Erasmus School of Economics

Natural Disasters in Europe: A Post-Disaster Syndicated Lending Analysis

Lotte de Jager

SNR: 682935

July 2024

Supervised by Dr. M. Colombo
Second reader Dr. M. Gabarro

Preface

Before you lies the thesis: "Natural Disasters in Europe: A Post-Disaster Syndicated Lending Analysis", which I have written to obtain the masters degree Financial Economics at Erasmus University. I have worked on this thesis throughout the second half of the academic year 2023-2024. I can honestly state that I have done so with great pleasure. My interest in banking is the main driver of my choice of obtaining the master program in Financial Economics. I developed this interest further in the seminar "Advanced Money, Credit, & Banking", which inspired me in many ways and has introduced me to Dr. M. Colombo, who I am very grateful to have as a supervisor. During the process of writing my thesis, I have learned a lot about climate risk, the syndicate loan market, and I have further developed my econometric skills. I am certain that these skills will be invaluable throughout the rest of my academic career.

At last, I want to thank many people for supporting me in this process. First and foremost my supervisor Dr. M. Colombo, who has displayed a great interest and enthusiasm for the topic and the process overall. I am incredibly grateful for the helpful feedback and the relevant literature he introduced me to. I would also like to thank everyone in my personal life for their encouragement and support throughout this process. I hope you will all read my thesis with great pleasure.

Lotte de Jager
Rotterdam, July 31, 2024

Abstract

This thesis examines the impact of natural disasters on syndicated loan activity in Europe. The research investigates whether a natural disaster is associated with an increase in syndicated loan volume, and how it affects the structure of syndicated loans. My analysis reveals that the occurrence of a natural disaster is only weakly correlated to an increase in the number of loans, and to a slight decrease in total deal volume on a provincial monthly level. The influence of natural disasters on syndicate structure is significant, but not for all specific components. This structure can be defined in terms of the number of lenders, lead arranger share, the presence of collateral, maturity, and deal spread, all on an individual loan level. There is a strong positive relation between the occurrence of a natural disaster and the share retained by the lead arranger, and a strong negative association between the occurrence of a disaster and the number of lenders. Furthermore, there is a clear negative relationship between the occurrence of a disaster and the deal spread. Syndicated loans awarded in the aftermath of a natural disaster have longer maturities on average and are more likely to be secured. The study also explores the moderating effect of borrower-lender proximity, which is hypothesized to lessen information asymmetry after a disaster. However, my research does not indicate the presence of a mitigating effect of geographical proximity on natural disasters and syndicated loan characteristics. This finding contradicts the initial hypothesis. The research highlights what role bank credit has in post-disaster recovery efforts. It also emphasizes the complex relationship between information asymmetry and syndicate structure in the context of natural disasters. Future research could focus on the specific information problems that arise during natural disasters and their influence on loan decisions.

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1 Introduction

Many individuals, governments and institutions are aware of the adverse effects of climate change. In 2016, 196 nations signed the Paris Agreement: an international treaty where the intention is set to limit global warming to 1.5°C (UNFCC, n.d.). While great efforts have been undertaken to mitigate global warming, climate change is not merely a possible future scenario. Many believe that climate change has already led to significant changes in the weather pattern and temperatures today, leading to an increased frequency of natural disasters (Banholzer et al., 2014). These natural disasters come with severe economic consequences. According to the World Bank (2024), climate-related disasters in Europe have cost around €15.5 billion per year between 1980 and 2022. Banks play an important role in disaster recovery, as they provide additional liquidity and credit to affected businesses. (Barth et al., 2019). Furthermore, Duqi et al. (2021) find that banks aid in recovery after a disaster, especially banks that operate under low levels of competition. These banks are willing to lend to borrowers even when their creditworthiness might be impaired, by extending them mortgages to rebuild property. Increased bank lending in the aftermath of a natural disaster is not only due to external influences such as increased loan demand and regulatory pressures, banks also have internal incentives to lend. By lending to affected borrowers, banks avoid default on other loans and preserve business opportunities (Schubert, 2024).

Many academics establish that following a natural disaster, there is indeed an increased demand for credit. Ivanov et al. (2022) recognize that following natural disasters, there is an increase in corporate credit demand in affected regions. The sequential question is whether bank credit is constrained, or whether they have the opportunity to meet this increased demand. The authors establish that for banks to meet this increased credit demand, they will restrict credit in unaffected regions. Additionally, they explore whether banks raise funding or merely restrict credit in other regions. Ivanov et al. (2022) do find that the amount of disaster damages is positively related to the level of overall deposits. While this suggests that banks may attract deposit funding to meet an increased demand for credit, this does not paint the full picture. Deposits might increase due to an inflow of other sources, for example by the government aid programs. Even more so, the authors find that banks do not change deposit rates in response to a natural disaster. However, Cortés and Strahan (2017) find that banks increase deposit rates in connected but unaffected markets to fund the increase in credit demand. They also find that credit is reallocated, and in addition to the study by Ivanov et al. (2022), they provide evidence that banks increase mortgage securitization in connected non-affected markets. Berg and Schrader (2012) study bank lending in Ecuador in response to volcanic eruptions. In line with other papers, the authors find that due to the shocks, credit demand will increase. Second, due to an increased risk, banks will grant loans to a smaller fraction of applicants. They find that after a natural disaster, not only loan demand increases, but also loan characteristics change. Berg and Schrader (2012) find that while credit is restricted, borrowers with pre-existing relationships with the banks are less likely to be affected. Their results show that reduced information asymmetry, via pre-existing relationships, improves access to credit in times of disaster.

