Natural Disasters and Corporate Default Risk

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Abstract

We examine whether and how exposure to natural disaster intensity can affect a firm's default risk. Using data on a large sample of US companies from 1994 to 2017, we document that firms headquartered in a location with higher exposure to natural disaster intensity are associated with higher default risk. This association is robust to various endogeneity tests and the alternative measures of natural disaster intensity and default risk. Furthermore, we find that firms' lower financial accessibility, lower debt capacity, and higher operational risk aggravate this positive association. As a corollary to these findings, we also show that financial institutions charge higher spreads and demand unfavorable credit terms for firms with higher default risk resulting from an increased exposure to natural disaster intensity. Overall, these results collectively suggest the detrimental effect of natural disasters on a firm's financial stability. These findings indicate that the current disaster assistance from government may be insufficient and, therefore, calls for more support to firms located in disaster affected and neighboring areas, as they are more likely to experience financial distress and default.

Key words: default risk, financial distress, natural disaster, disaster intensity

JEL Classifications: Q54, G12

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1. Introduction

The significant climate changes such as global warming in the past decades have increasingly made natural disasters a threat to sustainable economy, business and human lives. Since 1980s, the occurrence of natural disasters and the resulting direct financial losses have increased by more than three times (Hoeppe, 2016).[1] The World Bank (2016) estimates that, each year, natural disasters cost the global economy $520 billion and drive 26 million people back into poverty.[2] Spurred by climate change, a growing number of international environmental organizations (e.g., Intergovernmental Panel on Climate Change) warn that the frequency and magnitude of natural disasters are expected to grow significantly in the future (Field et al., 2012). In addition, Weather Risk Management Association (2016) also cautions that the devasting economic consequences of natural disasters might eventually have substantial impacts on firms.

Some anecdotal evidence suggests that natural disasters might lead to a systematic bankruptcy in local affected areas, firms' default then triggers the wave of unemployment.[3] For example, Warren (2005) uses data reported by Federal Reserve Bank of Boston and notes that the bankruptcy filing rate climbed by 50% in affected states, and the filing rate remained higher than that in the pre disaster period even three years after disasters. This anecdotal evidence suggests that natural disasters can increase the probability of a firm's default and bankruptcy. However, to the best of our knowledge, the extant literature provides little or no empirical thorough evidence on the effect of a firm's exposure to natural disaster intensity on its default risk. Thus, motivated by Baltas et al. (2021) who calls for more research on the effect of extreme hazards on financial markets is needed (especially on business failure, financing channels and/or resources damages), our research empirically examines whether and how a firm's exposure to natural disaster intensity affects its default risk in the US.

[1] According to the Centre for Research on Epidemiology of Disasters (CRED), there were 7,347 major recorded disaster events claiming 1.23 million lives, affecting 4.2 billion people resulting in approximately $2.97 trillion in global economic losses during the period of 2000 to 2019.
[2] According to Boushey, Kaufman, and Zhang (2021), the economic damages from natural disasters have risen to over 100 billion dollars per year to US economy.
[3] ABC News indicates that Hurricane Katrina led to a wave of unemployment, in which 30% and 12% of jobs disappeared in the affected states of New Orleans and Louisiana, respectively (Herman, 2016). This substantial disappearance of jobs might have been due to firms' systematic default/bankruptcy chaos after Hurricane Katrina.

We conjecture two competing hypotheses. Primarily, natural disasters could be considered as climate-related physical risks which destroy a firm's physical capital and disrupt its normal operation. In this circumstance, a firm's financial needs increase substantially (Baltas et al., 2021). However, in the presence of higher information asymmetry and increased uncertainty after natural disasters, financial institutions either do not approve new lending or require higher premiums/unfavorable credit terms (Javadi & Masum, 2021). With insufficient internal funds (Brown et al., 2021; Baltas et al., 2021; Massa & Zhang, 2021), accepting such higher borrowing costs or unfavorable credit terms further causes natural disaster-prone firms to enter financial distress and exhibit higher default risk.

Alternatively, natural disasters can cause managers to be more risk averse. This translates into more conservative corporate financing policy (i.e., lower leverage, more cash holdings) and pursuing higher financial flexibility (see, e.g., Bernile et al., 2017; Feng & Johansson, 2018). In the event of natural disasters, such firms can meet their financial needs with withheld cash/retained earnings rather than seeking external financing at increased costs. Therefore, natural disaster-prone firms have a lower likelihood of entering financial distress, leading to lower default risk.

To test these alternative hypotheses, we employ the extensive panel data of publicly listed US firms from 1994 to 2017. Based on the Emergency Events Database (EM-DAT) maintained by the Centre for Research on the Epidemiology of Disasters (CRED), we construct a novel proxy, disaster frequency, which is the number of natural disasters that occurred in the state where a firm is headquartered during a given year. Following prior studies (see, e.g., Huynh et al., 2020; Javadi & Masum, 2021), we use state-level location to determine a firm's exposure. The reasons are twofold. First, previous studies (see, e.g., Pirinsky & Wang, 2006; Chaney et al., 2012) indicate that a firm's operational facilities are usually in the same state as its headquarters but not necessarily in the same county. Thus, adopting a state-level location, it can mitigate misclassification. Second, the effect of natural disasters can spill over to neighboring areas/counties, lending support to the use of state-level measure. The default risk is measured by a well-known proxy of distance-to-default (*DD*) (Bharath & Shumway, 2008). By regressing natural disaster intensity on default risk and controlling for the set of control variables, fixed effects and clustering robust standard errors at multiple levels, our study consistently finds statistically significant and economically meaningful results that a firm located in areas with higher exposure to natural disaster intensity is more likely to exhibit higher financial distress and default.

We then employ an array of additional tests to mitigate concerns of potential endogeneity originating from sample selection and omitted variable bias. We replicate results by propensity score matched sample to rule out that the association is driven by underlying differences among firms located in areas with higher/lower exposure to natural disaster intensity. Our baseline results remain consistent to the use of entropy balanced sample, which can address the imbalance in covariates. Furthermore, we pass the Oster's (2019) omitted variable bias test, suggesting the strong stability of our documented positive association between natural disaster intensity and a firm's default risk. Finally, we employ a difference-in-differences (DiD) setup by using the relocation of a firm's headquarters as a quasi-experiment. Consistent with our main findings, we show a substantial increase in a firm's default risk after a relocation to a state with an increased natural disaster intensity compared to one that relocated in the state with decreased natural disaster intensity.

We next evaluate the robustness of our results for alternative measures of natural disaster intensity and default risk. By following Javadi and Masum (2021), we construct two natural disaster severity variables based on financial loss and human loss obtained from SHELDUS database.[4] We consistently document a negative and statistically significant relationship between natural disaster intensity and distance-to-default, suggesting that firms with higher exposure to natural disaster severity have higher default risk. Several studies (see, e.g., Kabir et al., 2020; Atif & Ali, 2021) use credit default swap (CDS) spreads as an alternative proxy for default risk. Using CDS spreads with different maturities (1-year, 3-year, and 5-year), we also find a significantly positive relationship, indicating that firms with higher exposure to natural disaster intensity also pay higher CDS spreads.

In cross-sectional tests, our study further investigates the circumstances under which the negative effect of natural disaster intensity on default risk is more concentrated. We find that this association becomes weaker if a firm has greater access to external finance, higher debt capacity and lower operational volatility. The underlying arguments are as follow: the financially unconstrained firms have less difficultly accessing external finance to meet

[4] Spatial Hazard Events and Losses Database that is administrated by Arizona State University.

financial needs in the event of natural disasters; Firms with higher debt capacity are less reliant on debt financing even during normal times, and therefore, financial institutions do not demand higher financing costs for financial flexible firms; Firms with lower operational volatility are less sensitive to natural disaster induced liquidity shock. This heterogeneity of documented association indicates the government that financial assistance can be prioritized to firms with higher financial constraints, lower debt capacity and higher operational risk.

In terms of economic implications, we evaluate how financial institutions react to a firm's negative exposure to natural disaster intensity. Using US syndicated loan data from DealScan, we find that financial institutions charge higher borrowing costs and require tighter financial covenants for firms that have higher default risk resulting from higher exposure to natural disaster intensity. However, we do not find a direct association between natural disaster intensity and loan price/non-price terms. This suggestive evidence indicates that debt market participants perceive the aftermath financial consequence of natural disaster intensity as one crucial component that shapes loan contracts.

Our study makes several important contributions to the literature. First, we contribute to the fast-growing literature investigating which factors can determine default risk. Prior studies have predominantly established associations of default risk with a firm's internal factors including financial leverage (Cathcart et al., 2020), debt maturity choices (Goyal & Wang, 2013), mergers and acquisitions (Koerniadi et al., 2015), innovation (Hsu et al., 2015), stock liquidity (Broggard et al., 2017; Nadarajah et al., 2021), corporate governance (Ali et al., 2018; Baghdadi et al., 2020), ownership type (Kabir et al., 2020; Abinzano et al., 2021), ESG disclosure (Atif & Ali, 2021), and carbon emissions (Capasso et al., 2020; Kabir et al., 2021). Relatively, few studies have documented the critical role of external environment in affecting firm's default risk such economic policy uncertainty (Nguyen et al., 2022). We extend this strand of literature by showing a statistically significant association between default risk and a firm's exposure to natural disaster intensity. The abovementioned factors primarily come from a firm's fundamentals and macroeconomic conditions. Our study is among the first to uncover the critical role of ecological factors (natural disaster intensity) in determining default risk for US firms.

Second, our study also contributes to the credit risk literature. Prior studies identify that higher CDS spreads are associated with higher liquidity risk (Corò et al., 2013), excessive financial leverage, lower profitability, and higher return volatility (Fu et al., 2021). Recently, Apergis et al. (2022) show that the COVID-19 pandemic increases a firm's CDS spreads through increased financial distress. Our study complements and extends their work by showing that higher natural disaster intensity also leads to higher credit risk through a similar mechanism of financial distress.

Third, our study complements the existing discussion of lenders' views on climate risk. Javadi and Masum (2021) document a positive association between a firm's climate risk and the cost of debt. Baltas et al. (2021) find that firms have limited access to conventional financing tools in the short term after natural disasters. Cevik and Miryugin (2022) show that the firms operating in countries with greater susceptibility to climate-related disruptions experience difficulty in access to debt financing even at higher interest rates. Our study takes another perspective and provides novel insights into the fact that debt market participants view a firm's exposure to natural disaster intensity (and therefore default risk) as a relevant factor in determining borrowing costs and loan terms.

Fourth, our study contributes to the literature on the role of climate-related physical risk in influencing firm-level outcomes. Recently, Pan and Qiu (2022) find a negative effect of acute physical risk from flooding on the performance of Chinese firms. Griffin et al. (2022) document a negative influence of chronic physical risk from extreme temperature heat spells on firm performance in the EU and UK. Likewise, Cevik and Miryugin (2022) show that the firms operating in countries with greater susceptibility to climate-related disruptions are less productive and profitable. Extending this stream of literature beyond financial performance, we show the devastating effect of natural disasters intensity on the likelihood of financial distress and default risk of US firms. Our study therefore provides an empirical support to the UN Sustainable Development Goal 13 which calls for urgent action to combat climate change and its devastating impacts.

This study is organized as follows. Section 2 reviews the relevant literature and develops the hypotheses. Section 3 describes the data and methodology design. Section 4 presents the main empirical results of the association between natural disasters intensity and default risk. Section 5 encapsulates the robustness analyses including endogeneity tests and alternative proxies. Section 6 covers the additional analyses examining the mechanisms and economic implications of the association. Finally, in Section 7, we offer concluding remarks.

2. Brief literature and hypotheses development

2.1 Default risk

Corporate default, by definition, occurs when the firm's cash flows are insufficient to pay financial obligations as required (Zeitun et al., 2007). In general, the downward shift in the level of firm's future cash flows or upward shift in the volatility of firm's future cash flows increases the likelihood of the firm's default (Ali et al., 2018). Avoiding a firm's default is of paramount importance because of its devastating consequences. For example, Brogaard et al. (2017) suggest some devasting consequences if a firm defaults, including the interruption of the firm's operations, adverse impact on a firm's relationship with both customers and employees, and the potential legal costs. Since the development of structural model (i.e., Altman model), prior literature finds that a firm's fundamental information (such as liquidity position, leverage, profitability, market value and the efficient use of assets) has strong power to forecast default risk (Altman, 1968). The market-based default measure of Merton's distance to default model (Merton, 1974) further shows that a firm's volatility is also important.

