ln(Assets)$_t$	0.0521***	0.0520***	0.0523***	0.0486***	0.0485***	0.0485***
	(8.20)	(8.22)	(8.31)	(7.93)	(7.92)	(7.97)
Cash$_t$	-0.2419***	-0.2421***	-0.2438***	-0.2059***	-0.2058***	-0.2069***
	(-6.15)	(-6.17)	(-6.25)	(-6.96)	(-6.98)	(-7.04)
ROA$_t$	-0.3634***	-0.3636***	-0.3649***	-0.4279***	-0.4282***	-0.4292***
	(-6.08)	(-6.07)	(-6.10)	(-6.49)	(-6.48)	(-6.49)
MB$_t$	0.0088***	0.0088***	0.0088***	0.0000	0.0000	0.0000
	(8.03)	(8.07)	(8.14)	(0.06)	(0.04)	(0.06)
Tangiblity$_t$	-0.0387	-0.0378	-0.0401	-0.0098	-0.0096	-0.0112
	(-0.85)	(-0.84)	(-0.89)	(-0.25)	(-0.25)	(-0.29)
HHI$_t$	-0.1435	-0.1466	-0.1443	-0.0203	-0.0214	-0.0233
	(-0.66)	(-0.67)	(-0.66)	(-0.11)	(-0.11)	(-0.12)
Dividend$_t$	-0.1047	-0.1054	-0.1041	-0.1633	-0.1642	-0.1624
	(-0.83)	(-0.83)	(-0.82)	(-1.47)	(-1.48)	(-1.47)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year x Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Clustering	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,059	8,059	8,059	8,059	8,059	8,059
Adj. R-squared	0.671	0.671	0.671	0.677	0.678	0.678

Notes: This table reports estimates from the difference-in-differences (DID) facility-level tests. Financial leverage (either *Book Leverage* or *Market Leverage*) is the dependent variable. *PostShock* is an interaction binary variable which equals "1" in post-MajorShock years for facilities with a greater than 60% in *WasteRate*. All other independent variables are defined in Appendix B. All models include firm and year x industry fixed effects. *T*-statistics are computed using standard errors corrected for clustering at the firm level and reported in parentheses. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.