EFFECTS OF NATURAL DISASTERS ON LENDER BORROWER RELATIONSHIP

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EFFECTS OF NATURAL DISASTERS ON LENDER BORROWER RELATIONSHIP

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Effects of Natural Disasters on Lender-Borrower Relationship

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DECLARATION OF ORIGINALITY

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- this thesis contains no material that has been submitted or accepted for a degree or diploma in any other educational institution;
- his is a true copy of the thesis approved by my advisor and thesis committee at Boğaziçi University, including final revisions required by them.

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ABSTRACT

Effects of Natural Disasters on Lender Borrower Relationship

The classical objective of firm value maximization has ceased being the most important target. What has been discussed in literature and in practice is more about sustainable value creation and the focus is not on monetary terms. The most widely referred concept is ESG (Environmental, Social, and Governance) analyses through which firms are evaluated based on the impact of their actions on the environment, society, and within their governance practices, and widely accepted as a component in financial relationships. There is a rich literature explaining the relationship between ESG score changes and loan costs (Gianetti et al., 2023; Becchetti and Manfredonia, 2022). Natural disasters have recently been introduced as a concept that can be thought of with the ESG concept. Huang et al. (2022) reveal that following a natural disaster firms tend to be more transparent while making ESG-related disclosures. In this study, we explore natural disasters and bank loan cost relationships by referring to loan spreads, and we introduce ESG profiles as a mediating metric. We use loan-level data from DealScan, natural disaster data from SHELDUS, ESG data from RepRisk, and company financial information from Compustat. Conducting a hierarchical regression model, we observe a positive significant relationship between natural disaster occurrences and loan spread increases. Introducing the RepRisk profile of firms, we try to estimate the mitigating impact of each pillar of ESG and ESG in general. We find a significant relationship between environmental, social, governance, and ESG events and loan spread increases, however, some of these relationships contradict our expectations in terms of directions.

ÖZET

Doğal Afetlerin Borç Veren ve Borçlu İlişkisi Üzerindeki Etkileri

Firmalar için uzun yıllar boyunca klasik hedef olan firma değeri maksimize etme artık en önemli amaç olmaktan çıkmıştır. Literatürde ve pratikte, parasal terimler dışındaki kavramlarda sürdürülebilir değer yaratma konusu, son zamanlarda daha çok konuşulan bir hedef haline gelmiştir. Bu bağlamda en çok başvurulan kavram, firmaların eylemlerinin çevreye, topluma ve yönetişim uygulamalarına olan etkisine göre değerlendirildiği ve finansal ilişkilerin bir bileşeni olarak kabul edilen ÇSY (Çevresel, Sosyal ve Yönetişim) analizleridir. ÇSY puan değişiklikleri ile kredi maliyetleri arasındaki ilişkiyi açıklayan literatür oldukça zengindir (Gianetti ve diğerleri, 2023; Becchetti ve Manfredonia, 2022). Doğal afetlerin son dönemde literatürde ÇSY kavramıyla birlikte konumlandırıldığı görülmüştür. Huang ve diğerleri (2022), bir doğal afetin ardından firmaların ÇSY açıklamalarında daha şeffaf olmaya eğilimli olduklarını ortaya koymuştur. Bu çalışmada, kredi maliyetlerini bağımlı değişken olarak ele aldık ve doğal afetler ve banka kredisi maliyet ilişkilerini, firmaların ÇSY profilini aracı bir ölçüt olarak sunarak inceledik. Kredi düzeyindeki verileri DealScan veri setinden, doğal afet verilerini SHELDUS veri setinden, ÇSY verilerini RepRisk veri setinden ve şirket mali bilgilerini Compustat veri setinden topladık. Hiyerarşik regresyon modeli uyguladığımızda doğal afetler ile kredi maliyetleri artışları arasında pozitif yönde anlamlı bir ilişki gözlemledik. Firmaların RepRisk profilini sunarak, ÇSY'nin ve ÇSY kırılımlarının ayrı ayrı olmak üzere hafifletici etkisini tahmin etmeye çalıştık. Çevresel, sosyal, yönetişim ve ÇSY olayları ile kredi maliyet artışları arasında, bazılarının yön olarak beklentilerimizle çeliştiği fakat istatistiksel olarak anlamlı olduğu ilişkiler bulduk.

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CHAPTER 1

INTRODUCTION

In classical finance, the ultimate goal of a corporation is emphasized as maximizing the firm value. Nevertheless, in the past couple of decades, the focus has shifted, placing greater emphasis on responsible value creation. Unlike the relatively straightforward task of constructing a valuation model, evaluating the sustainability of operations presents a more complicated challenge. To address this, established metrics have been developed to assess the degree of responsibility in value creation. One such widely adopted metric is ESG scoring, routinely considered by both investors and lenders as a standard practice in their financial decision-making processes when evaluating the corporate profile.

The intensity of natural disasters has become a focal point of discussion—questioning whether they have genuinely intensified over time and how much they cost society. These costs vary from tangible damages to intangible losses. While estimating the intangible consequences might be challenging, the monetary outlays required for recovery can be explicitly assessed immediately following a natural disaster's impact on a region. This explicit cost assessment should span from micro to macro levels, encompassing small and medium-sized enterprises (SMEs) up to governmental bodies. Given the broad spectrum of stakeholders affected, exploring the tangible impacts of natural disasters on funding relationships emerges as a noteworthy subject for discussion within the existing literature.

In 2023, the world witnessed a multitude of natural disasters, with notable events including the earthquake in Turkey and Syria and the flood in Libya—each incurring costs in the billions of dollars. Regardless of whether the severity of natural

disasters is on the rise, their occurrence remains inevitable, leading to substantial and costly damages. Addressing the financial reflections of these unpredictable events and ensuring sustainable financial and economic development necessitate a critical examination of how they are managed within financial decision-making processes.

ESG-related activities have been extensively examined in the realm of lender-borrower relationships. Conversely, literature with a specific emphasis on the influence of natural disasters on lending relationships is still in its developmental stage. Integrating the concept of natural disasters into ESG practices poses challenges, yet this established framework can serve as a mediating factor in exploring potential impacts.

CHAPTER 2

LITERATURE REVIEW

This research focus is based on three main themes - natural disasters, borrowing relationships, and ESG practices. To provide the basic knowledge, the literature review starts by introducing natural disasters - the definition and types, how and by whom they are closely followed and monitored, the natural disaster profile of countries, and the impacts of natural disasters. Followingly, financial institutions and debt instruments are introduced. The second part of the literature includes the definition and types of financial institutions, the reason we have them, and the definition of capital structure and debt instruments. This research uses loan-level data; therefore, only debt securities of the capital instruments are referred to in the literature. Lastly, the ESG concept is reviewed as the third part of the literature. In that part, the evolution and practical importance of the concept are represented.

2.1 Natural disasters

2.1.1 The definition and types

Parker (1992) defines a disaster as an unexpected event inhibiting the coping mechanism of human beings or nature, due to natural or man-made reasons, and resulting in unwanted consequences. Nevertheless, it is accepted that providing one standard disaster definition and a precise list of disaster types is difficult. The following classification of disasters into three broad categories is considered to be covering almost every type of disaster. These categories are namely (i) man-made, (ii) hybrid, and (iii) natural disasters (see Figure 1) (Shaluf, 2007).

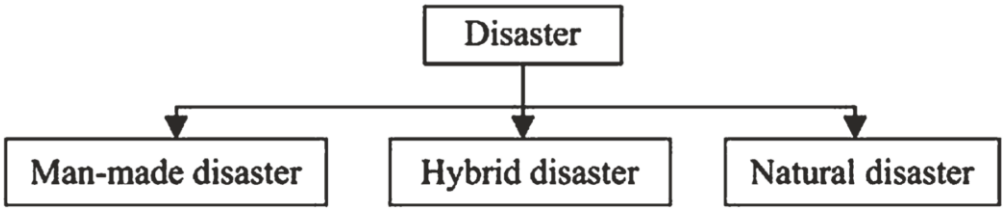

Figure 1. Disaster types

Similar to the disaster definition of Parker (1992), Alexander (1993) defines a natural disaster as an unexpected and rapid physical event, due to natural causes, that results in negative outcomes and; therefore, affects society in terms of lives and properties. This being a broad description, more specific definitions can also be made. For instance, from an economic perspective, a natural disaster can be considered as a natural event that interrupts the economic system so that it cannot maintain its main functions such as production, employment, and consumption (Hallegatte & Przyluski, 2010). The distinction between a natural and man-made disaster is coming from the underlying cause. Unlike a natural disaster, any catastrophic event that happened because of human decisions is considered to be a man-made disaster. A mine collapse could be given as an example of a man-made disaster, as there is no natural force causing this event to happen. Hybrid disasters, lying in between natural and man-made disasters, are unforeseeable events due to both natural and human-decision-related causes. Erosion is a proper example to think of - deforestation catalyzing the landslide by rainwater (Shaluf, 2007).

Pidgeon (1997) puts natural disaster types into four categories: (i) events happening on the earth's surface, (ii) topographical events, (iii) meteorological/hydrological events, and (iv) biological events. Some of the examples under each category are listed below (See Figure 2).

Natural Disaster Types			
On the earth's surface	Topographical	Meteorological / hydrological	Biological
Earthquakes Tsunamis Volcanic eruptions	Landslides Avalanches	Windstorms Floods Droughs	Epidemics Pandemics

Figure 2. Natural disaster types
Note. Pidgeon, N. (1997). The limits to safety? Culture, politics, learning and man-made disasters. *Journal of Contingencies and Crisis Management, 5*(1), 1–14

2.1.2 Agencies

There are agencies operating globally with the aim of better managing before- and after-disaster periods. Such agencies could also undertake the responsibility of delivering proper training to people, providing useful information, and gathering and sharing data regarding the disasters. The United Nations Environment Program (UNEP-APELL) and the World Health Organization (WHO) are two of the most active agencies.