Moreover, a fast-growing literature also suggests that the default risk of a firm increases with higher stock illiquidity (Brogaard et al., 2017; Nadarajah et al., 2021), lower innovation (Hsu et al., 2015), weaker corporate governance (Ali et al., 2018; Baghdadi et al., 2020), lower ESG disclosure (Atif and Ali, 2021), more carbon emissions (Capasso et al., 2020; Kabir et al., 2021). Specifically, Brogaard et al. (2017) find that higher stock liquidity encourages investors to acquire information and trade on the market, leading to higher price efficiency. Since firms can make an effective investment decision based on signals conveyed from the stock market, they are expected to have higher and stable future cash flow, leading to lower default risk. Baghdadi et al. (2020) find that the board co-option (a proxy of weaker corporate governance) leads to the ineffectiveness of board monitoring, and therefore, a firm's manager is likely to make arbitrary and erratic decisions. In this circumstance, such firms are expected to have higher financial performance volatility, leading to higher default risk. Similarly, Atif and Ali (2021) argue that a firm's ESG disclosure reduces default risk can be explained by two perspectives. First, ESG disclosure reduces information asymmetry, suggesting a lower financing cost. Second, ESG disclosure are favored by capital participants, leading to a higher financial profitability and lower performance volatility. The common ground of the aforementioned factors is that they can ultimately directly or indirectly affect a firm's performance volatility (i.e., cash flow) and/or external financing condition. These two circumstances can drive a firm to enter financial distress and therefore default.

In addition to internal factors causing firms to default, empirical studies have also shown the crucial role of external environment in the likelihood of firm's survival. For instance, in a recent study, Nguyen et al. (2022) examine the association between economic policy uncertainty and a firm's default risk. They find that in the heightened uncertainty related to economic policies, the firms tend to exhibit higher volatility of financial performance and cost of debt and a lower level of cash reserves and financial performance. Consequently, these changes in the firm's fundamental factors in the presence of high economic policy uncertainty increase the firm's likelihood of default.

2.2 Natural disasters

Prior literature notes that natural disasters can lead to substantial direct and indirect economic losses (Leaning & Guha-Sapir, 2013). For instance, Cavallo and Noy (2010) mention that natural disasters can cause significant damage to a firm's fixed assets, inventories, raw materials, equipment, natural resources and so forth. Altay and Ramirez (2010) argue that natural disasters can destroy local infrastructure facilities, and therefore, the entire regional supply chain in both disaster-prone and neighboring areas can be interrupted. In such circumstances, a firm's financial needs surge significantly during the post disaster period to repair its damaged assets and recover from operational interruptions, as evidenced by Belasen and Polachek (2008). From this regard, two competing views, namely financial distress and risk aversion, from traditional corporate finance and behavioral finance literature suggest different propositions for a firm's response to a liquidity shortfall to avoid default in the times of natural disasters.

2.2.1 Financial distress channel

Extensive studies suggest that it is difficult for affected firms to use their internal sources (such as cash holdings and retained earnings) to meet abnormal financial needs resulting from natural disasters (see, e.g., Barrot & Sauvagnat, 2016; Brown et al., 2021). Instead, affected firms should seek for external financing. However, Baltas et al. (2021) argues that affected firms have substantially less access to conventional finance channels since a firm's collateral (used to pledge a loan) is destroyed by natural disasters. To elaborate further, Massa and Zhang (2021) find that even large firms have to switch from bond financing to bank loans immediately after natural disasters. This is because the systematic selling of bonds by bondholders after hurricanes, leads to substantially higher cost of issuing debt. In this context, both small and large firms heavily rely on bank borrowing after natural disasters, suggesting a substantial increase for local credit demand.

In contrast, from the perspective of credit supply, natural disasters adversely impact local economic conditions (Hallegatte et al., 2007) and this uncertainty can impact financial institutions, as reflected by their higher sensitivity in approving new loans (Klomp, 2014). Recent studies from Koetter et al. (2020) and Duqi et al. (2021) further argue that information asymmetry increases after natural disasters because lenders have little knowledge about which firms' assets are damaged or business operations are adversely affected. Thus, financial institutions increase the interest rates of business loans in natural disaster-prone areas to compensate for higher information asymmetry and increased volatility of collateral value (Brown et al., 2021; Javadi & Masum, 2021).

In this circumstance where insurance is not viable (Ibragimov et al., 2008; Sharma & Rotthoff, 2020) and government financial assistance is limited (Duqi et al., 2021), firms in disaster-prone areas have difficulty meeting financial needs with internal sources due to lower retained earnings and cash flow in normal periods (Hsu et al., 2018; Brown et al., 2021). In the presence of higher information asymmetry (Koetter et al., 2020; Duqi et al., 2021) during the post disaster period, financial institutions are likely to increase the cost of borrowing, provide unfavorable credit terms for such firms (Brown et al., 2021; Javadi & Masum, 2021; Massa & Zhang, 2021). Accepting such higher financing costs can lead to financial distress, increasing a firms' probability to default. Hence, we propose our main hypothesis as follows:

H1: *Firms located in areas more exposed to natural disaster intensity are more likely to default*

2.2.2 Risk averse channel

A strand of literature investigates how the occurrence of natural disasters alters an individual's risk perception. Dessaint and Matray (2017) investigate a firm's reaction to liquidity shock arising from hurricanes. They observe that managers overreact to hurricanes by changing a firm's cash holding policies. Specifically, firms located in both directly affected and adjacent areas significantly increase their cash holdings after hurricanes. Since hurricanes should not bring real liquidity shocks in adjacent areas, this phenomenon indicates that managers are risk averse in response to hurricanes (Dessaint & Matray, 2017).

Moreover, a growing number of studies (see, e.g., Cameron & Shah, 2015; Cassar et al., 2017) suggest a long-lasting change in the risk perceptions of individuals in the aftermath of natural disasters, becoming more risk averse. Bernile et al. (2019) find that experience with natural disasters can change managers' risk perceptions and therefore affect a firm's financing policy. For instance, CEOs who experienced natural disasters with severe consequences become more risk averse than CEOs who have not experienced a disaster or experienced a disaster with no profound impact. Bernile et al. (2019) further suggest that the phenomenon of risk averse can persist in either normal times or disaster periods for such firms. This can be reflected in various ways, including (but not limited to) more cash holdings, lower leverage, more usage of internal funds to meet financial needs and less engagement in risky acquisitions. Therefore, we argue that firms in natural disaster-prone areas are likely to have a lower level of risk-taking (Bernile et al., 2019) and higher degree of financial flexibility (Elnahas et al., 2018).

In addition to aforementioned studies, Brown et al. (2021) provide more circumstantial evidence by exploring a firm's financing behavior after natural disasters. They find that only financially inflexible firms withdraw more funds from credit lines and require higher credit allowances after natural disasters. Therefore, financially flexible firms do not intensively rely on bank financing in the response to higher financial needs resulting from natural disasters. This implies that such firms might use alternative financing approaches such as internal funds, to meet financial needs after natural disasters. In an extreme circumstance in which the internal funds are insufficient, Brown et al. (2021) also argue that financial institutions do not increase the cost of borrowing or request unfavorable credit terms for financially flexible firms after natural disasters. This is consistent with Lim and Nguyen (2020) who find financial institutions perceive a firm's soft information as relevant factor in shaping a loan term.

Based on the above discussion, as natural disasters can alter managers' risk perceptions, we predict that increased cash holdings (and conservative financial policies) provide a buffer for higher uncertainty and raise financial needs in the event of natural disasters. In these circumstances, rather than seeking external finance with higher financing costs, such firms are likely to use their withheld cash/retained earnings to meet their financial needs, resulting in a lower default risk. Therefore, we propose our alternative hypothesis as follows:

H2: *Firms located in areas more exposed to natural disaster intensity are less likely to default*

3. Research Method

3.1 Data and sample

We source natural disaster related data from EM-DAT[5] by following prior literature (see, e.g., Yamaura, 2014; Baltas et al., 2021). Following default risk literature (Atif & Ali, 2021; Kabir et al., 2021; Nadarajah et al., 2021), we collect a firm's default risk data from the Credit Research Initiative (CRI) database administrated by the National University of Singapore. The firm's financial information and stock return data are acquired from the COMPUSTAT and CRSP US stock database, respectively.

We begin by retrieving data on all US public firms that appeared in both COMPUSTAT Industrial files and CRSP stock files. We use the state name of each firm's headquarters location as shown in COMPUSTAT to merge natural disaster data from EM-DAT. Since financial firms and utility firms are subject to different types of risk nature, we exclude firms from our sample if the SIC ranges from 40-49 and 60-69. After applying these selection rules, the final sample consists of 24,906 firm-year observations for 3,753 unique firms with headquarters located in 48 different US states for the period from 1994 to 2017.

3.2 Measuring natural disaster intensity

Prior natural disaster studies (see, e.g., Skidmore & Toya, 2002; Yamamura, 2014; Bernile et al., 2017) typically measure local natural disaster exposure by three observable variables: frequency, individuals affected, and economic consequence of disasters. Consistent with Yamamura (2014), we adopt natural disaster frequency (*DisFreq*) as the main proxy to measure natural disaster intensity. *DisFreq* is defined as the count of total natural disasters that occurred during year *t* in the state where firms' headquarters are located. To increase interpretability, we then take the natural logarithm of *DisFreq*, namely, *lnDisFreq*. This is the most direct way to reflect natural disaster intensity, which one can see from two perspectives. First, compared to other measures (i.e., financial loss or individual affected), *DisFreq* is not affected by underlying characteristics across different states. For instance, as indicated by O'Brien et al. (2006), fatalities caused by natural disasters differ systematically between developed and developing regions. Second, our proposed *DisFreq* measure can capture not only disaster intensity but also severity. We exploit the recording threshold of EM-DAT, which requires that recorded natural

[5] EM-DAT is a global database that records natural disasters only if they meet at least one of following criteria: (1) more than 10 fatalities, (2) more than 100 people affected, (3) a declared state of emergency or (4) a call for international assistance.

disasters exceed a certain severity/magnitude. This can address the case of a high frequency but particularly low severity of natural disasters.

3.3 Measuring default risk

Our measure of default risk follows Bharath and Shumway (2008) who propose a reduced form of the Merton's distance-to-default (*DD*) model. This naïve reduced model can capture the functional form of Merton's model, while unknown parameters (firm value and volatility of firm) do not need to be solved by the iterative procedure. In doing so, Bharath and Shumway (2008) find that reduced model provides better out-of-sample forecast accuracy than Merton's, and consequently has been adopted by extensive literature (see, e.g., Brogaard et al., 2017; Baghdadi et al., 2020; Nadarajah et al., 2021). In a conceptual framework, *DD* indicates the distance between the firm's value of total assets and the book value of total liabilities in the next one year. A higher *DD* indicates that a firm's value is substantially higher than its liabilities, signaling lower default risk and vice versa. A detailed methodology to derive *DD* has been documented in Appendix B.

3.4 Measuring control variables

We include a set of control variables, accounting for correlated omitted variables. First, following Brogaard et al. (2017) and Baghdadi et al. (2020), we control for return on assets (*ROA*), excess return (*EXCESS*), stock illiquidity (*AMIHUD*), cash dividend payout (*Div/Assets*), and interest coverage (*Ln_IntCov*). *ROA* is defined as earnings before extraordinary items relative to total assets. A higher *ROA* indicates higher profitability and thus the firm being more capable of repaying financial obligations, and therefore, a lower default risk. *EXCESS* is the difference between a firm's annual stock return and CRSP value-weighted market return. Shumway (2001) suggests that firms with higher default risk are discounted by the capital market and therefore have lower excess returns. *AMIHUD* is computed as the annual average of the daily ratio of the absolute value of stock return divided by the dollar trading and amount, and then multiplied by 1 million (Amihud, 2002). A higher *AMIHUD* indicates higher stock illiquidity, leading to higher information asymmetry and lower governance quality (Brogaard et al., 2017). Therefore, *AMIHUD* is expected to be positively associated with default risk. *Div/Assets* is a firm's cash dividend relative to total assets and is expected to be negatively associated with default risk. *Ln_IntCov* is the natural logarithm of interest coverage which reflects a firm's cashflow to meet interest payments. Therefore, *Ln_IntCov* is expected to be negatively associated with default risk.

Furthermore, following prior studies (Hsu et al., 2015; Cathcart et al., 2020; Nadarajah et al., 2021), we further control for firm size (*SIZE*), firm age (*AGE*), financial leverage (*LEV*), current ratio (*LIQ*), market-to-book ratio (*MTB*), firm innovation (*R&D*), gross sales (*GROSS*), tangibility (*TANG*), and stock return volatility (*VOLAT*). *SIZE* is defined as the natural logarithm of a firm's total assets in book value. *AGE* is computed as the difference between the observation's fiscal year and the year of the firm's incorporation. Larger firms are more stable over time. Firms with a longer history have a greater ability to survive and accumulate a better reputation. Hence, *SIZE* and *AGE* are expected to have a negative association with default risk. *LEV* is defined as long-term debt to total assets, which is expected to have a positive association with default risk. *LIQ* is current assets over current liabilities, and a higher *LIQ* indicates a greater ability to repay short-term financial obligations. Thus, *LIQ* is expected to have a negative association with default risk. Firms having a higher *MTB* indicates greater growth opportunities, and therefore, such firms should be more profitable and face lower borrowing costs (Chen & Zhao, 2006). Therefore, *MTB* is expected to have a negative association with a firm's default risk. Moreover, *R&D* is computed as the ratio of research and development expenses relative to total assets. Firms with either missing or do not report research and development expenses are assumed to be zero (Nadarajah et al., 2021). The market participants demand lower premium for innovative firms since innovative firms outperform than their competitors. *GROSS* is the natural logarithm of a firm's gross profit that represents management efficiency. Thus, both R&D and *GROSS* are expected to have negative association with default risk. *TANG* can be defined as the ratio of net property planet and equipment over book value of total assets. Wang et al. (2017) argue that tangible assets depreciate less value than intangible assets if a firm defaults. Therefore, higher *TANG* is associated with lower default risk. *VOLAT* is the standard deviation of a firm's stock returns in past 12 months based on daily data. The higher *VOLAT* indicates higher uncertainty, and therefore, a higher default risk.

Finally, we include two state-level control variables. *Ln_Gdpmill* is the natural logarithm of the corresponding state's GDP measured as in millions of US dollars. *Ln_Popmill* is the natural logarithm of the corresponding state's total population measured in millions. These two state-level controls can capture the observable underlying differences across states. However, they are, not necessarily causally associated with default risk.

3.5 Empirical model

We formally investigate a firm's exposure to natural disaster intensity on its default risk by estimating the following regression Eq. (1):

$$DD_{i,t} = \alpha + \beta_1 lnDisFreq_{i,t} + \gamma Z's_{\ i,t} + Year\ FE + Industry\ FE + State\ FE + \varepsilon_{i,t} \quad (1)$$

The unit observation is the firm-year. *i* indexes firm *i* and *t* indexes year *t*. The dependent variable is *DD*, a proxy for the firm's default risk. A higher *DD* signals lower default risk and vice versa. The independent variable, *lnDisFreq*, is the natural logarithm of natural disaster frequency and proxies for natural disaster intensity in a given state where the headquarter of the firm i is located. *Z* is a list of control variables. The main coefficient of interest in our study is $\beta 1$, which be interpreted as, ceteris paribus, the effect of a firm's exposure to natural disaster intensity on its default risk.

Our regression model includes year fixed effects, industry fixed effects and state fixed effects, capturing unobservable heterogeneity over time (i.e., economic shocks), time-invariant unobservable heterogeneity across different industries and states. We identify a firm's industry by 2-digit standard industrial classification codes (SICs). Following Javadi and Masum (2021), we cluster robust standard errors at the firm-level since the effect of natural disasters correlates within firms. Finally, we winsorize all variables at both the of 1% and 99% levels to address outliers.

4. Main results

4.1 Summary statistics

Table 1 reports descriptive statistics for all variables used in the baseline model. The mean of the natural disaster measure, *DisFreq*, suggests that there are 4.03 natural disasters occurring in the US on average each year during our sample period. This is consistent with Smith (2022), who reports a mean *DisFreq* of 4.83 from the 1980s to the 2000s. The default risk measure, *DD*, has a mean of 4.45, which is slightly lower but generally consistent with Atif and Ali (2021), who report a mean of 5.88. The dispersion can result from adopting different sample period and firms. In terms of control variables, our study is consistent with and qualitatively similar to prior studies (see, e.g., Jiraporn & Lee, 2017; Broggard et al., 2017; Baghdadi et al., 2020). This provides us confidence in the integrity of the data and representativeness of our sample.

< Insert Table 1 Here >

4.2 Baseline results

In the baseline regression, we use *lnDisFreq* as the main measure for natural disaster intensity. All columns include year, industry, and state fixed effects, accounting for time-invariant unobservable heterogeneities across years, industries, and states. Specifically, in column (1), our study regresses *DD* on *lnDisFreq* and a set of firm-level control variables that are determinants of default risk. In column (2), our study further includes two more state-level control variables that capture the observable macroeconomic heterogeneities across states. In columns (1) and (2), following Javadi and Masum (2021), we cluster the standard errors at the firm level. Similarly, in column (3), we replicate our baseline regression but this time cluster the standard errors at both state and firm levels.[6] Following Brown et al. (2021), who suggest that one-way (firm level) standard clustering is more conservative than two-way clustering, our study adopts the former methodology throughout the empirical analysis. The baseline results are presented in Table 2.

The coefficient on *lnDisFreq* is negative and statistically significant, implying that default risk increases with a firm's higher exposure to natural disaster intensity. A similar magnitude of *lnDisFreq* across different regression models, evidences the negative impact of natural disasters on the affected firms' probability of default regardless of variation in model specifications. Focusing on the last two specifications, which have the richest controls and set of fixed effects, the effect of natural disaster intensity on default risk is not only statistically significant but also have reasonable economically meaningful, with a 1% increase in *lnDisFreq* associated with a decrease in *DD* of 0.001[7]. These results suggest that firms located in areas more exposed to natural disaster intensity are more likely to default, therefore, we accept H1.

[6] This two-way clustering is suggested by Javadi and Masum (2021) in their robustness test which can further account for the possibility that default risk correlates across firms in the same state.
[7] Since the baseline model is in linear-log (*DD~lnDisFreq*):
$\Delta DD = B1\ln(DisFreq + \Delta DisFreq) - B1\ln(DisFreq)$, change in DD if lnDisFreq changes by Δ ;
$\Delta DD = B1\ln\left(\frac{DisFreq+\Delta DisFreq}{DisFreq}\right)$, when $\frac{\Delta Disaster}{Disaster}$ close to zero -> ln(1+x) $\approx$ x ;
$\frac{\Delta DD}{100\times\frac{1\%\times\Delta Disfreq}{Disfreq}} = \frac{B1}{100}$, this can be interpreted as, when *lnDisFreq* increases by 1%, the DD changes by $\frac{B1}{100}$ (that is -0.0775*0.01$\approx$ -0.001).

In all specifications, most firm-level controls are statistically significant at a minimum of 5 % and have the expected sign, which is consistent with previous literature (see, e.g., Broggard et al., 2017; Baghdadi et al., 2020; Atif & Ali, 2021). For example, the larger and more profitable firms are less exposed to default risk, whereas more levered firms have higher default risk. Firms with higher *MTB* are valued more highly by investors and therefore are farther from financial distress and default.

< Insert Table 2 Here >

5. Robustness analyses

5.1 Tests of endogeneity

Our study documents significant and negative effect of a firm's natural disaster intensity on default risk. However, there may be some unobservable, endogenous factors driving these effects which questions the reliability of analysis. In this section, we address these concerns and explore any possible endogeneity issues.

5.1.1 Propensity score matched sample

The potential source of endogeneity comes from self-selection bias, for example, firm's choice of its headquarters location is not random. Bernstein et al. (2019) show that the price of properties located in the area less exposed to a rise in sea level is substantially higher than properties otherwise opposite. From this perspective, less profitable firms may be more likely to be located in more disaster-prone areas since they cannot afford the higher land price. In such circumstances, our documented results may be driven by systematic underlying differences (i.e., profitability) among firms located in more and less disaster-prone areas rather than a firm's exposure to natural disaster intensity.

To mitigate self-selection bias concern, we follow Atif and Ali (2021) and use propensity score matching (PSM). We first create an indicator variable for high natural disaster intensity (*DHDisFreq*), in which equals one if the *DisFreq* in a firm's location is higher than median

DisFreq and zero otherwise[8]. Based on this indicator variable, we assign firms located in areas more (less) exposed to natural disasters to the treatment (control) group. Next, we run the logit regression for *DHDisFreq* with all firm-level control variables to estimate the PSM score. We use the nearest neighbour methodology (one-to-one), set the caliper at 0.01, and disable the option for replacement. After applying aforementioned filters, we still have a reasonable sample of 17,454 firm-year observations. We use PSM matched sample to replicate the baseline regression with the same controls and set of fixed effects. We cluster robust standard error at the firm level in column (1) and state-firm level in column (2) of Panel A, Table 3. Following Atif and Ali (2021), we also implement a diagnostic test[9] to check the matching quality and we report these results in Panel B and Panel C, Table 3.

The coefficients on *lnDisFreq* remain negative and statistically significant at a 5% level in columns (1) and (2) of Panel A, Table 3. Results remain based on matched sample, suggesting that the negative effect on default risk is attributed by the difference of a firm's exposure to natural disaster intensity, other than the systematic difference among a firm's choice of location. Therefore, we mitigate the concern for self-selection bias. In addition, the matching quality is also satisfactory. Panel B and C of Table 3 indicate that all variables (except the *DD*) are indistinguishable between treatment and control groups. These results imply that matching quality is sufficient as all observable underlying differences are removed, and a firm's characteristics cannot explain the choice of headquarters locations. Taken together, we show that the self-selection bias is not a concern in our study after the implementation of PSM.

< Insert Table 3 Here >

5.1.2 Entropy balanced sample

Although PSM is a commonly approach used in casual inference, this approach may suffer from some limitations as noted by Shipman et al. (2017). They argue that PSM can raise a threat to external validity since observations can systematically be excluded due to the lack of

[8] We alternatively separate a firm located in high/low disaster-prone area based on the average *DisFreq* in each year. The results are consistent.

[9] In (unreported results), we also we run two logit regressions for *DHDisFreq* with all firm-level controls before and after matching. It shows that, before matching, the choice of location is associated with a systematic difference in a firm's underlying characteristics. For example, less profitable, higher levered, or less innovative firms are more likely to be located in more disaster-prone areas. However, all coefficients become statistically insignificant after matching. Consistently, results reveal that pseudo-R squared reduces from 5% to 0.1% before and after matching.

matched counterfactuals (pairs). In order to solve such limitation, we follow Hainmueller (2012) to adopt entropy balancing method which directly focus on covariate balance and therefore reducing estimation error and model dependency.

Similar to PSM, we assign firms located in areas more (less) exposed to natural disasters to the treatment (control) group based on median *DisFreq*. As advised by Hainmueller (2012), we reweight balance for first three moments (mean, variance, skewness) between treatment and control group, and we report the proof of balance in Panel A, Table 4. Then, we use entropy balanced sample to replicate the baseline regression with the same controls and set of fixed effects, and we report these results in Panel B, Table 4.

The Panel A, Table 4 reveals that the mean, variance, and skewness for each covariate is balanced across the treatment and control group, after implementing the entropy balancing approach. Panel B, Table 4 shows that the coefficient on *lnDisFreq* remains negative and statistically significant at a 10% level. This is quantitatively similar and qualitatively consistent with baseline results (i.e., Table 2) and results replicated by propensity score matched sample (i.e., Table 3).

< Insert Table 4 Here >

5.1.3 Omitted variable bias: the use of Oster (2019) test

The omitted variable bias is a common issue in empirical finance research. Conventionally, researchers rely on their own judgements to gauge the threat of omitted variable bias. We argue that the omitted variable bias is unlikely since we include 16 control variables (suggested from prior literature) along with various combinations of fixed effect(s). Since the exercise of judgement is subjective, we construct a formal test for omitted variable bias as introduced by Oster (2019). This novel approach has been extensively adopted by recent corporate finance studies (see, e.g., Bhabra et al., 2022; Chowdhury et al., 2022).