Founded in 1986, UNEP-APELL aims to create awareness and have the community prepared for potential hazards. Likewise, WHO, another UN agency, delivers strategic risk assessments regarding disasters and the results, and targets to take emergency action promptly (WHO, n.d.).

These agencies could also have their definition and categorization of disasters. For instance, UNEP-APELL divides the disaster types into four: (i) natural disasters, (ii) technological disasters, (iii) transport disasters, and (iv) tailing dam failures. Also, the agency has a database providing data on natural and technological disasters (UNEP, 2019).

2.1.3 World natural disaster profile

One comprehensive measure scoring and ranking countries in terms of their natural disaster risk profiles is WorldRiskIndex (WRI) which calculates the risk as the intersection point of exposure and vulnerability. Exposure refers to the population dispersion in risky locations - natural disaster safe or not. Vulnerability, on the other extreme, refers to the level the society is likely to be damaged by natural disasters. Under vulnerability, several concerns are raised such as, how resilient the society is towards natural disasters, what resources the society has to ease the negative results, how the society accepts a natural disaster and starts the recovery process to be reflected in long-term activities. Considering such indicators, and also referring to some key indicators released by supranational institutions, WRI is disseminated annually.

There are several findings from last year's report worth highlighting. The very first one is that global disaster risks are clustered around regions where poverty and inequality are major issues. Secondly, when continents are compared according to their risk profiles, America ranks first followed by Asia, like in previous years, and Europe remains way below the median risk of all continents. Last but not least, among 193 countries ranked, the Philippines ranked first with the highest risk, followed by Indonesia and India (Auer-Frege et. al., 2023). In line with the findings, in 2022, the United States was named as the country that experienced the most natural disasters, where Indonesia and the Philippines came second and fourth, respectively (CRED,2023).

2.1.4 Effects and measurement of natural disasters

It is beyond doubt that not every country is affected by a natural disaster to the same degree. Low-to-middle-income countries suffer more from a disaster, as governments' budget allocation may not prioritize preparedness for a potential risk that includes training of people and staff, infrastructural changes or fortifications, and emergency plans. On the contrary, in developed economies, actions are taken before natural disasters as they invest time and money in such precautions essential for the decrease of the number of deaths and other impacts. These economies also take advantage of established banking systems and private sectors that are also important contributors to the recovery in addition to governments (Kreimer, 2001).

In foreseeing the potential impact, it is useful to assess the frequency and intensity of natural disasters. For instance, a tsunami happens at a very low frequency, but its impact is quite intense. Compared to a natural disaster with low intensity, a tsunami would be more deadly; thus, the preparation for it should be quite different.

Although natural disasters are not preventable, proper measures could have a significant influence in decreasing the number of deaths. An appropriate demonstration is the change in the number of deaths caused by natural disasters between the first and second halves of the 20th century. The numbers in the first half were reaching a peak at a million, whereas the numbers in the second half were not exceeding half of a million. Surprisingly though, the annual death numbers caused by natural disasters are reported to constitute 0.01% of the overall deaths globally (Ritchie, Rosado, & Roser, 2024).

2.1.5 Costs and other impacts

Natural disasters result in unwanted consequences and these consequences come with costs. These costs, also referred to as losses, can be examined as (i) direct and (ii) indirect costs. Direct costs represent the damage natural disaster causes immediately. In scenarios where the losses to goods and services can be replaced at an assessable price, the cost is categorized as direct market loss. In the other scenario, it is not possible to assess the price it takes to recover the damages a natural disaster caused; therefore, referred to as direct non-market loss. Some examples of direct non-market losses can be considered as deaths and damages to the ecosystem. Indirect losses, on the other hand, are not occurring directly due to the disaster, but due to the consequences it created. For instance, an earthquake would cause some operations of production facilities to stop which, in return, would cost the economy. The longer the recovery progress from consequences takes, the more costly the indirect impact becomes. Likewise, if a disaster has an impact on more than one sector, the indirect cost is going to be higher (Hallegatte & Przyluski, 2010). Following the period after natural disasters, what is discussed as cost generally refers to the direct losses. However, for a comprehensive recovery process, considering indirect losses has the same degree of importance. Indirect losses may need rigorous focus since they are hard to express in a quantifiable way and their emergence may take a longer time (Kreimer, 2001).

Natural disasters influence different facets of life. Unquestioningly, the economic impacts of natural disasters come to one's mind first when thinking of these possible influences. For a better examination of economic impacts, focus is divided into short-to-medium and long-term periods. Short-to-medium-term impacts refer to the damages resulting in malfunctioning in economic systems for up to 5

years. Deaths and injuries in labor forces and damages to physical assets create an immediate cost to economies through interruptions in production and that is considered to be more effective for the near future (Panwar & Sen, 2018). Recovery from the damages observed in shorter periods is to take time; therefore, these damages are in effect also for long-term periods. In either time frame, once again, impacts are more pronounced for emerging economies since the money needed for recovery could be used for investments with a higher marginal contribution than the same investment would make to an advanced economy. Countries with higher literacy rates, higher income per capita, and high openness to trade help ease the economic impacts and recover at a faster pace (Noy, 2009).

2.2 Financial institutions and debt instruments

2.2.1 Definition and types of financial institutions

Financial institutions act as a liaison between savers and borrowers and play an intermediary role in economic systems. Savers are the ones with excess money that they are willing to invest and create sources for funds. Also referred to as "investors" or "depositors", savers can be households or institutions. Borrowers, on the other hand, lack funds and need credits to fund their investments or purchases.

Financial institutions have an indispensable position in economic systems because they foster growth by allocating financial resources. In the absence of such institutions, only businesses and individuals with money on hand were able to engage in production activities or purchase goods, while the rest without money on hand today were not able to engage in transactions. The great responsibility of financial institutions brings regulatory bodies into the picture. As dysfunctioning of

these institutions would cause a panic in the system, and might even create a crisis, governments closely regulate their activities.

To better understand what makes financial institutions irreplaceable, the "information asymmetry" concept should be well discussed. When one party is more informed than the other or does not represent its financial position honestly, parties generate different evaluations of the transaction. The groundbreaking approach to the phenomena is proposed by Akerlof (1970). Often referred to as "Lemons Market", he models the asymmetric information problem through the market for used cars. About the situation of cars, sellers know more than buyers; therefore, have incentive to sell bad cars at the same price as good cars. As bad cars are being sold and used by buyers, there is a sentiment regarding the quality of the cars in the market. The number of buyers willing to pay the price of good cars decline since they question the probability of cars being of good quality. As a return, the average car quality drops, and only bad cars ("lemons") remain in the market. The same is true for the credit market. Informed borrowers misrepresenting themselves could receive funds at a lower cost; however, lenders need time to assess the riskiness of borrowers as the payment period helps lenders to collect information about the borrower. In scenarios where information asymmetry problems are severe, lenders tend to select bad quality borrowers and this is referred to as adverse selection. The other consequence of asymmetric information is the moral hazard problem occurring when one of the parties gets into the transaction with bad intentions. This party is generally the borrower and uses the fund to invest in risky projects with the motivation that the lender is not able to monitor its activities after the transaction (Diamond, 1989).

Adverse selection and moral hazard problems can be overcome with monitoring. Before the transaction, a detailed examination helps lenders produce

information regarding the borrower and eliminates information asymmetry between parties. Likewise, close monitoring of the activities of borrowers after the transaction enables lenders to be informed whether risky investments are undertaken or not. Even though it eases the impacts of adverse selection and moral hazard, monitoring is a costly control mechanism. Financial institutions have expertise in monitoring and the ability to scale the cost. This is what puts them into an irreplaceable position in the economic systems.

Financial institutions offer a wide range of goods and services. This range causes the emergence of financial institutions with different focuses. Some of the most common examples are as follows. Commercial banks are responsible for collecting deposits from creditors and selling them as credits to borrowers. Investment banks provide services for transactions between corporations like initial public offerings (IPOs) and mergers and acquisitions (M&As). The scope of investment companies is to issue and invest in securities. As an example of non-bank financial institutions, insurance companies offer protection for real or financial assets.

2.2.2 Capital structure theories

Capital structure refers to the proportion of debt and equity usage of companies, to maintain their ongoing operations and undertake new investments. The foundations of modern capital structure theory were laid by Modigliani and Miller (1958). They proposed that, under the assumption that no taxes and no bankruptcy cost exist, the value of a levered firm should be the same as the value of an unlevered firm. Paying no tax being an unrealistic scenario, they proposed that using as much debt as possible is the optimal capital structure because interest paid over debt decreases the

taxable income. Debt issuance acts as a “tax shield”; therefore, increases the value of the levered firm by the amount of tax shield. However, debt issuance has a cost of financial distress, which may end in bankruptcy, and it was neglected in their model. As a correction to the initial model, bankruptcy cost and personal tax over gains are imposed. The correction introduces that there is an optimal mix of debt and equity financing where the marginal benefit of tax shield is balanced with the cost of debt financing and referred to in the literature as trade-off theory (Modigliani & Miller, 1963; Miller, 1977).

Pecking order theory, an alternative to trade-off theory, is proposed by Myers and Majluf (1984). The logic of this theory is based on asymmetric information phenomena - managers know more about the prospects of firms than that outside investors do. Therefore, among three sources of finance - internal funds, debt, and new equity, equity issuance is interpreted as the overvaluation of shares. This information asymmetry is expected to be compensated for and cause a decline in share prices. Debt financing, on the other hand, reflects the positive anticipation and trust of the company in the project and confidence in its ability to repay. What this theory suggests, all in all, is that equity should be used in financing as a last resort.