Specifically, Oster (2019) develops an identified boundary through considering the stability of coefficient (inclusion/exclusion of controls), R-square of regressions and along with their movements. Altonji et al. (2019) argue that the null hypothesis in which the omitted variable(s) drives the result can be rejected when the identified boundary does not include a zero. Based on Oster (2019), the identified boundary [$\tilde{\beta}$, β^*] can be derived as follow:

$$\beta^*=\tilde{\beta} -\delta^*[\dot{\beta} - \tilde{\beta}] (R_{max} - \tilde{R})/(\tilde{R}-\dot{R}) \quad (2)$$

where $\tilde{\beta}$ and $\dot{\beta}$ are coefficients of research variable (*lnDisFreq*) predicted from the controlled and uncontrolled regressions. $\tilde{R}$ and $\dot{R}$ are R-square of controlled and uncontrolled regressions. The controlled regression includes all control variables and combination of fixed effects, as per in baseline regression. Correspondingly, the uncontrolled regression excludes control variables and fixed effects. As Oster (2019) argues that the value of 1 is an appropriate cut-off for δ^*, we therefore assume δ^* equals 1. This indicates that observables are at least as important as unobservable. In default, the R_{max} equals one (Oster, 2019). Under these assumptions, Oster (2019) argues that *"only about 9 to 16 percent of results would survive"*. Following Mian and Sufi (2014), we also adopt a conservative assumption in which R_{max} = min (2.2 $\tilde{R}$, 1). Furthermore, we follow Chowdhury et al. (2022) to relax assumptions for R_{max} to show that these results are not sensitive to the change of underlying assumptions. We present these results in Table 5, and it shows that the identified boundary in all scenarios does not include a zero. This suggests that omitted variable bias is highly unlikely in our baseline regression.

< Insert Table 5 Here >

5.1.4 Quasi-natural experiment with headquarters relocations

Based on Hasan et al. (2017), the relocations of firms' headquarters can provide an ideal empirical setting to test causal association since relocations can carry change in firm's exposure to natural disaster intensity. Specifically, our study expects to observe that a firm's default risk increases after relocating to a state with higher natural disaster intensity. In contrast, a firm's default risk is expected to decrease if it relocates to a state with lower natural disaster intensity. From this perspective, the difference in default risk before and after firms' relocations should be positive when firms relocate to more natural disaster-prone areas compared to firms relocating to less disaster-prone areas.

We obtain a firm's historical headquarters address from SEC filings. We define firms as relocating from a low (high) to a high (low) natural disaster intensity state when the *DisFreq* of a pre-relocation is lower (higher) than that of a post-relocation state. Following Hasan et al. (2017), our study excludes observations with multiple historical relocations to mitigate confounding event windows. We also exclude the year of relocation since a firm's natural disaster intensity is changing. To allow sufficient time to observe this change, we require firms to have available data from four years before and after relocations. Based on the above selection criteria[10], the final sample consists of 144 firm-year observations from 1994 to 2017. Of these, 6 firms (48 firm-year observations) relocated from a less to a more natural disaster-prone state, whereas 12 firms (96 firm-year observations) relocated from a more to a less natural disaster-prone state.

We implement a difference-in-difference regression to test this causal effect. We modify the baseline regression by including three additional variables, namely, *Post*, *DDisIncrease*, and their interaction term (*DDisIncrease*Post*). The time indicator variable, *Post*, equals one for observations in the post-relocation period and zero for those in the pre-relocation period. The treatment indicator variable, *DDisIncrease*, equals one if a firm relocates to a more disaster-prone state (treatment group), while it equals zero if a firm relocates to a less disaster-prone state (control group). We include the same set of controls and cluster standard errors at the firm level as in the baseline regression. Angrist and Pischke (2008) caution that fixed effects included in a difference-in-difference model cannot be affected by the treatment itself. Therefore, following a similar fashion as Hasan et al. (2017), we do not include year and state fixed effects since they are perfectly collinear with the time and treatment indicators.

One concern regarding difference-in-difference test is that the change in default risk before and after relocations is potentially driven by underlying differences in firm characteristics other than changes in firm exposure to natural disaster intensity. To mitigate this endogeneity concern, following Atif and Ali (2021), we perform propensity score matching. We first run a logit regression to measure the propensity score based on several key firm characteristics. Due to limited sample size, we are unable to match based on the full baseline controls. Thus, we adopt one-to-one nearest neighbour to match firms relocating to a higher natural disaster intensity state (treatment group) with firms relocating to a lower intensity state (control group). This matching further reduces the sample to 104 firm-year observations.

[10] For example, imagine that firm A relocated its headquarters in 2005. In this circumstance, we require that there are no missing observations for both the period 2001-2004 and the period 2006-2009.

Panel A of Table 6 reports these difference-in-difference regressions results based on the unmatched sample in column (1) and the matched sample in column (2). The coefficients on the interaction term are -2.093 and -1.60, respectively, and they are statistically significant at a minimum of the 10% level. The negative coefficients imply that firms' default risk increases significantly when they relocate to a more natural disaster-prone state compared with firms relocating to a less natural disaster-prone state. This evidence can support the causal effect of a firm's exposure to natural disaster intensity on default risk. Panel B of Table 6 reports the results for the diagnostic test that assesses matching quality. The p-values of matching variables are higher than the threshold, suggesting that there is no significant underlying difference between the treatment and control groups across core firm characteristics (*ROA, LEV, LIQ, SIZE, MTB*) after matching.

< Insert Tables 6 Here >

5.2 Alternative measures

5.2.1 Alternative measures of natural disaster intensity

In the first robustness test, we propose alternative measures for a firm's exposure to natural disaster intensity. The analyses thus far have been based on *lnDisFreq* obtained from the EM-DAT database. Gall et al. (2009) criticize the inconsistency among different natural disaster databases. Therefore, we construct measures directly from an alternative source: the Spatial Hazard Events and Losses Database (SHELDUS). Specifically, *FinLoss* is the (natural logarithm of) the annual direct financial loss arising from crop and property damages by natural disasters. *HumLoss* is the (natural logarithm of) the total fatalities and injuries resulting from natural disasters, each state-year. They can better capture the severity of natural disasters.

We replicate the baseline regression with these alternative measures and report the results in Table 7. The coefficients on the alternative measures are negative and statistically significant at a minimum of the 5% level in all specifications. All control variables also have the expected signs. The reported coefficients imply that, ceteris paribus, a 1% increase in natural disaster severity, as reflected by *FinLoss* (*HumLoss*), is associated with a 0.0003 (0.0003)[11] reduction in *DD*. These results indicate that the negative effect of natural disaster intensity on a firm's default risk is robust to alternative measures, however, the economically magnitudes decrease in comparative with the use of *lnDisFreq*.

< Insert Table 7 Here>

5.2.2. Alternative measure of default risk

As another robustness test, we alternatively measure a firm's default risk by the natural logarithm of CDS spreads (*ln_CDS*). This is the annualized percentage of the notional value insured by CDS and we obtain data from CRI database[12]. A CDS contract can transfer a firm's default risk from buyers to sellers for pre-determined period. In this regard, Das et al. (2009) view this spread as the price of default risk. Thus, a firm with higher default risk should be subject to higher spreads. The literature documents that firms trading CDS contracts have higher lending efficiency and are perceived to have lower risk since CDS contracts provide insurance-like tools (Saretto & Tookes, 2013). Moreover, Javadi and Masum (2021) provide further evidence that a firm's exposure to climate risk is positively associated with the cost of bank loans but fail to extend this conclusion to firms with active CDS trading in the market. Thus, we expect that it should be more challenging to establish a statistically significant relationship than for *DD*. We investigate this issue by regressing *ln_CDS* on *lnDisFreq*. We utilize the same specification as in the baseline regression. The empirical results are reported in Table 8. In columns (1) through (3), we sequentially present the results for CDSs with maturities of one year, three years and five years.

The coefficients on *lnDisFreq* across all columns are positive and statistically significant at the 1% level. This implies that firms with greater exposure to natural disaster intensity pay higher spreads, which is the higher price for default risk. Since CDS spreads can also be viewed as a proxy for a firm's credit risk, we can also conclude that firms with higher natural disaster

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[11] $\frac{\Delta DD}{100\times\frac{1\%\times\Delta FinLoss\ (or\ HumLoss)}{FinLoss\ (or\ HumLoss)}} = \frac{B1}{100}$, this can be interpreted as, when *FinLoss(HumLoss)* increases by 1%, the *DD* changes by $\frac{B1}{100}$ (for FinLoss, -0.033*0.01≈-0.0003, for HumLoss, -0.026*0.01 ≈-0.0003).

[12] It worth noticing that CRI database provides the actuarial spread for credit default swaps which is equivalent to CDS spread but ignoring the upfront fee since they assume the risk-neutral market. Existing default risk literature from Atif and Ali (2021) and Kabir et al. (2020) also assumes they are technically and theoretically identical.

intensity are associated with higher credit risk. By regressing on CDS contracts with different maturities, the empirical results suggest that the documented effect of natural disaster intensity on CDS spreads can be observed in both short and long term, although this effect becomes weaker in the long term. Finally, note that, in unreported results, we alternatively use natural disaster severity measures (*FinLoss* and *HumLoss*) to replicate this regression. Consistently, the coefficients on natural disaster severity measures are also positive and are statistically significant at a minimum of the 5% level, implying that a firm with higher exposure to disaster severity has the higher CDS spreads (higher default/credit risk). This further reflects the robustness of our documented association in the main results.

< Insert Table 8 Here >

6. Additional Analyses

6.1 Mechanisms of the association

6.1.1 Effect of financial access

By definition, firms are financially constrained if they have limited or no access to external financing (Iliasov & Kokoreva, 2018). Prior studies (see, e.g., Musso & Schiavo, 2008; Kim et al., 2021) argue that financially constrained firms sell their assets at a discount to finance their normal operating activities. This eventually results in reduced firm value and weakens its ability to obtain external financing during a credit crisis. Moreover, financially constrained firms face underinvestment, where they are unable to invest in attractive projects with higher expected returns due to limited access to external finance. In the scope of our research, aligned with aforementioned studies, financially unconstrained firms located in natural disaster-prone areas should be expected to experience a less pronounced negative effect of natural disaster intensity on default risk. In this case, access to external finance is an important moderator.

To investigate the role of a firm's credit access, we employ two frequently adopted financial constraint measures: the KZ index (Kaplan & Zingales, 2000) and the WW index (Whited & Wu, 2006). A higher KZ (WW) index reflects a firm's lower access to external finance and vice versa. Therefore, we define the indicator variable for a firm's higher financial access (*DHFinAcces*) equals one if KZ (WW) index is lower than the industry-year median and zero otherwise. The detailed variable definitions are documented in Appendix A. In this section, we rerun the baseline regression by adding this indicator variable (*DHFinAcces*) and its interaction term with natural disaster intensity (*lnDisFreq*DHFinAcces*). *DHFinAcces* is determined by the aforementioned proxies for finance access variable which takes the value 1 if firm's finance accessibility is higher than year-industry median, 0 otherwise. Consistently, we utilize same controls and set of fixed effects as in the baseline model.

The results reported in Table 9 columns 1 and 2 show that the coefficients on the interaction term (*lnDisFreq*DHFinAcces*) are positive and statistically significant at least at the 10% level. Moreover, the coefficients on *lnDisFreq* remain negative and statistically significant at the 1% level. These results suggest that the negative effect of natural disaster intensity on default risk remains important even after controlling for a firm's access to external credit. The positive interaction term, however, indicates that this effect becomes weaker for firms with higher access to external finance. Taken together, these results confirm that a firm's access to external credit plays an important moderating role.

< Insert Table 9 Here >

6.1.2 Effect of debt capacity

In this section, our study investigates the moderating role of a firm's debt capacity. Fahlenbrach et al. (2020) argue that the impact of a sudden negative cashflow shock is less negative on firms with greater debt capacity, as reflected by their employing lower leverage and less long-term debt. However, note that there is a substantial difference between financial access and debt capacity. Firms employing undesirable excessive leverage (lower debt capacity) are perceived to be riskier in the debt market. Fahlenbrach et al. (2020) provide an example that, although large firms have a higher level of financial access, they are still unable to absorb more debt if they have lower debt capacity. Hence, Fahlenbrach et al. (2020) find that the negative effect of COVID-19 on a firm's stock return is more pronounced for firms with lower debt capacity but not for those with lower financial access. In our research context, firms located in more disaster-prone areas but with greater debt capacity can limit/reduce refinancing risk in the event of natural disasters. Alternatively, firms with lower debt capacity are exposed more to refinancing risk and thus face greater difficulty in financing their liquidity shortfalls. In this circumstance, we expect that firms with high (low) debt capacity are less (more) likely to face financial distress while facing natural disasters.

Following prior studies (Keefe & Yaghoubi, 2016; Fahlenbrach et al., 2020), we use three proxies to measure a firm's debt capacity. The first proxy, *LEV,* evaluates a firm's financial leverage in which debts consist of short- and long-term debt[13]. The second proxy, *LLEV,* further restricts the leverage to include only long-term debt. The final measurement is debt maturity (*DebtMat*), which counters the structure of a firm's debt maturity. A lower *DebtMat* indicates a lower percentage of long-term debt out of total debt. The detailed definitions for each variable are documented in Appendix A. Similarly, we rerun the baseline regression by including an indicator variable for a firm's debt capacity (*DHDebtCap*) and its interaction term (*lnDisFreq* DHDebtCap*). *DHDebtCap* is determined by the aforementioned proxies for debt capacity as which takes the value 1 if firm's debt capacity is higher than year-industry median, 0 otherwise. Except for *LEV,* which is omitted from columns (1) to (2) to avoid multicollinearity, we use the same controls and set of fixed effects as in the baseline regression.