2.2.3 Debt instruments

Debt instruments are tools used for capital raising purposes through agreements between two parties with specified terms. These terms include the loan amount - how much to be lent, maturity date - the due date the loan is expected to be repaid, payment method and schedule - how and on which specific days payments will be made, and interest rate - the cost of borrowing to the borrower. The parties are the

lender - who is willing to lend the amount requested, and the borrower - who asks for the loan and agrees to pay upon the specified terms.

Two general types of debt instruments are loans and bonds. In loan agreements, lenders are generally financial institutions. Bonds, on the other hand, are designed to collect money from the public, instead of a specific institution or couple of institutions coming together to fund jointly. Bond issuance can be made by governments, municipalities, and corporations. In bond financing, the amount to be lent is shared among many lenders - i.e. public, based on their preferences. That decreases the risk compared to loan agreements in which one party is providing the full amount of the fund and bears all the risk alone. Therefore, bond issuance enables funding at a lower interest rate compared to loan issuance. Bond payments are referred to as coupon payments and are cost to the borrower. Paid according to the rate predetermined in the agreement, these payments are usually made semi-annually. The principal amount is paid in total on maturity. In loan agreements, on the other hand, payments consist of part of the principal amount and interest payment over the remaining amount. Like bond agreements, interest to be paid through the life of the loan is stated in the agreement.

Debt agreements are not necessarily between one lender and one borrower. Both sides can have more than one party involved. Syndicated loans, for instance, are a type of loan agreement with multiple lenders. When the amount to be given is too large for a single lender to provide or the risk is beyond the tolerable level for a specific financial institution to bear, more than one lenders come together and agree upon jointly funding the borrower. Such loans are referred to as syndicated loans (Amiram, Beaver, Landsman, & Zhao, 2017).

Debt instruments can be classified according to different criteria. In its most general form, they are grouped based on maturities. Instruments with maturities up to one year are considered as short-term obligations whereas others maturing in a period longer than one year are referred to as long-term obligations. Another classification criterion is the seniority level of debt - the order of investor groups being repaid in case of bankruptcy. The top priority belongs to the group investing in senior secured debt instruments that are backed with collaterals. The ranking is followed by senior unsecured, senior subordinated, and subordinated debt instruments. The higher the ranking of instruments, the higher they are priced and the lower the risk they bear. In parallel, riskiness can be used as one other classification point. Corporations or banks evaluate the payment ability of the issuer and assign risk profiles to potential borrowers. Also referred to as "credit analysis", this process can be outsourced for parties that are not able to conduct necessary evaluations within the organization. The three most prestigious worldwide credit rating agencies are Moody's, Standard & Poor's, and Fitch Ratings. Slightly differing from each other's rating scale, a generalized interpretation can be attributed. Among rating groups of bonds, the top half is called "investment-grade" whereas the other half is referred to as "non-investment grade" instruments. Similar to these references, loans are also grouped into two and named "investment-grade loans" and "leveraged loans". For both of the debt instruments, the first classifications indicate the safeness of the profiles of the issuers.

2.3 ESG

2.3.1 Definition and history

ESG score refers to environmental, social, and governance, and represents those components as a single factor by taking different indicators into account for each. For clarification, CO_2 emission, undertaking non-profit projects concerning the well-being of society, and transparency within the organizations can be considered as examples under environmental, social, and governance components, respectively.

It is worth highlighting the differences between the terms Corporate Social Responsibility (CSR) and ESG as they are frequently mixed and mistakenly used interchangeably. CSR is an older concept than ESG and dates back to the early 1900s. No unified definition was provided back then; however, a thorough description made by Carroll (1979) is accepted widely. In his conceptual model, he defines CSR as "the social responsibility of business encompasses the economic, legal, ethical, and discretionary expectations that society has of organizations at a given point in time." In the last couple of decades, the increasing pressure and concern of investors regarding the sustainability of the corporations' activities have brought CSR on the stage again and caused the emergence of the ESG concept - a version of CSR focusing on environmental, social, and governance activities. The concept adopts metrics to quantify the degree of responsibility for actions corporations take within a specific perspective (Hazen, 2021).

A controversial point regarding the ESG concept and its implementation is that releasing ESG-related information is voluntary; therefore, there is no regulatory body enforcing such disclosures in a standard format. Despite its voluntary nature, disclosing ESG-concerned information is a common practice for corporations, especially for public firms, as shareholders have a strong appetite to learn to which

extent the operations are responsible. However, the lack of standardization causes debates in the literature. One example of these debates is the weak influence of the Securities and Exchange Commission (SEC) regarding disclosure regulation. There is a demand for the SEC to provide more involvement in corporations' ESG disclosure and constitute a standard form of reporting by both industrial stakeholders and scholars. So far, the SEC has only been involved in giving advising services to firms disclosing ESG-related information (Hazen, 2021). Another example of controversy can be given as the transparency concern with the ESG-related disclosures of firms. As there is no regulatory body enforcing standard reporting, firms voluntarily disseminating information should also build trust in the eyes of the stakeholders. Related to that, whether firms are likely to over-promote positive news with the potential of improving their ESG scores and are highly likely to choose not to disclose negative news creates a concern. The voluntary nature of the disclosure creates information asymmetry since outsiders do not have access to the information to help them test the accuracy of the news. Therefore, disclosing ESG-related information can be used as a tool by firms to manage their reputation. For instance, firms underperforming environmentally tend to make more comprehensive disclosures in order to protect their environmental pillar scores (Cho et al., 2012). Linguistically investigated, again, firms with unsatisfying environmental performance are found to use more positive language while making disclosures to conceal their bad performance (Cho et al., 2010). Surprisingly, this is not always the case and some firms are also disclosing negative information with the intuitive expectation of harmful impact on their ESG scores. Firms that also reveal negative information are considered to establish more candid communication with the stakeholders; therefore, their authenticity is considered stronger. As a return, when

they publish positive information, stakeholders question the reliability less compared to the releases of firms not sharing negative information (Cho et al., 2022). One other question arises because rating agencies are generally paid by the companies to be rated. Companies in question hire rating agencies, provide information to them, and pay for the process to be undertaken so that these companies have their ESG ratings published by established institutions. However, that paying side is the company to be rated creates doubt about whether the rating agencies are independent or not (Windolph, 2011).

Although there are unsolved concerns regarding ESG scores and disclosures, there is a significant demand by investors to be informed regarding the company operations and their level of sustainability. To gratify the demand, rating agencies emerged as trusted third parties to evaluate operations and generate ESG scores. On the other hand, the extent of the ESG score is not well-defined. The events to be considered are not pre-listed and there is no right or wrong way of computing the score. This fact makes defining and computing the metric both difficult and subjective and causes the establishment of different rating agencies with each of them having their way of score calculations (Escrig-Olmedo et al., 2019).

As the number of parties relying on the calculations of these agencies is significant, the responsibility these agencies undertake is delicate; therefore, requires them to establish and maintain the methodology meticulously.

Despite the equivocal nature of different methodologies, the advantages rating agencies present are undeniable. Firstly, there is no feasible way for stakeholders, investors, or researchers to assess a company's operations and the degree to which they are sustainable. This fact makes companies informed parties and the rest as an uninformed side which resulted in an information asymmetry

problem. Rating agencies serve as liaisons - trusted third parties, in collecting necessary information and processing them to deliver a meaningful output. Secondly, the stronger the trust these agencies build in the eyes of the public, the wider the use of their calculations. In return, widely used metrics become a standard to a certain extent, and comparison of company performances becomes easier (Clement et al., 2023). Furthermore, most ESG rating agencies also provide their metrics with a stock index through which the performance is directly reflected in prices. For firms, belonging to such an index can act as both a control mechanism and a reputational indicator which can be considered as an additional advantage rating agencies bring in (Mackenzie et al., 2013).

Three of the ESG rating agencies widely being referred to can be listed as MSCI, Refinitiv, and RepRisk.

MSCI is an ESG rating agency providing rating services to companies around the world for over a decade. MSCI metric focuses on a total of 10 themes for environmental, social, and governance pillars. Under these themes, a sum of 33 key issues are identified and reviewed for the ESG score. Scores are adjusted according to industries and disseminated at a seven-point letter ranging from AAA (highest ESG score) to CCC (lowest ESG score) (MSCI, 2024).

Refinitiv is a financial data and infrastructure provider and delivers ESG score assessments, as well. Having one of the greatest coverage, the database relies on corporate public reports and global media sources and reports different types of scores. Like MSCI, Refinitiv also defines a total of 10 themes under E, S, and G pillars. The score is delivered as an output for each of these pillars separately, as well as an aggregate single ESG score (Refinitiv, n.d.).

RepRisk, different from other ESG score providers, integrates AI and machine learning into its methodology. There are a couple of features RepRisk ESG Risk Platform promotes as their key strength. It overviews important ESG-related updates of more than 255,000 firms on a daily basis and in 23 languages. To that extent, RepRisk is known as one of the most comprehensive ESG databases. The sources of the database are different media channels, regulatory bodies, and online sources from local to international level but the agency excludes self-disclosures of companies as the authenticity of such disclosures is still in question. Thanks to its precisive features, RepRisk ESG Risk Platform, created in 2006, is a trusted due diligence provider to different types of organizations around the world. The platform shares its analyses as two outputs - RepRisk Index (RRI) and RepRisk Rating (RRR). RRI ranges from 1 (lowest) to 100 (highest) and shows the level of criticism the company experiences. If the company is facing a high level of criticism, the score rises and approaches zero if there is no criticism regarding the company. RRR, on the other hand, states the ESG score of companies as letter grades ranging from AAA (highest) to D (lowest) (Reprisk, 2023).