The results are presented in columns (1) through (3) of Table 10. Consistent with earlier findings, coefficients on *lnDisFreq* are negative and statistically significant at the 1% level in all columns. As expected, coefficients on the interaction term across all specifications are positive and statistically significant at the 1% level except in column (3), which is significant at the 10% level. These results suggest that, given the same level of natural disaster intensity, firms with higher debt capacity have significantly lower exposure to default risk than firms without. Moreover, the magnitude of the coefficient on interaction term appears to be larger in column (2). This is consistent with the argument that firms have already employed higher levels of long-term debt find it more difficult to absorb more debt, in response to future cash flow shortfalls. It also clear that the magnitude of the interaction term is lower in column (3), where we use maturity structure. This suggests that the level of debt takes a more prominent position than the debt maturity structure (i.e., percentage of long-term debt) in moderating this association. Taken together, firms with a higher debt capacity are more capable of absorbing new debts during a liquidity shock and are therefore subject to the lower exposure to default risk than firms with lower debt capacity.

< Insert Table 10 Here >

[13] In doing so, we can solve the critique that, by using data provided in COMPUSTAT, nonfinancial liabilities can be implicitly included as assets (Welch, 2007).

6.1.3 Effect of operational volatility

In this section, we investigate the role of a firm's operational volatility on the natural disaster-default risk association. Javadi and Masum (2021) find that the positive association between climate change and the cost of bank loans is far more pronounced in industries with greater operational exposure. In our context, firms with greater exposure to operational risk are also more severely affected by natural disasters. For instance, Baltas et al. (2021) indicate that, in the event of natural disasters, a firm whose operations rely intensively on physical capital has substantial lower access to conventional finance channels. In this circumstance, firms with lower operational volatility and those located in natural disaster-prone areas should expect to have a less pronounced negative effect of natural disaster intensity on default risk. Thus, a firm's operational volatility is also an important moderator.

We use three measures to capture a firm's operational volatility. Following Keefe and Yaghoubi (2016), the first proxy, *CFVolat,* is cash flow volatility in the broad sense which can assess a firm's general risk. Following Dierker et al. (2015), the second proxy, *OperaCFVolat,* is operational cash flow volatility, which specifically targets a firm's operation. The third proxy, *OperaProfVolat,* is operational profit volatility that can reflect a firm's risk from the earning perspective. In a similar fashion, we rerun the baseline regression by adding an indicator variable for a firm's operational volatility (*DLvolat*) and its interaction term (*lnDisFreq***DLvolat*). *DLvolat* is determined by the aforementioned proxies for operational volatility as which takes the value 1 if firm's volatility is lower than year-industry median, 0 otherwise.

We present the results sequentially from columns (1) through (3) of Table 11. Consistent with earlier findings, the coefficients on *lnDisFreq* remain negative and statistically significant at least at the 5% level after controlling for a firm's operational volatility. The coefficients on the interaction term in all columns are positive and statistically significant at a minimum of 10%. This implies that the negative effects of natural disaster intensity on default risk become weaker for firms with lower operational volatility. This could be explained by that such firms are less adversely affected by natural disasters due to less physical capital being exposed to natural disasters. Taken together, the positive coefficients on the interaction term confirm the moderating role of firm operational volatility.

< Insert Table 11 Here >

6.2 Economic implications

In this section, we attempt to investigate the economic implications of the association between natural disasters intensity and corporate default risk. One possible outcome is that firms located in natural disaster-prone areas have higher default risk and therefore face increased costs of debt or unfavourable credit terms from financial institutions. This outcome can lead such firms to enter deeper financial distress and therefore even more likely to default. Thus, our study proposes two propositions: such firms have higher financing costs and tighter initial financial covenants associated with syndicated loans.

To verify these two propositions, our study first acquires US syndicated loan data from DealScan, which is managed by the Thomson Reuters Loan Pricing Corporation. DealScan provides price and nonprice data for syndicated loans at either the facility or package level. The unit observation is at the facility level, and they are then grouped into a deal. In this section, our study measures the cost of bank loans and tightness of covenants at the facility-year level. Our research uses COMPUSTAT-DealScan linking table provided by Chava and Robert (2008) to merge two databases. Following Javadi and Masum (2021), we drop observations if they have negative all-in-drawn spreads or financial leverage that is greater than one. This results in 12,983 distinct facilities and 9,111 deals for 2,801 US firms. On average, firms in our sample typically have a loan size of 597 million, pay all-in-drawn spreads of 215 basis points, have a maturity of 42 months, and have 7 lenders participating. This is comparable with previous studies on the cost of bank loan (see, e.g., Fields et al., 2012; Javadi & Masum, 2021).

Following prior studies (see, e.g., Fields et al., 2012; Javadi & Masum, 2021), we use the (natural logarithm of) all-in-drawn spreads, *Ln_Spreads*, to measure the cost of bank loans. This is the annual spread that firms paid over the London Bank Offered Rate. For the nonprice terms, a growing number of studies (see, e.g., Chava & Robert, 2008; Demiroglu et al., 2010) investigate the tightness of financial covenants rather than relying on counting the number of covenants. The philosophy behind this is that greater tightness of financial covenants can reduce a firm's incentive to take excessive risk. However, a higher number of financial covenants does not necessarily imply greater tightness if the associated financial covenants are loose[14].

Hence, we follow Chava and Robert (2008) who focus exclusively on the initial tightness of financial covenants for current ratio, net worth, and tangible net worth. The reasons are twofold. First, measurements of these financial covenants are standardized. Second, lenders have a higher propensity to impose tighter restrictions on a firm's liquidity management capacity since natural disasters result cashflow shortfalls. Specifically, we construct the initial tightness ratio as the difference between a firm's actual accounting number and initial covenant threshold divided by per standard deviation. A lower such ratio indicates greater initial tightness and vice versa.

We regress *Ln_Spreads* on *lnDisFreq*, its interaction term (*lnDisFreq*DHdefault*) and a list of control variables. *DHdefault* is an indicator variable for high default risk which equals one if a firm's *DD* is lower than the industry-year median, and zero otherwise. Similarly, for the initial tightness of financial covenants, we estimate a probit regression by replacing *Ln_Spreads* with *DHTight,* which is an indicator variable for high tightness which equals one if corresponding financial covenants are tighter than industry-year median, and zero otherwise. Consistently, we employ the same set of fixed effects and clustering methodology as but different controls than in the baseline regression.

Since we investigate the cost of bank loans, we adopt a new set of control variables to better mitigate omitted variables. Following prior studies (see, e.g., Chen at al., 2020; Ambrocio et al., 2022), we first include a set of control variables associated with firm characteristics, including *SIZE, ROA, LEV, MTB, AGE, EXCESS, TOBINQ, and AMIHUD*. Following Javadi and Masum (2021), the second set of controls is associated with loan characteristics, which are the (natural logarithm of) loan size (*Ln_LoanSize*), number of lenders (*Ln_Lenders*), and loan maturity (*Ln_Mat*). Following Maskara (2010), we also include a list of indicator variables to control for a loan's purpose and type. The detailed variable definitions are documented in Appendix A.

[14] Imagine that firm A with current tangible net worth of 20 (million in USD) and seek for loan A. Firm B with tangible net worth of 6 (million in USD) and seek for loan B. Lenders approve two loans and require both firms to hold at least 5 (million in USD) of tangible net worth. Although loan A and loan B have the same number of financial covenants, the tightness of loan B is more restrict than loan A.

The empirical results are presented in Table 12. In column (1), the coefficient on the interaction term (*lnDisFreq* DHdefault)* is positive and statistically significant at the 10% level. This suggests that firms with higher default risk resulting from increased natural disaster intensity face a higher cost of bank loans. The coefficient of 0.0558 indicates that, when *lnDisFreq* increases by 1%, a firm with higher default risk resulting from higher natural disaster intensity is charged 0.06% higher spreads than a firm otherwise with a lower default risk. This confirms that lenders recognize that a higher natural disaster intensity can lead to higher default risk and therefore charge higher premium. However, we do not find a direct association between natural disaster intensity and the cost of bank loan, given that the coefficient on *lnDisFreq* is statistically insignificant. In columns (2) through (3), the coefficients on the interaction term are also positive and statistically significant at the 10% level. This suggests that firms with higher default risk resulting from higher natural disaster intensity are more likely to be demanded for tighter initial financial covenants on current ratio or tangible net worth. Similarly, we cannot find a direct association between a firm's natural disaster intensity and the tightness of financial covenants. In (unreported) results, we fail to find such a significant association with financial covenants on net worth. One possible explanation is that tangible assets can be sold in the event of financial distress to meet cashflow shortfalls. Consequently, lenders extensively target a firm's ability to respond liquidity shocks (such as the current ratio, tangible net worth) which is a result of natural disasters. Taken together, these results provide suggestive evidence that firms with higher default risk resulting from higher natural disaster intensity not only experience the higher borrowing costs but also receive unfavourable credit terms.

< Insert Table 12 Here >

7. Conclusion

This is the first study to examine the influence of ecological factor (i.e., natural disaster) on firm's chances of failure (i.e., default risk) in the context of US. Consistent with our main prediction, we find that firms with greater exposure to natural disaster intensity are associated with increased default risk. We further show that this association is primarily driven by firms with lower financial accessibility, lower debt capacity and higher operational volatility. Our results can survive from a battery of additional tests, such as propensity score matching, entropy balancing method, Oster (2019) omitted variable bias test and quasi-experiment of headquarters' relocations. In robustness tests, we also find that this association is not sensitive to alternative measures of natural disaster intensity and default risk. Finally, as an economic implication, we find that a firm with higher default risk resulting from increased exposure to natural disaster intensity can be requested for higher premium and tighter requirement of financial covenants by financial institutions.

Our findings also have important policy implications. They suggest that firms located in areas with higher exposure to natural disaster intensity are more likely to experience financial distress and, therefore, default. We observe this association by adopting the state-level measure. This implies that this negative effect holds in the state-wide. Thus, policymakers should be aware that the negative effect of natural disaster intensity on firms is statewide rather than only in direct affected counties. Furthermore, we find that firms with higher default risk resulting from increased exposure to natural disaster intensity face higher external borrowing costs and receive unfavorable credit terms. Therefore, policymakers should distribute more disaster financial/loan assistance to firms located in both direct disaster-affected areas and their neighboring areas. In distribution of financial assistance, policymakers should assign higher priority to assist firms with lower financial accessibility, lower debt capacity, and higher exposure to operational risk since they are more pronounced to said negative effect.

The possible extensions to our study include but are not limited to: (1) the investigation of disaster–default linkage using similar methodology in multi-countries accounting for institutional differences, (2) the exploration of the moderating role of corporate governance, ESG disclosure, and economic policy uncertainty in the disaster–default linkage, (3) the use of the natural disasters intensity in default prediction models as a key input to predict actual or ex-post default and bankruptcy events, (4) the potential extension of this research to financial firms or bank holding companies, and to other important features of capital markets such as stock liquidity.

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Table 1 - Descriptive Statistics

This table presents descriptive statistics for the sample of 24,906 firm-year observations excluding financial and utility firms. Columns (1) through (3) report the sample size, mean and standard deviation and columns (4) to (6) reports the 25%, 50% and 75% percentiles respectively. The definition for each variable has been documented in Appendix A.

	N	Mean	SD	P25	Median	P75
	(1)	(2)	(3)	(4)	(5)	(6)
DD	24,906	4.452	2.775	2.438	3.980	5.957
DisFreq	24,906	4.030	2.545	2.000	4.000	5.000
lnDisFreq	24,906	1.491	0.506	1.099	1.609	1.792
SIZE	24,906	6.329	1.803	5.011	6.258	7.553
ROA	24,906	0.050	0.068	0.020	0.051	0.085
LEV	24,906	0.201	0.180	0.042	0.173	0.304
R&D	24,906	0.025	0.044	0.000	0.000	0.030
VOLAT	24,906	0.425	0.243	0.254	0.367	0.529
AGE	24,906	22.399	15.878	9.000	18.000	33.000
EXCESS	24,906	0.056	0.528	-0.256	-0.017	0.242
TANG	24,906	0.272	0.214	0.107	0.213	0.376
GROSS	24,906	5.303	1.751	4.002	5.249	6.490
MTB	24,906	2.766	3.103	1.264	2.050	3.349
LIQ	24,906	2.361	1.510	1.394	1.977	2.842
AMIHUD	24,906	0.003	0.013	0.000	0.000	0.000
Div/Assets	24,906	1.015	1.862	0.000	0.000	1.398
Ln_Intcov	24,906	2.384	1.559	1.361	2.116	3.101
Ln_Popmill	24,906	2.390	0.767	1.821	2.441	2.975
Ln_Gdpmill	24,906	13.028	0.852	12.485	13.005	13.629

Table 2 - Baseline Regression

This table presents regression results on the association between firm's exposure to natural disaster intensity and default risk. Detailed variable definitions are provided in Appendix A. All regressions include year-, industry- and state-fixed effects. We cluster standard error at firm level in columns (1) through (2), and state-firm level in column (3). The p-value is reported in parentheses. ***, **, * denoted significance at 1%, 5%, and 10% level, respectively.

	DD	*DD*	*DD*
	(1)	(2)	(3)
lnDisFreq	-0.0753**	-0.0775***	-0.0775***
	(0.011)	(0.008)	(0.009)
SIZE	0.1031**	0.1017**	0.1017**
	(0.019)	(0.020)	(0.021)
ROA	3.8215***	3.8178***	3.8178***
	(0.000)	(0.000)	(0.000)
LEV	-1.8190***	-1.8219***	-1.8219***
	(0.000)	(0.000)	(0.000)
R&D	0.5494	0.5512	0.5512
	(0.253)	(0.249)	(0.250)
VOLAT	-2.8273***	-2.8325***	-2.8325***
	(0.000)	(0.000)	(0.000)
AGE	0.0068***	0.0067***	0.0067***
	(0.000)	(0.000)	(0.000)
EXCESS	0.3253***	0.3253***	0.3253***
	(0.000)	(0.000)	(0.000)
TANG	1.0626***	1.0719***	1.0719***
	(0.000)	(0.000)	(0.000)
GROSS	0.2861***	0.2878***	0.2878***
	(0.000)	(0.000)	(0.000)
MTB	0.0473***	0.0472***	0.0472***
	(0.000)	(0.000)	(0.000)
LIQ	0.2546***	0.2553***	0.2553***
	(0.000)	(0.000)	(0.000)
AMIHUD	-7.3431***	-7.3313***	-7.3313***
	(0.000)	(0.000)	(0.000)
Div/Assets	0.2312***	0.2315***	0.2315***
	(0.000)	(0.000)	(0.000)
Ln_IntCov	0.2776***	0.2776***	0.2776***
	(0.000)	(0.000)	(0.000)
Ln_Popmill		0.0926	0.0926
		(0.867)	(0.867)
Ln_Gdpmill		-0.6335*	-0.6335*
		(0.079)	(0.079)
Constant	1.5122***	8.5624**	8.5624**
	(0.000)	(0.019)	(0.019)
Year Fixed Effects	YES	YES	YES
Industry Fixed Effects	YES	YES	YES
State Fixed Effects	YES	YES	YES
Observations	24,906	24,906	24,906
Adj. R^2	0.62	0.62	0.62

Table 3 - Natural Disaster Intensity and Default Risk (PSM Matching)

Panel A of Table 3 presents OLS regression results on the association between a firm's exposure to natural disaster intensity and default risk based on PSM matched sample. All regressions include year-, industry- and state-fixed effects. We cluster standard error at firm level in columns (1) and state-firm levels in column (2). Detailed variable definitions are provided in Appendix A. The p-value is reported in parentheses. ***, **, * denoted significance at 1%, 5%, and 10% level, respectively. Panels B and C present the mean difference of variables between treatment and control groups after PSM matching.

Panel A – Regression

	DD	*DD*
	(1)	(2)
lnDisFreq	-0.082**	-0.082**
	(0.019)	(0.018)
SIZE	0.105**	0.105**
	(0.033)	(0.032)
ROA	3.849***	3.849***
	(0.000)	(0.000)
LEV	-1.873***	-1.873***
	(0.000)	(0.000)
R&D	0.499	0.499
	(0.394)	(0.394)
VOLAT	-3.014***	-3.014***
	(0.000)	(0.000)
AGE	0.006***	0.006***
	(0.001)	(0.001)
EXCESS	0.307***	0.307***
	(0.000)	(0.000)
TANG	1.081***	1.081***
	(0.000)	(0.000)
GROSS	0.272***	0.272***
	(0.000)	(0.000)
MTB	0.079***	0.079***
	(0.000)	(0.000)
LIQ	0.261***	0.261***
	(0.000)	(0.000)
AMIHUD	-6.538***	-6.538***
	(0.000)	(0.000)
Div/Assets	0.227***	0.227***
	(0.000)	(0.000)
Ln_IntCov	0.288***	0.288***
	(0.000)	(0.000)
Ln_Popmill	0.063	0.063
	(0.921)	(0.921)
Ln_Gdpmill	-0.61	-0.61
	(0.159)	(0.159)
Constant	8.591**	8.591**
	(0.049)	(0.049)
Year Fixed Effects	YES	YES
Industry Fixed Effects	YES	YES
State Fixed Effects	YES	YES
Observations	17,454	17,454
Adj. R^2	0.627	0.627

Panel B – PSM estimator				
	Treated	Control	Difference	t-stat
DD	4.6205	4.4753	0.1452	3.41***

Panel C – Mean Difference				
	Treated	Control	Difference	t-values
SIZE	6.4427	6.4468	-0.0041	-0.15
ROA	0.0498	0.05018	-0.00038	-0.38
LEV	0.20529	0.20574	-0.00045	-0.17
R&D	0.02264	0.02204	0.0006	0.97
VOLAT	0.41407	0.41573	-0.00166	-0.46
AGE	23.176	23.202	-0.026	-0.10
EXCESS	0.05228	0.05372	-0.00144	-0.19
TANG	0.2737	0.27517	-0.00147	-0.45
GROSS	5.3918	5.392	-0.0002	-0.01
MTB	2.7726	2.7492	0.0234	0.50
LIQ	2.355	2.3418	0.0132	0.59
AMIHUD	0.00246	0.00244	0.00002	0.07
Div/Assets	1.043	1.0612	-0.0182	-0.62
Ln_IntCov	2.3854	2.3762	0.0092	0.40
lnpopmill	2.53	2.5332	-0.0032	-0.29
lngdpmill	13.185	13.187	-0.002	-0.21

Table 4 - Natural Disaster Intensity and Default Risk (Entropy balanced)

Panel A of Table 4 presents the proof of convergence in mean, variance, and skewness for all variables after entropy balancing. Panel B of Table 4 reports OLS regression results on the association between a firm's exposure to natural disaster intensity and default risk based on entropy balanced sample. All regressions include year-, industry- and state-fixed effects. We cluster standard error at firm level. Detailed variable definitions are provided in Appendix A. The p-value is reported in parentheses. ***, **, * denoted significance at 1%, 5%, and 10% level, respectively.

Panel A - Entropy balancing quality

First three moments before entropy balancing

(Before)	Treatment Group			Control Group		
Variables	Mean	Variance	Skewness	Mean	Variance	Skewness
SIZE	6.565	3.31	0.1696	6.183	3.161	0.2659
ROA	0.0502	0.0043	-0.7443	0.0499	0.0048	-0.8031
LEV	0.2089	0.0317	0.8876	0.1956	0.0325	1.042
R&D	0.0218	0.0017	2.605	0.0265	0.0021	2.242
VOLAT	0.4056	0.0539	1.552	0.4364	0.0620	1.481
AGE	23.62	275.8	0.7221	21.65	236.2	0.8073
EXCESS	0.0497	0.2574	1.753	0.0601	0.2919	1.757
TANG	0.2853	0.0509	1.06	0.264	0.0425	1.128
GROSS	5.486	3.109	0.2274	5.191	3.011	.2846
MTB	2.863	10.21	2.639	2.831	10.49	2.45
LIQ	2.329	2.215	1.977	2.379	2.315	1.976
AMIHUD	0.0023	0.0001	7.07	0.0030	.0002	6.144
Div/Assets	1.113	3.738	2.502	0.9539	3.277	2.868
Ln_IntCov	2.391	2.392	0.9721	2.378	2.451	0.87
Ln_Popmill	2.591	0.4995	-0.5358	2.269	0.6037	-0.0935
Ln_Gdpmill	13.26	0.6467	-0.3025	12.88	0.7192	-0.1059

First three moments after entropy balancing

(After)	Treatment			Control		
Variables	Mean	Variance	Skewness	Mean	Variance	Skewness
SIZE	6.565	3.31	0.1696	6.565	3.31	0.1696
ROA	0.0502	0.0043	-0.7443	0.0502	0.0043	-0.7443
LEV	0.2089	0.0317	0.8876	0.2089	0.0317	0.8876
R&D	0.0218	0.0017	2.605	0.0218	0.0017	2.605
VOLAT	0.4056	0.0539	1.552	0.4056	0.0539	1.552
AGE	23.62	275.8	0.7221	23.62	275.8	0.7221
EXCESS	0.0497	0.2574	1.753	0.0497	0.2574	1.753
TANG	0.2853	0.0509	1.06	0.2853	0.0509	1.06
GROSS	5.486	3.109	0.2274	5.485	3.109	0.2274
MTB	2.863	10.21	2.639	2.863	10.21	2.639
LIQ	2.329	2.215	1.977	2.329	2.215	1.977
AMIHUD	0.0023	0.0001	7.07	0.0023	0.0001	7.07
Div/Assets	1.113	3.738	2.502	1.113	3.738	2.502
Ln_IntCov	2.391	2.392	0.9721	2.391	2.392	0.9721
Ln_Popmill	2.591	0.4995	-0.5358	2.591	0.4995	-0.5363
Ln_Gdpmill	13.26	0.6467	-0.3025	13.26	0.6472	-0.3025

Panel B – Regression	
	DD
	(1)
lnDisFreq	-0.058*
	(0.082)
SIZE	0.072
	(0.141)
ROA	3.888***
	(0.000)
LEV	-1.873***
	(0.000)
R&D	0.746
	(0.169)
VOLAT	-3.051***
	(0.000)
AGE	0.006***
	(0.002)
EXCESS	0.317***
	(0.000)
TANG	1.067***
	(0.000)
GROSS	0.308***
	(0.000)
MTB	0.068***
	(0.000)
LIQ	0.258***
	(0.000)
AMIHUD	-7.295***
	(0.000)
Div/Assets	0.237***
	(0.000)
Ln_IntCov	0.288***
	(0.000)
Ln_Popmill	0.09
	(0.891)
Ln_Gdpmill	-0.668
	(0.118)
Constant	9.269**
	(0.029)
Year Fixed Effects	YES
Industry Fixed Effects	YES
State Fixed Effects	YES
Observations	24,906
Adj. R^2	0.632

Table 5 – Oster (2019) omitted variable bias test

This table presents assumptions used for Oster (2019) test and bounds for our research variable of *lnDisFreq* as shown in baseline regression.

Dependent Variable=*DD*			
Independent Variable = *lnDisFreq*			
Oster (2019) Assumptions	R_{MAX}	Identified Set	Includes Zero
$\delta = 1$ $R_{MAX} = \min(1.25\tilde{R},1)$	R_{MAX}=min(1.25*0. 6254,1)=0.7818	[-0.2148, -0.0775]	NO
$\delta = 1$ $R_{MAX} = \min(1.5\tilde{R},1)$	R_{MAX}=min(1.5*0. 6254,1)=0.9381	[-0.3519, -0.0775]	NO
$\delta = 1$ $R_{MAX} = \min(1.8\tilde{R},1)$	R_{MAX}=min(1.8*0. 6254,1)=1	[-0.4062, -0.0775]	NO
$\delta = 1$ $R_{MAX} = \min(2.0\tilde{R},1)$	R_{MAX}=min(2.0*0. 6254,1)=1	[-0.4062, -0.0775]	NO
$\delta = 1$; $R_{MAX} = \min(2.2\tilde{R},1)$	R_{MAX}=min(2.2*0. 6254,1)=1	[-0.4062, -0.0775]	NO
$\delta = 1$ $R_{MAX} = 1$	R_{MAX}= 1	[-0.4062, -0.0775]	NO
Controlled Coefficient	-0.0775	Uncontrolled Coefficient	0.4651
Controlled R-square	0.6254	Uncontrolled R-square	0.0071

Table 6 - **Quasi-Experiment: Firm's Relocations for Headquarters**

Panel A of this table reports the modified difference-in-difference analysis of firm's exposure to natural disaster intensity on default risk based on firm's relocations for headquarters. We use unmatched sample in column (1) and PSM matched sample in column (2). All regressions include industry fixed effects and cluster the robust standard error at firm-level. The p-value is reported in parentheses. ***, **, * denoted significance at 1%, 5%, and 10% level, respectively. Panel B of this table reports the diagnostic test for PSM matching quality.