One advantage ESG metric provides for investors, stakeholders, and other interested parties is that, in addition to the financial risk the firm bears, other risks are also reflected. The wide use of the metric is now considered a competitive advantage when firms could result in high ESG scores (Galbreath, 2013). Additionally, the information ESG scoring provides is not limited to the industry but also researchers and academicians frequently refer to these outputs in their studies (Mackenzie et al., 2013).

CHAPTER 3

PREVIOUS STUDIES, RESEARCH DESIGN & HYPOTHESES

It is undeniable that changes in our environment unfold at an observable pace, prompting society to shift away from prioritizing financial returns as the sole consideration. This evolving concern is already evident in the lending practices of financial institutions. Perhaps owing to its comprehensive coverage of various components or its well-established methods of quantification, the ESG concept has emerged as a core metric in evaluating firms as borrowers. The extensive literature on this subject offers diverse insights into these phenomena.

Newton et al. (2022) critically investigate the influence of ESG scores on the dynamics of lender-borrower matching. Their findings indicate that companies yielding high ESG scores are inclined to form lending relationships with banks that share similarly strong ESG scores. Additionally, within these relationships, firms with superior ESG ratings tend to secure loans at a lower cost, benefitting from less rigorous covenant procedures.

Contrastingly, the striking results uncovered by Giannetti et al. (2023) present a different perspective. Through an examination of ESG disclosures made by banks, their study reveals no reduction in lending to environmentally less sustainable (brown) firms, even as the comprehensiveness of these disclosures increases. In the context of long-term relationships, these banks persist in extending credit to brown firms without an associated increase in costs.

Becchetti and Manfredonia (2022) delve into the correlation between fluctuations in ESG scores and loan costs. Their study utilizes RepRisk as an ESG database, which assesses scores based on news coverage, hence referred to as reputational risk within the paper. The authors highlight relationship banking as a

strategic hedge for companies facing adverse events that harm their CSR (Corporate Social Responsibility) profile. Firms initiating a relationship with banks when their CSR indicators are favorable experience less impact on loan costs during periods of negative media coverage. Conversely, any action leading to a decline in reputation results in an increase in lending costs, with a more pronounced effect on firms that have not previously established a banking relationship.

Similarly, Javadi and Masum (2021) yield parallel results in their paper questioning if banks consider climate change as a risk factor to be considered while making a loan contract. Their findings show that firms located in areas with higher exposure to climate risk contract debt at a higher spread.

In their recent studies, Huang et al. (2022) adopt a more focused perspective, examining shifts in ESG disclosures by firms after the occurrence of natural disasters. Their findings reveal that following such events, firms tend to enhance the transparency of their ESG-related disclosures. This heightened transparency is attributed to an amplified perceived risk by investors. Such an increase in transparency can be interpreted as a strategic response by managers, aimed at mitigating the perceived risk and concerns of investors.

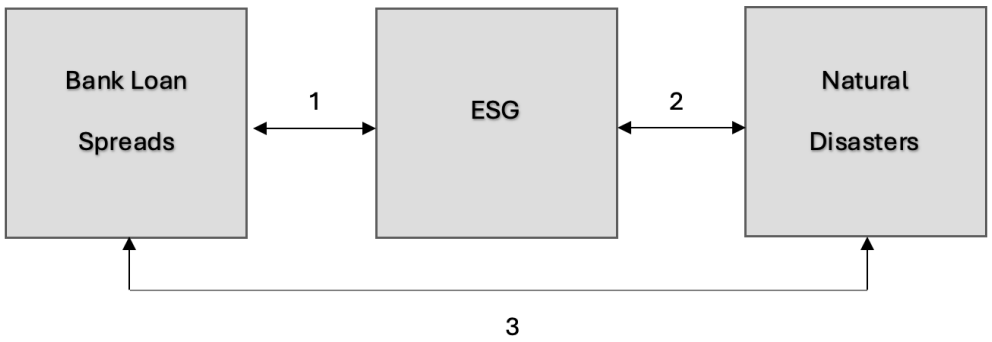

Figure 3. Literature depiction

As discussed above, contemporary literature sheds light on the impacts of ESG disclosures, CSR activities, and climate risks on loan costs. Represented with arrow number 1 in Figure 3, the research of Newton et al. (2022), Gianetti et al. (2023), Becchetti and Manfredonia (2022), and Javadi and Masum (2021) contribute to that part of the literature. The work of Huang et al. (2022) examines natural disasters and whether they affect ESG disclosures which is represented with arrow number 2.

To provide a different perspective, we aim to answer the research question of whether natural disasters cause any changes in borrowing costs by approaching the question by looking at the natural disasters happening in the county in which the headquarters of the companies are located. In our model, we refer to ESG reputation as a mediating metric and try to see if a strong ESG profile could protect firms from loan cost increases following a natural disaster. We showed our research focus among existing literature with arrow number 3.

Upon reviewing the existing literature, it is apparent that natural disasters heighten investors' risk perception, compelling businesses situated in disaster-prone regions to improve transparency in their ESG disclosures. In addition, there is mounting evidence that ESG profiles of companies have a strong influence over borrowing costs. Having said that, we propose two following main hypotheses of the study:

H1: The occurrence of natural disasters in the twelve months prior to a deal is positively associated with an increase in loan spreads.

H2: The ESG reputation of borrowers moderates the positive relationship between natural disaster occurrences and loan spreads, such that this positive relationship is weaker for borrowers with a lower number of RepRisk events.

Given RepRisk's detailed approach to capturing events, we anticipate that analyzing each pillar (Environmental, Social, and Governance) individually, as well as the overall ESG score, will provide more insightful results. Therefore, we have divided H2 into four separate hypotheses:

H2a: The environmental reputation of borrowers moderates the relationship between natural disaster occurrences and loan spreads such that firms with a lower number of RepRisk events in the last twelve months experience a weaker positive relationship between natural disaster occurrences and loan spreads.

H2b: The social reputation of borrowers moderates the relationship between natural disaster occurrences and loan spreads such that firms with a lower number of RepRisk events in the last twelve months experience a weaker positive relationship between natural disaster occurrences and loan spreads.

H2c: The governance reputation of borrowers moderates the relationship between natural disaster occurrences and loan spreads such that firms with a lower number of RepRisk events in the last twelve months experience a weaker positive relationship between natural disaster occurrences and loan spreads.

H2d: The ESG reputation of borrowers moderates the relationship between natural disaster occurrences and loan spreads such that firms with a lower number of RepRisk events in the last twelve months experience a weaker positive relationship between natural disaster occurrences and loan spreads.

Table 1. Hypotheses of the Study

		Hypothesis
H1	H1a	The occurrence of natural disasters in the 12 months prior to a deal is positively associated with an increase in loan spreads
H2	H2a	The environmental reputation of borrowers moderates the relationship between natural disaster occurrences and loan spreads such that firms with a lower number of RepRisk events in the last 12 months experience a weaker positive relationship between natural disaster occurrences and loan spreads
	H2b	The social reputation of borrowers moderates the relationship between natural disaster occurrences and loan spreads such that firms with a lower number of RepRisk events in the last 12 months experience a weaker positive relationship between natural disaster occurrences and loan spreads
	H2c	The governance reputation of borrowers moderates the relationship between natural disaster occurrences and loan spreads such that firms with a lower number of RepRisk events in the last 12 months experience a weaker positive relationship between natural disaster occurrences and loan spreads
	H2d	The ESG reputation of borrowers moderates the relationship between natural disaster occurrences and loan spreads such that firms with a lower number of RepRisk events in the last 12 months experience a weaker positive relationship between natural disaster occurrences and loan spreads

CHAPTER 4

DATA & METHODOLOGY

4.1 Datasets

One of the main data sources of this research is Thomson Reuters LPC DealScan ("DealScan") - a dataset under LSEG Loan Connector and is renowned for being the most extensive dataset of commercial loan contracts globally, with a primary data source being SEC filings. Our dependent variable is the loan cost named All-In Spread Drawn ("AISD") in the dataset. This variable is reflected as the additional basis points the borrower pays over the London Interbank Offered Rate ("LIBOR") including the annual fee the lender group charges for the agreement. This standardization enables the comparison between different loan agreements. We also use the information related to the borrower company and the date the loan is considered as active (WRDS, n.d.).

Natural disaster information is from the Spatial Hazard Events and Losses ("SHELDUS") disseminated by the Center for Emergency Management and Homeland Security at Arizona State University. SHELDUS provides information regarding the hazards that take place in the U.S. The details this database reveals regarding hazards are the date on which the event took place, the location - both the state and the county, and the losses - estimated damage in monetary terms, injuries, and fatalities. SHELDUS is generally updated on a yearly basis. The version used in this research is Version 20.0 which was released in February, 2022. The main source of the database is the Natural Centers for Environmental Information (previously named National Climate Data Center) (CEMHS ASU, 2022).

RepRisk is an institution that conducts ESG-related research incorporating artificial intelligence ("AI") into its methodology, setting itself apart with this unique approach. The AI conducts an overview of public information sources on a daily basis, searches for news that has the potential of damaging the financial performance of companies or causing companies to damage society, and groups such information based on the degree of relevance. Public sources include printed, online, and social media, as well as governmental bodies and regulators, but exclude self-disclosures of companies due to questions about authenticity. Sources are being reviewed from international to local levels and in 23 languages. These outputs are reviewed by analysts, reinforcing AI mechanisms with human judgment, before being released as final work. The event-driven outputs have been released since 2007 and the data coverage starts from January, 2007. The research scope is determined by 28 ESG-related topics, which are selected based on international ESG standards and regulations. RepRisk covers both listed and non-listed companies, in any sector and in any size, all around the world. By the end of September, 2023, the number of companies RepRisk covered exceeded 255,000. The institution releases the output in two forms: The RepRisk Index ("RRI") and The RepRisk Rating ("RRR"). RRI quantifies the ESG risk exposure of companies ranging from 0 (lowest) to 100 (highest). Firms having a higher risk exposure give results closer to 100 and the score moves towards 0 as their risk exposure declines. RRR, on the other hand, provides the same risk exposure but in letter rating format for easier comparison purposes. Firms with the lowest risk exposure have a score of AAA whereas firms with the highest risk-exposure are scored D (RepRisk, 2023).