Panel A - DID

	DD	*DD*
	(1)	(2)
Post	1.550***	1.623**
	(0.000)	(0.010)
DDisIncrease	0.751	2.241
	(0.414)	(0.315)
*DDisIncrease*Post*	-2.093***	-1.650*
	(0.007)	(0.064)
SIZE	0.775	-0.256
	(0.261)	(0.832)
ROA	6.736*	2.129
	(0.069)	(0.481)
LEV	-3.878	-3.790
	(0.137)	(0.195)
R&D	0.94	22.910
	(0.967)	(0.324)
VOLAT	-2.660***	-3.047***
	(0.001)	(0.001)
AGE	-0.017	-0.082
	(0.412)	(0.408)
EXCESS	0.462	0.523
	(0.416)	(0.428)
TANG	4.069	5.012
	(0.179)	(0.215)
GROSS	-0.385	-0.211
	(0.600)	(0.873)
MTB	-0.009	-0.054
	(0.893)	(0.164)
LIQ	0.009	0.069
	(0.927)	(0.648)
AMIHUD	-51.994	-64.05
	(0.265)	(0.194)
Div/Assets	0.01	-0.080**
	(0.857)	(0.017)
Ln_IntCov	0.562***	0.422**
	(0.002)	(0.045)
Ln_Popmill	-2.640*	-1.896
	(0.095)	(0.477)
Ln_Gdpmill	2.542*	1.873
	(0.076)	(0.433)
Constant	-25.977*	-13.071
	(0.085)	(0.571)
Industry Fixed Effects	YES	YES
State Fixed Effects	NO	NO
Year Fixed Effects	NO	NO
PSM Matched	NO	YES

Observations	144	104
Adj. R^2	0.61	0.62

Panel B - Diagnostic Test

PSM – Mean Difference

Variable	Treated	Control	Difference	t-values
ROA	.03647	.03495	0.001	0.33
LEV	.25797	.24845	0.009	0.80
LIQ	2.0893	2.151	-0.061	0.83
SIZE	6.2727	6.305	-0.032	-0.31
MTB	2.3236	2.1965	0.127	0.74

Table 7 - Alternative Measures of Natural Disaster Intensity

This table presents regression results on the association between firm's exposure to natural disaster severity and default risk. Detailed variable definitions are provided in Appendix A. All regressions include year-, industry- and state-fixed effects. We cluster standard error at firm level. The p-value is reported in parentheses. ***, **, * denoted significance at 1%, 5%, and 10% level, respectively.

	DD	*DD*
	(1)	(2)
FinLoss	-0.033***	
	(0.000)	
HumLoss		-0.026**
		(0.041)
SIZE	0.111**	0.111**
	(0.01)	(0.01)
ROA	3.791***	3.787***
	(0.000)	(0.000)
LEV	-1.818***	-1.817***
	(0.000)	(0.000)
R&D	0.54	0.529
	(0.246)	(0.256)
VOLAT	-2.790***	-2.792***
	(0.000)	(0.000)
AGE	0.007***	0.007***
	(0.000)	(0.000)
EXCESS	0.328***	0.328***
	(0.000)	(0.000)
TANG	1.074***	1.074***
	(0.000)	(0.000)
GROSS	0.277***	0.277***
	(0.000)	(0.000)
MTB	0.047***	0.047***
	(0.000)	(0.000)
LIQ	0.258***	0.258***
	(0.000)	(0.000)
AMIHUD	-6.557***	-6.578***
	(0.000)	(0.000)
Div/Assets	0.230***	0.230***
	(0.000)	(0.000)
Ln_IntCov	0.275***	0.275***
	(0.000)	(0.000)
Ln_Popmill	-0.046	-0.044
	(0.930)	(0.933)
Ln_Gdpmill	-0.454	-0.417
	(0.181)	(0.220)
Constant	7.231**	6.343*
	(0.036)	(0.065)
Year Fixed Effects	YES	YES
Industry Fixed Effects	YES	YES
State Fixed Effects	YES	YES
Observations	27,278	27,278
Adj. R^2	0.62	0.62

Table 8 - Alternative Measure of Default Risk

This table presents regression results on the association between firm's exposure to natural disaster intensity and credit risk (CDS spreads). Columns (1) through (3) sequentially present regression results with maturity of CDS for one-year, three-year and five-year. Detailed variable definitions are provided in Appendix A. All regressions include year-, industry- and state-fixed effects. We cluster standard error at firm level. The p-value is reported in parentheses. ***, **, * denoted significance at 1%, 5%, and 10% level, respectively.

	Ln_CDS 1 Year	*Ln_CDS* 3-Year	*Ln_CDS* 5-Year
	(1)	(2)	(3)
lnDisFreq	0.080***	0.063***	0.051***
	(0.000)	(0.000)	(0.000)
SIZE	-0.027	0.003	0.012
	(0.313)	(0.901)	(0.513)
ROA	-3.464***	-2.589***	-2.111***
	(0.000)	(0.000)	(0.000)
LEV	1.412***	1.089***	0.862***
	(0.000)	(0.000)	(0.000)
R&D	-0.533*	-0.257	-0.161
	(0.061)	(0.293)	(0.416)
VOLAT	2.239***	1.765***	1.425***
	(0.000)	(0.000)	(0.000)
AGE	-0.003***	-0.004***	-0.003***
	(0.000)	(0.000)	(0.000)
EXCESS	-0.475***	-0.317***	-0.237***
	(0.000)	(0.000)	(0.000)
TANG	-0.832***	-0.659***	-0.526***
	(0.000)	(0.000)	(0.000)
GROSS	-0.111***	-0.111***	-0.089***
	(0.000)	(0.000)	(0.000)
MTB	-0.031***	-0.025***	-0.019***
	(0.000)	(0.000)	(0.000)
LIQ	-0.168***	-0.142***	-0.115***
	(0.000)	(0.000)	(0.000)
AMIHUD	10.842***	6.251***	4.771***
	(0.000)	(0.000)	(0.000)
Div/Assets	-0.077***	-0.098***	-0.084***
	(0.000)	(0.000)	(0.000)
Ln_IntCov	-0.161***	-0.147***	-0.118***
	(0.000)	(0.000)	(0.000)
Ln_Popmill	-0.411	-0.156	-0.073
	(0.170)	(0.560)	(0.740)
Ln_Gdpmill	0.194	0.18	0.147
	(0.335)	(0.314)	(0.314)
Constant	1.543	2.102	2.476*
	(0.453)	(0.246)	(0.095)
Year Fixed Effects	YES	YES	YES
Industry Fixed Effects	YES	YES	YES
State Fixed Effects	YES	YES	YES
Observations	24,912	24,912	24,912
Adj. R^2	0.61	0.61	0.61

Table 9 - Effect of Financial Access

This table presents the regression results on the moderating effect of financial aceess on the association between firm's exposure to natural disaster intensity and default risk. Detailed variable definitions are provided in Appendix A. All regressions include year-, industry- and state-fixed effects. We cluster standard error at firm level. The p-value is reported in parentheses. ***, **, * denoted significance at 1%, 5%, and 10% level, respectively.

	DD	
	(1)	(2)
	KZ Index	*WW Index*
lnDisFreq	-0.1252***	-0.1205***
	(0.001)	(0.001)
*lnDisFreq*DHFinAcces*	0.1048**	0.0887*
	(0.033)	(0.087)
DHFinAcces	-0.1521*	0.06
	(0.051)	(0.483)
SIZE	0.1012**	0.0531
	(0.022)	(0.254)
ROA	3.8208***	3.6827***
	(0.000)	(0.000)
LEV	-1.8171***	-1.8134***
	(0.000)	(0.000)
R&D	0.5531	0.5506
	(0.248)	(0.250)
VOLAT	-2.8335***	-2.8320***
	(0.000)	(0.000)
AGE	0.0067***	0.0068***
	(0.000)	(0.000)
EXCESS	0.3253***	0.3249***
	(0.000)	(0.000)
TANG	1.0711***	1.0804***
	(0.000)	(0.000)
GROSS	0.2883***	0.2910***
	(0.000)	(0.000)
MTB	0.0472***	0.0467***
	(0.000)	(0.000)
LIQ	0.2552***	0.2548***
	(0.000)	(0.000)
AMIHUD	-7.3333***	-7.4860***
	(0.000)	(0.000)
Div/Assets	0.2307***	0.2324***
	(0.000)	(0.000)
Ln_IntCov	0.2773***	0.2787***
	(0.000)	(0.000)
Ln_Popmill	0.0915	0.118
	(0.868)	(0.830)
Ln_Gdpmill	-0.6272*	-0.6289*
	(0.082)	(0.081)
Constant	8.5632**	8.7666**
	(0.019)	(0.016)
Year Fixed Effects	YES	YES
Industry Fixed Effects	YES	YES
State Fixed Effects	YES	YES
Observations	24,906	24,906
Adj. R^2	0.62	0.62

Table 10 - Effect of Debt Capacity

This table presents the regression results on the moderating effect that firm's debt capacity has on the association between firm's exposure to natural disaster intensity and default risk. Detailed variable definitions are provided in Appendix A. All regressions include year-, industry- and state-fixed effects. We cluster standard error at firm level. The p-value is reported in parentheses. ***, **, * denoted significance at 1%, 5%, and 10% level, respectively.

	DD		
	(1)	(2)	(3)
	LEV	*LLEV*	*DebtMat*
lnDisFreq	-0.1393***	-0.1557***	-0.1050***
	(0.000)	(0.000)	(0.004)
*lnDisFreq*DHDebtCap*	0.1465***	0.1723***	0.0812*
	(0.004)	(0.001)	(0.086)
DHDebtCap	0.6184***	0.5118***	0.0565
	(0.000)	(0.000)	(0.444)
SIZE	0.1456***	0.1473***	0.0927**
	(0.001)	(0.001)	(0.034)
ROA	3.6321***	3.7729***	3.7266***
	(0.000)	(0.000)	(0.000)
R&D	-0.2106	0.0315	0.9821**
	(0.656)	(0.947)	(0.041)
VOLAT	-2.8213***	-2.8586***	-2.8771***
	(0.000)	(0.000)	(0.000)
AGE	0.0095***	0.0093***	0.0093***
	(0.000)	(0.000)	(0.000)
EXCESS	0.2824***	0.3005***	0.3320***
	(0.000)	(0.000)	(0.000)
TANG	0.9509***	1.0459***	0.9368***
	(0.000)	(0.000)	(0.000)
GROSS	0.2191***	0.2319***	0.2657***
	(0.000)	(0.000)	(0.000)
MTB	0.0382***	0.0395***	0.0437***
	(0.000)	(0.000)	(0.000)
LIQ	0.2198***	0.2426***	0.2456***
	(0.000)	(0.000)	(0.000)
AMIHUD	-5.7375***	-6.4848***	-7.3800***
	(0.000)	(0.000)	(0.000)
Div/Assets	0.2145***	0.2121***	0.2253***
	(0.000)	(0.000)	(0.000)
Ln_IntCov	0.2583***	0.2679***	0.3973***
	(0.000)	(0.000)	(0.000)
Ln_Popmill	-0.6769*	-0.6184*	-0.5858
	(0.056)	(0.082)	(0.107)
Ln_Gdpmill	0.2191	0.1866	0.1079
	(0.690)	(0.734)	(0.848)
Constant	8.3973**	7.6198**	7.5822**
	(0.019)	(0.034)	(0.039)
Year Fixed Effects	YES	YES	YES
Industry Fixed Effects	YES	YES	YES
State Fixed Effects	YES	YES	YES
Observations	24,906	24,906	24,906
Adj. R^2	0.63	0.63	0.62

Table 11 - Effect of Operational Risk

This table presents the regression results on the moderating effect of operational risk on the association between firm's exposure to natural disaster intensity and default risk. Detailed variable definitions are provided in Appendix A. All regressions include year-, industry- and state-fixed effects. We cluster standard error at firm level. The p-value is reported in parentheses. ***, **, * denoted significance at 1%, 5%, and 10% level, respectively.