Lastly, financial and market-related information of companies are extracted from Compustat North America, a database of Compustat publishing financial,

statistical, and market information about active and inactive public companies in the U.S. and Canada. Compustat was founded by Standard and Poor's (S&P) in 1962 and provides information back to 1950. The database utilizes financial statements and supplementary releases from firms as sources (LSEG, 2024).

4.2 Methodology

While creating our data sample, we started by extracting loan-level data from DealScan. The coverage is from January, 2007 to December, 2020 since the earliest data coming from RepRisk is from 2007 and the latest data provided by the SHELDUS version that we have access to is from the end of 2020. We are left with borrower companies located in the United States and excluded the firms from other countries as SHELDUS provides natural disaster data for the U.S. We also filtered our dataset based on broad industry group information from DealScan. We excluded the firms from the following groups: banks, government, media/communication, non-bank financials, and utilities. Our analysis contains firms from the corporate group.

In order to incorporate other databases with DealScan, we followed the linking table provided by Chava and Roberts (2008) and added Compustat's unique company identifiers ("gvkey") of each firm. Based on gvkey, we added CUSIPs and referred to that code as a linking point with the RepRisk database. CUSIP is a unique code assigned to a stock or bond of a company located in the United States or Canada.

Before adding SHELDUS data, we made the following modifications. Firstly, we created a new variable by taking the sum of the number of natural disasters that happened in the last twelve months. Then, we turned it into a dummy variable taking

a value of 1 if there are natural disasters that took place in the last twelve months and 0 if otherwise is the case. SHELDUS provides data on a county basis and each county has a specific county code. We repeated this operation for each and every county. To match the natural disaster data with our data sample, we added the county code of borrower companies based on the headquarters information on DealScan.

To our RepRisk event sample that consists of events affecting the RepRisk score of firms, we applied similar modifications. For each firm, we proposed a cumulative approach considering whether there were events in the last twelve months prior to the deal date. If there were any events affecting the RepRisk score, the dummy variable 1 is assigned and if no event happened, the dummy variable is turned out as 0. Likewise, by referring to the same approach, we added the total number of events that happened in the last twelve months. This approach is iterated for the RepRisk event classes "Environmental", "Social", "Governance", and "ESG any". Both the RepRisk and DealScan databases include CUSIPs of firms, and we used those codes while adding RepRisk event dummies to our main sample. Based on the date the tranche became active, we incorporated dummy variables and the number of total events for the "Environmental", "Social", "Governance", and "ESG any" categories.

To be used as control variables, we extracted revenue, total assets, shareholders' equity, market value, long-term debt, short-term debt, total liabilities, net income, earnings before interest and taxes (EBIT), earnings before interest, taxes, and depreciation (EBITDA), and cash and short-term investment information from Compustat database. Before incorporating our analysis, we made some modifications to these values. Total assets are considered after taking the logarithms. Cash and short-term investment, EBIT, EBITDA, net income, and total liabilities are divided

by total assets and taken into account as ratios. Long-term debt is added to current liabilities and again divided by total assets to be used as a ratio, likewise. These variables are provided for fiscal years, and we extracted data for the period between January, 2007 and December, 2020. In order to merge Compustat variables to our main dataset, we used both Compustat IDs and the last twelve-month condition like we referred to in previous merging operations. Control variables are assigned for twelve months before the tranche date.

The DealScan, RepRisk, and Compustat databases used in this research are accessed through the Wharton Research Data Services (WRDS) of the Wharton School of the University of Pennsylvania.

In our final dataset, we have the "Tranche Active Date" which refers to the date the loan becomes active. Spread information (All-In-Spread Drawn) is added for each deal and the logarithmic function of spreads is enlisted. Control variables are added based on checking the period of twelve months back since the tranche's active date. The same logic is applied to the RepRisk and SHELDUS variables, as well. Going twelve months back from the tranche active date, the number of RepRisk events (separately listed for environmental, social, and governance pillars and any ESG events) and the number of natural disasters that occurred within the period are added. In addition to the numbers, both events are also represented in the dataset as dummies. Lastly, we created two types of cross-products – one is with the dummy versions of the variables and the other is with the number of events. We multiplied the number of natural disasters by the number of environmental, social, governance, and ESG events. As a result, we obtained 4 interaction terms. The same process is applied to dummy variables. We multiplied the dummy variable of natural disasters

in the last twelve months with the dummy variable of RepRisk events. From that operation, we formed 4 additional interaction terms.

All the explanations and sources of the variables are as shown in the Table 2.

Table 2. Definitions and Sources

Variable	Definition	Source
dealscandates	The activation date of the tranche	Thomson Reuters LPC DealScan
spread	All-in-drawn spread - the spread borrower pays over LIBOR	Thomson Reuters LPC DealScan
spread_log	The logarithmic function of spread	Thomson Reuters LPC DealScan
reprisk_id	IDs for firms in RepRisk database	RepRisk
environment_count	Number of events under the environmental category and impacting a firm's RepRisk score in the 12 months before the tranche date	RepRisk
environment_dummy	Dummy variable indicating if the borrower company had any RepRisk score-changing environmental event in the last 12 months since the tranche began	RepRisk
social_count	Number of events under the social category and impacting a firm's RepRisk score in the 12 months before the tranche date	RepRisk
social_dummy	Dummy variable indicating if the borrower company had any RepRisk score-changing social event in the last 12 months since the tranche began	RepRisk
governance_count	Number of events under the governance category and impacting a firm's RepRisk score in the 12 months before the tranche date	RepRisk
governance_dummy	Dummy variable indicating if the borrower company had any RepRisk score-changing governance event in the last 12 months since the tranche began	RepRisk
esg_any_count	Number of events under any category of ESG pillars and impacting a firm's RepRisk score in the 12 months before the tranche date	RepRisk
esg_any_dummy	Dummy variable indicating if the borrower company had any RepRisk score-changing event in the last 12 months since the tranche began	RepRisk
county_id	ID of the county where the borrower company's headquarters is situated	RepRisk
nd_count	Number of natural disasters occurring in the headquarters county in the last 12 months since the tranche began	SHELDUS
nd_dummy	Dummy variable indicating if the borrower company's headquarters experienced any natural disaster in the last 12 months since the tranche began	SHELDUS
Compustat Id	Global Company Key (gvkey) - IDs assigned to firms in Compustat database	Compustat
total assets(log)	The logarithmic function of total assets	Compustat
cash and st inv/total assets	The ratio of cash and short-term investment to total assets	Compustat
ebit/total assets	The ratio of earnings before interest and taxes to total assets	Compustat
ebitda/total assets	The ratio of earnings before interest, taxes and depreciation to total assets	Compustat
net income/total assets	The ratio of net income to total assets	Compustat
total liabilities/total assets	The ratio of total liabilities to total assets	Compustat
(long-term debt + current liabilities)/total assets	The ratio of (long-term debt + current liabilities) to total assets	Compustat
SheldusEnv_Count	The multiplication of the environmental event count and Sheldus event count	
SheldusSoc_Count	The multiplication of the social event count and Sheldus event count	
SheldusGov_Count	The multiplication of the governance event count and Sheldus event count	
SheldusESGAny_Count	The multiplication of the ESG event count and Sheldus event count	
SheldusEnv_Dummy	The multiplication of the environmental event dummy and Sheldus event dummy	
SheldusSoc_Dummy	The multiplication of the social event dummy and Sheldus event dummy	
SheldusGov_Dummy	The multiplication of the governance event dummy and Sheldus event dummy	
SheldusESGAny_Dummy	The multiplication of the ESG event dummy and Sheldus event dummy	

The dependent variable of the sample, i.e. spread, has a mean value of 214.60 basis points with a minimum of 2 and maximum of 1325 basis points. Due to the high

standard deviation of the variable, in the analysis, spread is taken into consideration as the logarithmic function. Firms in the sample experienced 1.1137 natural disasters in the county in which their headquarters is located, on average, in the last twelve months before deals with a minimum of 0 and a maximum of 9. The number of environmental, social, and governance events firms experienced twelve months before deals are on average 1.9411, 2.8333, and 1.9342, respectively. All have a minimum value of 0 and maximum values of 140, 283, and 139, again, respectively. When a broader look is given, any type of ESG event that firms experienced in the last twelve months has a mean value of 4.2205 with a minimum of 0 and a maximum of 385. Firms in the sample have a cash-to-asset ratio of 9.06%, a return on assets (*net income/total assets*) of 4%, and a debt-to-asset ratio of 65.19%, on average.

Descriptive statistics of the sample is provided in the Table 3.

Table 3. Descriptive Statistics

Variable	Number of Obs.	Mean	Median	Std. Dev.	Min	Max
spread	131625	214.60	175	133.02	2	1325
nd_count	140882	1.1137	1	1.3798	0	9
environment_count	124793	1.9411	0	5.7925	0	140
social_count	147165	2.8333	0	9.0543	0	283
governance_count	138985	1.9342	0	5.6744	0	139
esg_any_count	163059	4.2205	0	12.8613	0	385
total assets(log)	132983	8.6877	8.6044	1.5059	1.7469	14.8521
cash and st inv./total assets	132983	0.0906	0.0593	0.0998	0	0.9991
net income/total assets	132972	0.0400	0.0449	0.1089	-6.6432	1.8429
total liabilities/total assets	132842	0.6519	0.6297	0.2313	0.0102	4.8462
spread_log	131625	5.1996	5.1648	0.6129	0.6931	7.1892

The correlation between the dependent, independent, and control variables is shown in Table 4 and Table 5. Table 4 considers the independent variables provided as the number of events whereas Table 5 shows the correlations in which independent variables are given in the dummy format. As our dataset includes variables derived

from other variables, some correlations are unsurprisingly over 0.5. Our dependent variable, spread_log, correlates 0.8700 with spread due to that reason. Similarly, cross-products in our sample show a correlation above 0.5 with the component variables. For instance, SheldusEnv_Count and SheldusEnv_Dummy variables are highly correlated with environment_count and environment_dummy variables, respectively, which are one of the two factors of SheldusEnv_Count and SheldusEnv_Dummy. The same logic applies to the correlation between SheldusSoc_Count and social_count, SheldusGov_Count and governance_count, SheldusESGAny_Count and esg_any_count, SheldusSoc_Dummy and social_dummy, and SheldusGov_Dummy and governance_dummy. One other correlation type worth highlighting is the correlation of SheldusESGAny_count with environment_count, governance_count, SheldusEnv_Count, SheldusSoc_Count, and SheldusGov_Count. One of the factors of SheldusESGAny_count is esg_any_count which considers any event under environmental, social, and governance pillars. Therefore, these high correlations are not surprising. The same explanation is also valid for the high correlation of SheldusESGAny_Dummy between SheldusEnv_Dummy, SheldusSoc_Dummy, and SheldusGov_Dummy.

After analyzing the correlation matrix, we excluded some of the control variables. EBIT/total assets and EBITDA/total assets were highly correlated with both each other and net income/total assets; therefore, we excluded these two from the dataset. Another control variable (lt debt + current liabilities)/total assets was also highly correlated with total liabilities/total assets, and we removed it, as well.

Table 4. Correlation Matrix with Number of Events

Variables	spread	spread_log	total assets(log)	cash and st inv/total assets	net income/total assets	total liabilities/total assets	nd_count_12	environment_count	social_count	governance_count	esg_any_count	SheldusEnv_Count	SheldusSoc_Count	SheldusGov_Count	SheldusESGAny_Count
spread	1														
spread_log	0.8700*	1													
total assets(log)	-0.2802	-0.3460	1												
cash and st inv/total assets	-0.0094	-0.0362	-0.0054	1											
net income/total assets	-0.2285	-0.2185	0.0647	0.1192	1										
total liabilities/total assets	0.1412	0.1299	0.1612	-0.1316	-0.1947	1									
nd_count_12	0.0214	0.0221	-0.0474	-0.0377	-0.0301	-0.0364	1								
environment_count	-0.0915	-0.1284	0.3767	-0.0067	0.0144	0.0158	-0.0058	1							
social_count	-0.0939	-0.1361	0.4586	0.0269	0.0270	0.0693	-0.0545	0.7025*	1						
governance_count	-0.0881	-0.1407	0.5136*	0.0909	0.0398	0.0853	-0.0411	0.5544*	0.8065*	1					
esg_any_count	-0.1002	-0.1489	0.5080*	0.0512	0.0360	0.0827	-0.0440	0.7385*	0.9685*	0.9101*	1				
SheldusEnv_Count	-0.0445	-0.0807	0.2081	-0.0253	0.0086	-0.0354	0.2120	0.6435*	0.3551	0.2709	0.4001	1			
SheldusSoc_Count	-0.0436	-0.0925	0.2974	0.0049	0.0159	0.0032	0.2262	0.5662*	0.5607*	0.4489	0.5760*	0.8108*	1		
SheldusGov_Count	0.0084	-0.0441	0.2785	0.0730	0.0192	-0.0025	0.2445	0.3316	0.3395	0.5667*	0.4580	0.5137*	0.6930*	1	
SheldusESGAny_Count	-0.0284	-0.0784	0.3098	0.0322	0.0205	0.0025	0.2406	0.5504*	0.4985	0.5214*	0.5703*	0.8126*	0.9443*	0.8672*	1

**correlations above 0.5*

Table 5. Correlation Matrix with Dummy Varia

Variables	spread	spread_log	total assets(log)	cash and st inv/total assets	net income/total assets	total liabilities/total assets	nd_count_12_dummy	environment_dummy	social_dummy	governance_dummy	esg_any_dummy	SheldusEnv_Dummy	SheldusSoc_Dummy	SheldusGov_Dummy	SheldusESGAny_Dummy
spread	1														
spread_log	0.8700*	1													
total assets(log)	-0.2802	-0.3460	1												
cash and st inv/total assets	-0.0094	-0.0362	-0.0054	1											
net income/total assets	-0.2285	-0.2185	0.0647	0.1192	1										
total liabilities/total assets	0.1412	0.1299	0.1612	-0.1316	-0.1947	1									
nd_count_12_dummy	0.0322	0.0378	-0.0583	-0.0545	-0.0343	-0.0324	1								
environment_dummy	-0.0600	-0.0639	0.4060	0.0326	0.0434	0.1228	-0.0369	1							
social_dummy	-0.1100	-0.1151	0.4653	0.0244	0.0343	0.1345	-0.0621	0.6606*	1						
governance_dummy	-0.1044	-0.1006	0.4798	0.0724	0.0702	0.1096	-0.0788	0.4569	0.4894	1					
esg_any_dummy	-0.1092	-0.1114	0.4900	0.0511	0.0456	0.1272	-0.0615	0.7017*	0.8011*	0.7274*	1				
SheldusEnv_Dummy	-0.0048	-0.0013	0.2437	-0.0206	-0.0041	0.0508	0.4314	0.6517*	0.4093	0.2278	0.4569	1			
SheldusSoc_Dummy	-0.0258	-0.0250	0.2748	-0.0314	-0.0049	0.0732	0.4558	0.4092	0.6230*	0.2520	0.4977	0.7338*	1		
SheldusGov_Dummy	-0.0515	-0.0429	0.2842	-0.0082	0.0234	0.0480	0.4371	0.2588	0.2790	0.6118*	0.4463	0.5386*	0.5929*	1	
SheldusESGAny_Dummy	-0.0423	-0.0375	0.2807	-0.0231	-0.0019	0.0643	0.5107*	0.4236	0.4582	0.3751	0.6029	0.7760*	0.8442*	0.7726*	1

**correlations above 0.5*

CHAPTER 5

ANALYSIS & EMPIRICAL RESULTS

To test the hypothesized relationships, we proposed the following hierarchical regression model. Regressions are conducted both with the number of events and dummy versions of natural disaster and RepRisk event variables.

Hierarchical regression models consider groups of variables in the model as blocks. The first block generally includes control variables whose impact is intended to be held constant across blocks (Fein et al., 2022). Therefore, in the first step, we proposed the following equation with control variables:

Step 1:

$$(spread_log)_{i,t} = \beta_0 + \beta_1(total\ assets(log))_{i,t-12} + \beta_2(cash\ and\ st\ inv/total\ assets)_{i,t-12} + \beta_3(net\ income/total\ assets)_{i,t-12} + \beta_4(total\ liabilities/total\ assets)_{i,t-12} + \varepsilon_{i,t}$$

In the second step, we introduced the independent (natural disasters) and moderating variables (RepRisk profile):

Step 2:

$$(spread_log)_{i,t} = \beta_0 + \beta_1(total\ assets(log))_{i,t-12} + \beta_2(cash\ and\ st\ inv/total\ assets)_{i,t-12} + \beta_3(net\ income/total\ assets)_{i,t-12} + \beta_4(total\ liabilities/total\ assets)_{i,t-12} + \beta_5(nd_count)_{i,t} + \beta_6(environment_count)_{i,t} + \varepsilon_{i,t}$$

$$(spread_log)_{i,t} = \beta_0 + \beta_1(total\ assets(log))_{i,t-12} + \beta_2(cash\ and\ st\ inv/total\ assets)_{i,t-12} + \beta_3(net\ income/total\ assets)_{i,t-12} + \beta_4(total\ liabilities/total\ assets)_{i,t-12} + \beta_5(nd_dummy)_{i,t} + \beta_6(environment_dummy)_{i,t} + \varepsilon_{i,t}$$

$(spread_log)_{i,t} = \beta_0 + \beta_1(total\ assets(log))_{i,t-12} + \beta_2(cash\ and\ st\ inv/total\ assets)_{i,t-12} + \beta_3(net\ income/total\ assets)_{i,t-12} + \beta_4(total\ liabilities/total\ assets)_{i,t-12} + \beta_5(nd_count)_{i,t} + \beta_6(social_count)_{i,t} + \varepsilon_{i,t}$

$(spread_log)_{i,t} = \beta_0 + \beta_1(total\ assets(log))_{i,t-12} + \beta_2(cash\ and\ st\ inv/total\ assets)_{i,t-12} + \beta_3(net\ income/total\ assets)_{i,t-12} + \beta_4(total\ liabilities/total\ assets)_{i,t-12} + \beta_5(nd_dummy)_{i,t} + \beta_6(social_dummy)_{i,t} + \varepsilon_{i,t}$

$(spread_log)_{i,t} = \beta_0 + \beta_1(total\ assets(log))_{i,t-12} + \beta_2(cash\ and\ st\ inv/total\ assets)_{i,t-12} + \beta_3(net\ income/total\ assets)_{i,t-12} + \beta_4(total\ liabilities/total\ assets)_{i,t-12} + \beta_5(nd_count)_{i,t} + \beta_6(governance_count)_{i,t} + \varepsilon_{i,t}$