	DD		
	(1)	(2)	(3)
	CFVolat	*OperaCFVolat*	*OperaProfVolat*
lnDisFreq	-0.1071***	-0.1121***	-0.1195**
	(0.004)	(0.002)	(0.019)
*lnDisFreq*DLowvolat*	0.0835*	0.0975**	0.1152*
	(0.099)	(0.044)	(0.062)
DLowvolat	0.2866***	0.2866***	0.2634***
	(0.000)	(0.000)	(0.005)
SIZE	0.0498	0.0592	-0.1583**
	(0.260)	(0.192)	(0.019)
ROA	4.0032***	3.7920***	4.2297***
	(0.000)	(0.000)	(0.000)
LEV	-1.8452***	-1.7344***	-1.9623***
	(0.000)	(0.000)	(0.000)
R&D	0.9974**	1.5265***	-0.2832
	(0.035)	(0.002)	(0.606)
VOLAT	-2.7144***	-2.6887***	-2.7050***
	(0.000)	(0.000)	(0.000)
AGE	0.0049***	0.0048***	0.0036*
	(0.002)	(0.002)	(0.078)
EXCESS	0.3177***	0.3323***	0.3257***
	(0.000)	(0.000)	(0.000)
TANG	1.0415***	1.0023***	1.0559***
	(0.000)	(0.000)	(0.000)
GROSS	0.3088***	0.3100***	0.5295***
	(0.000)	(0.000)	(0.000)
MTB	0.0497***	0.0473***	0.0434***
	(0.000)	(0.000)	(0.000)
LIQ	0.2571***	0.2549***	0.2573***
	(0.000)	(0.000)	(0.000)
Div/Assets	0.2365***	0.2371***	0.2677***
	(0.000)	(0.000)	(0.000)
AMIHUD	-7.3742***	-6.4763***	-9.0345***
	(0.000)	(0.000)	(0.000)
Ln_IntCov	0.2711***	0.2769***	0.2432***
	(0.000)	(0.000)	(0.000)
Ln_Popmill	-0.5074	-0.6241*	-0.0935
	(0.157)	(0.084)	(0.835)
Ln_Gdpmill	-0.0697	-0.0773	0.187
	(0.898)	(0.889)	(0.792)
Constant	7.5190**	8.6668**	2.7411
	(0.039)	(0.018)	(0.547)
Year Fixed Effects	YES	YES	YES
Industry Fixed Effects	YES	YES	YES
State Fixed Effects	YES	YES	YES
Observations	24,906	23,459	15,070
Adj. R^2	0.63	0.63	0.64

Table 12 – Economic Implications

This table presents the regression results on the effect that firm's exposure to natural disaster intensity has on the association between firm's default risk and Ln(spreads) in column (1) and tightness of financial covenants in columns (2) through (3). Detailed variable definitions are provided in Appendix A. All regressions include year-, industry- and state-fixed effects. We cluster standard error at firm level. The p-value is reported in parentheses. ***, **, * denoted significance at 1%, 5%, and 10% level, respectively.

	(1) OLS	(2) Probit	(3) Probit
	Ln_Spreads	DHTight	
		Current Ratio	Tangible Net -Worth
lnDisFreq	-0.0126	0.0605	- 0.4621
	(0.609)	(0.779)	(0.323)
*lnDisFreq*DHdefault*	0.0558*	0.4541*	1.0159*
	(0.063)	(0.071)	(0.080)
DHdefault	0.0705	-0.6205	-1.0295
	(0.136)	(0.152)	(0.289)
SIZE	-0.1501***	0.0115	-0.0987
	(0.000)	(0.908)	(0.555)
ROA	-0.7400***	-2.0923***	-1.7063**
	(0.000)	(0.000)	(0.035)
LEV	0.8402***	-0.7970*	1.3079
	(0.000)	(0.063)	(0.140)
MTB	-0.0003	0.0134	0.0153
	(0.887)	(0.322)	(0.931)
AMIHUD	-0.1684	-0.5516	3.0733
	(0.911)	(0.895)	(0.988)
TOBINQ	-0.1151***	-0.019	-0.1123
	(0.000)	(0.830)	(0.977)
EXCESS	0.0377**	0.0267	-0.1991
	(0.017)	(0.797)	(0.275)
LIQ	-0.0257***	-0.4115***	-0.0906
	(0.004)	(0.000)	(0.155)
AGE	-0.0053***	-0.0164**	0.0388***
	(0.000)	(0.033)	(0.002)
Ln_LoanSize	-0.0461***	-0.0785	0.3013
	(0.001)	(0.470)	(0.212)
Ln_Lenders	-0.0412***	-0.08	-0.6674***
	(0.001)	(0.499)	(0.003)
Ln_Mat	0.0186*	0.1144	-0.315
	(0.078)	(0.290)	(0.126)
DRevolver	-0.1557***	0.2596**	0.4666***
	(0.000)	(0.022)	(0.006)
DPurp_Corppurp	-0.9112***	0.3743**	0.6675**
	(0.000)	(0.013)	(0.037)
DPurp_WorkingCap	-0.8569***	-0.0133	0.3367
	(0.000)	(0.934)	(0.230)
DPurp_Merger	-0.8591***		
	(0.002)		
DPurp_DebtPay	-0.092		
	(0.579)		
OtherPurp	-0.8037***		
	(0.000)		
Constant	7.0919***	-4.8839	-2.4464
	(0.000)	(0.203)	(0.225)

Year Fixed Effects	YES	YES	YES
Industry Fixed Effects	YES	YES	YES
State Fixed Effects	YES	YES	YES
Observations	22,662	838	299
Adj. R^2/ Pseudo R^2	0.48	0.24	0.30

Appendix A – Variable Definitions

Variable Definitions	
Default Risk Measures	
DD	The distance to default: reduced form proposed by Bharath & Shumway (2008).
CDS	Credit default swap spreads: the annualized percentage of the notional value insured.
lnCDS	The natural logarithm of credit default swap spreads.
Natural Disaster Intensity Measures	
DisFreq	Natural disaster frequency: the count of natural disasters occurred in state-year.
lnDisFreq	The natural logarithm of natural disaster frequency.
FinLoss	Financial loss: the natural logarithm of direct recorded financial damages (sum of property and crop loss) resulting from natural disasters in state-year.
HumLoss	Human loss: the natural logarithm of recorded human affected (sum of injuries and fatalities) resulting from natural disasters in state-year.
Control Variables	
ROA	Return on assets: ratio of earnings before extraordinary items to total asset.
GROSS	Gross sales: the natural logarithm of gross sales.
LEV	Leverage: total long-term liabilities over book value of assets.
LIQ	Liquidity: the ratio of current assets over current liabilities.
MTB	Market to book ratio: book assets minus common equity plus the common share outstanding multiply by share price at end of fiscal year, then be divided by book assets.
R&D	Research and development ratio: research and development expenses over total Assets. The R&D sets to zero if they are missing or not be reported.
EXCESS	Stock excess return: the difference between the stock's annual return and CRSP value weighted return.
VOLAT	Stock return volatility: the standard deviation of stock returns in the past 12 months.
AGE	Firm age: the number of years since a firm's incorporation.
SIZE	Firm size: the natural logarithm of total assets in book value.
AMIHUD	Stock illiquidity ratio: the annual average of the daily ratio of absolute value of stock return divided by dollar trading volume, multiplied by one million.
TANG	Tangibility: the net property plant and equipment / total assets.
Div/Assets	Payout ratio: the cash dividend relative to total assets (multiply by 100).
Ln_IntCov	Interest coverage ratio: the natural logarithm of income before interest expenses relative to interest expenses.
Ln_Popmill	Population: the natural logarithm of total population (million) at state level.
Ln_Gdpmill	Economic performance: the natural logarithm of total GDP (million $US) at state level.
Additional Variables	
DHDisFreq	Indicator variable (=1 if the *DisFreq* in a firm's location is higher than median *DisFreq*, =0 otherwise)
DHFinAccess	Indicator variable (=1 if firm's financial accessibility is higher than year-industry median, =0 otherwise).
KZ Index	Kaplan and Zingales index: it can be measured as (-1.002* $cashflow_{i,t}/assets_{i,t-1}$ - 39.368* $dividend_{i,t}/assets_{i,t-1}$ -1.315* $cash_{i,t}/assets_{i,t-1}$ + 3.139* $leverage_{i,t}$ + 0.283* $tobinq_{i,t}$).
WW Index	Whited and Wu index: it can be measures as (-0.091*cashflow – 0.062*Dividend + 0.021*long-term debt/assets + 0.102*firm's two-digital SIC industry sales growth – 0.035*firm's sales growth).

	where Dividend is an indicator variable (=1 if a firm pays cash dividend, =0 otherwise).
DHDebtCap	Indicator variable (=1 if firm's debt capacity is higher than year-industry median, =0 otherwise).
LEV	Financial leverage: (long-term and short-term debt) / (long-term and short-term debt + market value of equity).
LLEV	Long-term financial leverage: (total long-term debt) / (long-term debt + market value of equity).
DebtMat	Debt maturity structure: the percentage of debt that matures in three years.
DLVolat	Indicator variable (=1 if firm's volatility is lower than year-industry median, =0 otherwise).
CFVolat	Cashflow volatility: the annualized standard deviation of a firm's operating income before depreciation scaled by total assets and rolling for 20 quarters.
OperaCFVolat	Operational cashflow volatility: the annualized standard deviation of a firm's operating cashflow and rolling for 20 quarters.
OperaProfVolat	Operational profit volatility: the annualized standard deviation for operating profit adjusted by assets and rolling for 20 quarters.
Ln_Spreads	All-in-drawn spreads: the natural logarithm of all-in-drawn spreads.
Tight	Tight of covenants: the difference between a firm's actual accounting number and initial covenant threshold divided by the standard deviation of a certain accounting number. Lower this ratio indicates higher tightness.
DHTight	Indicator variable (=1 if financial covenants are tighter than year-industry median, =0 otherwise).
DHdefault	Indicator variable (=1 if firm's default risk is higher than year-industry median, =0 otherwise).
TOBINQ	Tobin's Q ratio: market value of assets over book value of assets
Ln_LoanSize	Loan size: the natural logarithm of loan size.
Ln_Lenders	Number of lenders: the natural logarithm of lenders in loan syndication.
Ln_Mat	Loan maturity: the natural logarithm of loan's maturity (in months).
DRevolver	Loan type indicator (=1 if type of loan is revolver, = 0 otherwise) The revolver loan includes 364-day facility, Revolver/Line < 1 year, Revolver/Line P 1 year, Revolver/Term Loan, Bridge Loan, Demand Loan, Guidance Line (Uncommitted), Limited Line, Multi-Option Facility, or Standby Letter of Credit.
DPurp_Corppurp	Loan purpose indicator (=1 if purpose of loan is expenditure in general corporate, = 0 otherwise).
DPurp_Workingcap	Loan purpose indicator (=1 if purpose of loan is to raise working capital, 0 otherwise).
DPurp_Merger	Loan purpose indicator (=1 if purpose of loan is to finance merge and acquisition, 0 otherwise).
DPurp_DebtPay	Loan purpose indicator (=1 if purpose of loan is to repay debt, 0 otherwise).
OtherPurp	Other purpose indicator (=1 if purpose of loan is not listed above, 0 otherwise).
Post	Time indicator variable (=1 if observation in post-relocation period, 0 otherwise).
DDisasterIncrease	Treatment indicator variable (=1 if a firm relocates to more disaster-prone state, 0 if a firm relocates to less disaster-prone state).

Appendix B – Distance-to-default (Bharath & Shumway, 2008)

The first step is to assume that the face value of firm debt is equivalent to the market value of firm debt, which is denoted as:

$$Markt\ Value\ (\ D) = Face\ Value\ of\ Debt\ (F)$$

The next step is to calculate the volatility of firm debt as follows:

$$\sigma_{\text{debt}} = 0.05 + 0.25 * \sigma_{\text{ equity}} \quad (1)$$

The third step is to derive the total volatility of the firm which considers both equity and debt. This calculation is as follows:

$$\sigma v = \frac{E}{E+F}\ \sigma E + \frac{F}{E+F}\ \ (0.05 + 0.25 *\ \sigma E)\ \ (2)$$

The fourth step is to use the firm's one-year historical return as a proxy for the expected return on firm assets. This can be denoted as:

$$\mu = r_{\text{i,t-1}} \quad (3)$$

Since the above steps provide all of the inputs for Merton's *DD* model, *DD* can be calculated as:

$$DD = \frac{\ln\left[\frac{E+F}{F}\right] + (r_{\text{i,t-1}} - 0.5\ \sigma_V^2)\ T}{\sigma_V \sqrt{T}} \quad (4)$$

where E is a firm's market value of equity and F is a firm's face value of debt. $r_{\text{i,t-1}}$ is the firm's one-year historical stock return. σE is a firm's return volatility during year t estimated from the monthly stock return from the previous year. σv can be calculated based on equation (1). The default setting for T is one year.