$(spread_log)_{i,t} = \beta_0 + \beta_1(total\ assets(log))_{i,t-12} + \beta_2(cash\ and\ st\ inv/total\ assets)_{i,t-12} + \beta_3(net\ income/total\ assets)_{i,t-12} + \beta_4(total\ liabilities/total\ assets)_{i,t-12} + \beta_5(nd_dummy)_{i,t} + \beta_6(governance_dummy)_{i,t} + \varepsilon_{i,t}$

$(spread_log)_{i,t} = \beta_0 + \beta_1(total\ assets(log))_{i,t-12} + \beta_2(cash\ and\ st\ inv/total\ assets)_{i,t-12} + \beta_3(net\ income/total\ assets)_{i,t-12} + \beta_4(total\ liabilities/total\ assets)_{i,t-12} + \beta_5(nd_count)_{i,t} + \beta_6(esg_any_count)_{i,t} + \varepsilon_{i,t}$

$(spread_log)_{i,t} = \beta_0 + \beta_1(total\ assets(log))_{i,t-12} + \beta_2(cash\ and\ st\ inv/total\ assets)_{i,t-12} + \beta_3(net\ income/total\ assets)_{i,t-12} + \beta_4(total\ liabilities/total\ assets)_{i,t-12} + \beta_5(nd_dummy)_{i,t} + \beta_6(esg_any_dummy)_{i,t} + \varepsilon_{i,t}$

In the third and final step, we introduced the interaction terms of natural disasters and RepRisk events to determine whether a strong reputation acts as a mediating factor in mitigating loan cost increases following a natural disaster:

Step 3:

$(spread_log)_{i,t} = \beta_0 + \beta_1(total\ assets(log))_{i,t-12} + \beta_2(cash\ and\ st\ inv/total\ assets)_{i,t-12} + \beta_3(net\ income/total\ assets)_{i,t-12} + \beta_4(total\ liabilities/total\ assets)_{i,t-12} + \beta_5(nd_count)_{i,t} + \beta_6(environment_count)_{i,t} + \beta_7(SheldusEnv_Count)_{i,t} + \varepsilon_{i,t}$

$$(\text{spread_log})_{i,t} = \beta_0 + \beta_1(\text{total assets(log)})_{i,t-12} + \beta_2(\text{cash and st inv/total assets})_{i,t-12} + \beta_3(\text{net income/total assets})_{i,t-12} + \beta_4(\text{total liabilities/total assets})_{i,t-12} + \beta_5(\text{nd_dummy})_{i,t} + \beta_6(\text{environment_dummy})_{i,t} + \beta_7(\text{SheldusEnv_Dummy})_{i,t} + \varepsilon_{i,t}$$

$$(\text{spread_log})_{i,t} = \beta_0 + \beta_1(\text{total assets(log)})_{i,t-12} + \beta_2(\text{cash and st inv/total assets})_{i,t-12} + \beta_3(\text{net income/total assets})_{i,t-12} + \beta_4(\text{total liabilities/total assets})_{i,t-12} + \beta_5(\text{nd_count})_{i,t} + \beta_6(\text{social_count})_{i,t} + \beta_7(\text{SheldusSoc_Count})_{i,t} + \varepsilon_{i,t}$$

$$(\text{spread_log})_{i,t} = \beta_0 + \beta_1(\text{total assets(log)})_{i,t-12} + \beta_2(\text{cash and st inv/total assets})_{i,t-12} + \beta_3(\text{net income/total assets})_{i,t-12} + \beta_4(\text{total liabilities/total assets})_{i,t-12} + \beta_5(\text{nd_dummy})_{i,t} + \beta_6(\text{social_dummy})_{i,t} + \beta_7(\text{SheldusSoc_Dummy})_{i,t} + \varepsilon_{i,t}$$

$$(\text{spread_log})_{i,t} = \beta_0 + \beta_1(\text{total assets(log)})_{i,t-12} + \beta_2(\text{cash and st inv/total assets})_{i,t-12} + \beta_3(\text{net income/total assets})_{i,t-12} + \beta_4(\text{total liabilities/total assets})_{i,t-12} + \beta_5(\text{nd_count})_{i,t} + \beta_6(\text{governance_count})_{i,t} + \beta_7(\text{SheldusGov_Count})_{i,t} + \varepsilon_{i,t}$$

$$(\text{spread_log})_{i,t} = \beta_0 + \beta_1(\text{total assets(log)})_{i,t-12} + \beta_2(\text{cash and st inv/total assets})_{i,t-12} + \beta_3(\text{net income/total assets})_{i,t-12} + \beta_4(\text{total liabilities/total assets})_{i,t-12} + \beta_5(\text{nd_dummy})_{i,t} + \beta_6(\text{governance_dummy})_{i,t} + \beta_7(\text{SheldusGov_Dummy})_{i,t} + \varepsilon_{i,t}$$

$$(\text{spread_log})_{i,t} = \beta_0 + \beta_1(\text{total assets(log)})_{i,t-12} + \beta_2(\text{cash and st inv/total assets})_{i,t-12} + \beta_3(\text{net income/total assets})_{i,t-12} + \beta_4(\text{total liabilities/total assets})_{i,t-12} + \beta_5(\text{nd_count})_{i,t} + \beta_6(\text{esg_any_count})_{i,t} + \beta_7(\text{SheldusESGAny_Count})_{i,t} + \varepsilon_{i,t}$$

$$(\text{spread_log})_{i,t} = \beta_0 + \beta_1(\text{total assets(log)})_{i,t-12} + \beta_2(\text{cash and st inv/total assets})_{i,t-12} + \beta_3(\text{net income/total assets})_{i,t-12} + \beta_4(\text{total liabilities/total assets})_{i,t-12} + \beta_5(\text{nd_dummy})_{i,t} + \beta_6(\text{esg_any_dummy})_{i,t} + \beta_7(\text{SheldusESGAny_Dummy})_{i,t} + \varepsilon_{i,t}$$

The assumptions for hierarchical regression are the same as the multiple linear regression. That error terms may not be independent, and variance may not be constant throughout time may cause a violation of basic assumptions. To deal with the potential heteroskedasticity and autocorrelation problems in our dataset, we conducted Newey-West (1994) adjustments to each regression equation. The provided results are after adjustments.

All the analyses are conducted in R Studio - a programming language for data wrangling and statistical analysis. For multiple regressions we conducted in each step, we used the 'lm()' function that R uses to fit a linear regression model by minimizing the sum of squared differences between the actual and predicted values of the dependent variable. We applied the HC1 sandwich estimator ('vcovHC') provided by the software to handle heteroskedasticity and autocorrelation problems in the data. Lastly, with the 'tidy()' function, we organized the estimates and results in a table form that we can interpret.

Table 6. Hierarchical Regression Results with Number of Events

	spread_log											
	estimates (β)											
	ENV			SOC			GOV			ESG_any		
Variable	Step 1	Step 2	Step 3	Step 1	Step 2	Step 3	Step 1	Step 2	Step 3	Step 1	Step 2	Step 3
intercept	6.2018***	6.1469***	6.1436***	6.2018***	6.1378***	6.1298***	6.2018***	6.1271***	6.1255***	6.2018***	6.1003***	6.1025***
total assets(log)	-.1400***	-.1353***	-.1352***	-.1400***	-.1346***	-.1339***	-.1400***	-.1333***	-.1326***	-.1400***	-.1302***	-.1304***
cash and st inv/total assets	.0486**	-.0406	-.0429	.0486**	.0591**	.0591**	.0486**	.0469*	.0410*	.0486**	.0650***	.0643***
net income/total assets	-.9952***	-.8795***	-.8802***	-.9952***	-.9278***	-.9281***	-.9952***	-1.0915***	-1.0903***	-.9952***	-.9649***	-.9648***
total liabilities/total assets	.3678***	.3943***	.3920***	.3678***	.3874***	.3864***	.3678***	.3992***	.4042***	.3678***	.3952***	.3958***
nd_count		.0105***	.0139***		.0139***	.0166***		.0139***	.0082***		.0131***	.0120***
environment_count		-.0052***	-.0028***						-.0074***			
SheldusEnv_Count			-.0022***						.0034***			
social_count					-.0028***	-.0016***						
SheldusSoc_Count						-.0017***						
governance_count								-.0033***	-.0074***			
SheldusGov_Count									.0034***			
esg_any_count											-.0020***	-.0023***
SheldusESGAny_Count												.0004**
Observation	105,444	73,201	73,201	105,444	88,218	88,218	105,444	82,445	82,445	105,444	97,584	97,584
R^2	.1851	.1792	.1801	.1851	.1804	.1809	.1851	.1776	.1794	.1851	.1813	.1814
Change in R^2			.0009			.0005			.0018			.0001
F	5,987***	2,663***	2,296***	5,987***	3,236***	2,782***	5,987***	2,967***	2,574***	5,987***	3,602***	3,089***
Adj. R^2	.1851	.1791	.1800	.1851	.1803	.1808	.1851	.1775	.1793	.1851	.1813	.1813
*p < 0.05, **p < 0.01, ***p < 0.001												

Table 7. Hierarchical Regression Results with Dummy Variables

	spread_log											
	estimates (β)											
	ENV			SOC			GOV			ESG_any		
Variable	Step 1	Step 2	Step 3	Step 1	Step 2	Step 3	Step 1	Step 2	Step 3	Step 1	Step 2	Step 3
intercept	6.2018***	6.1684***	6.1838***	6.2018***	6.1535***	6.1640***	6.2018***	6.1403***	6.1438***	6.2018***	6.1235***	6.1309***
total assets(log)	-.1400***	-.1399***	-.1401***	-.1400***	-.1372***	-.1372***	-.1400***	-.1346***	-.1346***	-.1400***	-.1329***	-.1330***
cash and st inv/total assets	.0486**	-.0307	-.0286	.0486**	.0546**	.0558**	.0486**	.0380*	.0393*	.0486**	.0569***	.0585***
net income/total assets	-.9952***	-.8666***	-.8596***	-.9952***	-.9198***	-.9169***	-.9952***	-1.0803***	-1.0798***	-.9952***	-.9574***	-.9558***
total liabilities/total assets	.3678***	.4007***	.4026***	.3678***	.3876***	.3868***	.3678***	.3991***	.3991***	.3678***	.3952***	.3949***
nd_dummy		.0374***	.0105*		.0426***	.0260***		.0348***	.0287***		.0359***	.0246***
environment_dummy		-.0150***	-.0574***									
SheldusEnv_Dummy			.0764***									
social_dummy					-.0209***	-.0442***						
SheldusSoc_Dummy						.0430***						
governance_dummy								-.0274***	-.0359***			
SheldusGov_Dummy									.0163*			
esg_any_dummy											-.0251***	-.0382***
SheldusESGAny_Dummy												.0239***
Observation	105,444	73,201	73,201	105,444	88,218	88,218	105,444	82,445	82,445	105,444	97,584	97,584
R^2	.1851	.1781	.1790	.1851	.1801	.1804	.1851	.1773	.1774	.1851	.1808	.1809
Change in R^2			.0009			.0003			.0001			.0001
F	5,987***	2,644***	2,280***	5,987***	3,229***	2,774***	5,987***	2,961***	2,539***	5,987***	3,590***	3,080***
Adj. R^2	.1851	.1780	.1790	.1851	.1800	.1804	.1851	.1772	.1773	.1851	.1808	.1809
*p < 0.05, **p < 0.01, ***p < 0.001												

The hierarchical regression model we built yields statistically significant results both with the number of events and dummy variables.

Control variables explain 18.51% of the variation in our dependent variable of the logarithmic function of loan spreads (R-square = 0.1851). The intercept is positive and statistically significant with a confidence level of 0.1%. Cash and st inv/total assets and total liabilities/total assets are positively related to the dependent variable and statistically significant at confidence levels of 5% and 0.1%, respectively. The logarithmic function of total assets and net income/total assets yield a negative significant relationship with the dependent variable at a confidence interval of 0.1%.

The number of natural disasters has a statistically significant positive relationship with spread increases with estimates ranging between three steps from 0.0082 to 0.0139 (both with p-values < 0.001). When this impact is tested with a dummy version of the variable, statistically significant betas move between 0.0105 (p-value < 0.05) and 0.0426 (p-value < 0.001), among three steps.

The individual relationship of environmental, social, and governance events and overall ESG events, all yield a negative significant relationship at the confidence level 0.1% in both versions of the model.

RepRisk events considered as mediating metrics yield different results between two versions of the model. The cross-product of the number of environmental events and the number of natural disasters is negatively related to the dependent variable (with p-value < 0.001); whereas the relationship is positive when dummy versions of the variables are used to create the cross-product (with p-value < 0.001). The same is the case for the social pillar – when the cross-product is obtained with the number of events, the relationship is significantly negative; however, the cross-product of

dummy variables yields a significantly positive relationship (both with p-values < 0.001). The mediating impact of governance events and any type of ESG events yields similar results under two versions. Either considered as the number of events or dummy variables, both governance events and ESG events yield positive and statistically significant results.

The contribution of mediating metrics in explained variation in the loan spreads is reflected in the differences of R-squares between Step 2 and Step 3. Proposing the environmental profile of firms as a mediating metric increases the R-square by 0.09% under two versions. The social profile of firms mitigates the impact of natural disasters by 0.05% (when the number of events is considered) and 0.03% (when the variable is considered as a dummy). The governance profile contributes by 0.18% (when the number of events is considered) and 0.01% (when the variable is considered as a dummy). When events under any one of the pillars are considered, ESG events both as numbers and as dummies, the contribution is 0.01%.

Table 8. Results of Hypotheses Testing

		Hypothesis	Result (with the number of events)	Result (with dummy variables)
H1	H1a	The occurrence of natural disasters in the 12 months prior to a deal is positively associated with an increase in loan spreads	Supported	Supported
H2	H2a	The environmental reputation of borrowers moderates the relationship between natural disaster occurrences and loan spreads such that firms with a lower number of RepRisk events in the last 12 months experience a weaker positive relationship between natural disaster occurrences and loan spreads	Rejected	Supported
	H2b	The social reputation of borrowers moderates the relationship between natural disaster occurrences and loan spreads such that firms with a lower number of RepRisk events in the last 12 months experience a weaker positive relationship between natural disaster occurrences and loan spreads	Rejected	Supported
	H2c	The governance reputation of borrowers moderates the relationship between natural disaster occurrences and loan spreads such that firms with a lower number of RepRisk events in the last 12 months experience a weaker positive relationship between natural disaster occurrences and loan spreads	Supported	Supported
	H2d	The ESG reputation of borrowers moderates the relationship between natural disaster occurrences and loan spreads such that firms with a lower number of RepRisk events in the last 12 months experience a weaker positive relationship between natural disaster occurrences and loan spreads	Supported	Supported

CHAPTER 6

CONCLUSION & DISCUSSION

This research aims to enhance the contemporary literature on ESG and bank loan contracting by introducing a natural disaster specification. The outcomes are expected to contribute to the existing literature by enhancing our comprehension of how financial institutions engage with companies undergoing natural disasters and what is the role of the pre-existing reputation of firms. In practical terms, the study seeks to offer valuable insights for executives, aiding in the development of standardized practices and considerations in response to the combined impact of ESG factors and natural disasters.

Having reviewed the literature, we hypothesized that ESG reputation established twelve months prior to the deal date protects firms against increases in loan costs following a natural disaster.

For that purpose, we started with testing the explanatory power of control variables in the variation of the loan cost of firms, i.e. *spread_log*. Unsurprisingly, *total assets(log)* and *net income/total assets* yield negative and significant relationships, and *total liabilities/total assets* shows a positive significant relationship with the dependent variable.

In the second step, we introduced natural disasters and RepRisk profiles of firms through two versions – as the number of events and as dummy variables. In line with the literature and our expectations, results show that natural disaster occurrence causes increases in the loan spreads and our H1 is supported under the two versions of the model. The striking result of this step is the relationship between RepRisk events and loan costs. Our findings reveal a negative relationship between

the decrease in the reputation of firms and the increase in loan spread is unintuitive. The underlying reason could be that RepRisk provides a detailed analysis and examines the reputation of firms from a variety of perspectives not all sharing the same degree of severity. However, in our analysis, we count every single RepRisk event and neglect the severity. In that sense, our analysis could overlook the breakdowns as reputation is a broad concept.

The third step of the model takes the RepRisk profile of firms as mediating metrics. The second version of the model, where we use dummy variables, reveals supporting results for H2a, H2b, H2c, and H2d and indicates that strong environmental, social, governance or ESG profiles protect firms against loan cost increases following a natural disaster. When the same question is tested with the number of events, increases in environmental and social events turned out to be decreasing loan spreads which leads us to reject H2a and H2b under the first version of the model. Again, the underlying reason could be that our model underestimates the severity of RepRisk events. Nonetheless, this model also supports our hypotheses H2c and H2d.

In addition to the significance of the relationship between interaction terms and the loan spread, hierarchical regression enables us to see whether these interaction terms indeed increase the explained variation in the dependent variable. For that purpose, we interpret the differences in R-squares between Step 2 and Step 3 of the model. The contribution of the environmental reputation as a mediating metric in explaining the variation in the loan spread is 0.09%, under the two versions of the model. The same contribution of the social reputation of firms is 0.05% if we conduct the analysis with the number of events and 0.03% when the same process is made through dummy variables. The reputation firms develop in the governance

pillar contributes to the explanation of the variance in loan spread by 0.18% with the number of events variable and 0.01% with the dummy version of the variable. Considering ESG events as the sole entity, the contribution of this variable is by 0.01% in each type of the model.

CHAPTER 7

LIMITATIONS & FURTHER STUDIES

In this study, interest rates are considered as the loan variable. However, for a more comprehensive analysis and to capture different impacts of natural disasters, additional loan variables such as covenants or loan amounts could be tested in different versions of the model.

This study treats each loan as a separate and individual agreement. However, some of these loans may be part of a line of credit. In such cases, agreements made prior to ESG and/or natural disaster shocks may not lead to changes in loan spreads. If this is indeed the case, these loans might skew the results. In an extended version of the study, it could be tested whether the lender-borrower relationship established beforehand can mitigate the impact of such shocks.

Our results with the reputation of firms are contradicting both with the literature and our expectations. A detailed analysis can be designed to reveal the reason behind this result. RepRisk provides the severity of the events and that can be used in recreating our independent variable – *the number of events*, by assigning weights based on the severity of each event. This approach enables the interpretation of results in a proper manner.

The first block of the hierarchical regression includes control variables to hold their contribution constant across steps. However, when moving from Step 1 to Step 2 and Step 3, a significant number of observations are lost. This prevents us from comparing the R-squares of the results from Step 1 with those from Step 2 and Step 3. Consequently, we are unable to determine the contribution of the control variables.

Last but not least, an approach similar to this study could be applied to emerging markets if data availability permits. Given literature suggesting that the impacts of natural disasters are more severe in emerging markets, the research question could focus on whether robust ESG policies enable companies to access necessary funds, act as a shield against cost increases, and mitigate the recovery process. This study could offer practical insights for companies operating in emerging markets.

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