Understanding these dynamics is important for analysing the consequences of natural disasters. In my research, I study the impact of natural disasters on syndicated lending practices. It raises the central research question: *How do natural disasters affect the loan volume and loan structure in the syndicated lending market in Europe?*. This question can be split up in two central hypotheses. Hypothesis 1 states that the loan volume on a province month level is positively related to the occurrence of a natural disaster. Loan volume is measured in different ways: the number of loans, the total deal volume and the total number of lead arrangers on a provincial level. Hypothesis 2 states that natural disasters exacerbate information asymmetry, which relates to the structure of the syndicate loans. Hypothesis 2 is split up into multiple sub-hypotheses: I propose that (1) the relationship between the occurrence of a disaster and number of lenders is negative, and (2) that the relationship between a disaster and the retained lead arranger share is positive. Furthermore, I expect that (3) the occurrence of a natural disaster is negatively related to the likelihood of a loan being secured and (4) that the occurrence of a disaster is negatively related to maturity. Lastly, I expect that (5) the occurrence of a natural disaster is positively related to deal spread. Additionally, it is expected that geographical proximity between the borrower and lender mitigates information asymmetry and therefore reduces the effect between a disaster and the syndicate structure. The hypothesis that natural disasters are followed by more loan volume is supported by many researchers ((Ivanov et al., 2022), (Cortés and Strahan, 2017), (Berg and Schrader, 2012)). The expectation that increased asymmetric information leads to a different syndicate structure, is based on the framework of Diamond (1991). This framework provides a continuum between private sole-lender bank loans on one side and public debt on the other side. Syndicate loans fall somewhere in the middle. Whether a firm will issue debt, on one side of the spectrum or the other, is based on the amount of credit reputation it has. With little credit reputation, there is a need for increased monitoring incentives, which increases the concentration of the loan (Sufi, 2007). This concentrated loan, with a high lead arranger share and few lenders and lead arrangers, resembles a private sole-lender loan more closely.

To investigate the impact of natural disasters on syndicated loan activity, this study analyses a sample of European syndicated loans between 2010 and 2023. Identifying 490 natural disasters within this period, the analysis distinguishes between disaster loans and non-disaster loans. Disaster loans are defined as syndicated loans that are originated within 12 months of the occurrence of a natural disaster in the same province. For robustness, I include an additional specification that follows a 6-month timeframe. The data is analysed using Ordinary Least Squares (OLS), negative binomial models, and logistic regression models. The data, aggregated to a province-month level for the first approach, examines the relationship between disaster occurrence and loan volume metrics: deal volume, number of loans, and number of lead arrangers. The models are extended with province-month fixed effects. For the second approach, individual loan-level data is analysed, controlling for country and year fixed effects. To further explore the impact of geographic proximity between borrowers and lenders, interaction terms between disaster occurrence and a proximity dummy are included in the models on an individual loan level.

The outcomes of my research indicate no clear relationship between the occurrence of a natural disaster and the loan volume. While an initial analysis indicates an increase in the number of loans following a natural disaster, this effect disappears when controlling for other factors. Conversely, total deal volume tends to decrease following disasters. The total number of lead arrangers is not strongly correlated with the occurrence of a natural disaster. Overall, the findings suggest that certain loan, lender and loan characteristics are better at explaining loan volume than the occurrence of a natural disaster. For the syndicated loan characteristics, I find a significant relationship to the occurrence of a natural disaster for some specific components. For syndicated loans following a natural disaster, the share retained by the lead arranger is larger. Additionally, these loans have fewer lenders on average. This is directly in line with the expectation that natural disasters heighten information asymmetry, and require more monitoring incentives by making the syndicated loan more concentrated. For the other deal components, I find significant relationships, but all contrary to the initial hypothesis once control variables are included. The fact that this relationship changes when control variables are included, shows that loan characteristics like maturity, deal spread and collateral are interdependent and not just related to the occurrence of a natural disaster. Furthermore, lender-borrower proximity does not moderate the relationship between disaster loans and loan characteristics, again highlighting an additional layer of complexity.

These results reveal how loan characteristics are influenced by more than just the occurrence of a natural disaster. My thesis is not the first to study the effect of natural disasters on bank lending practices. However, it focuses on unique aspects that contribute to existing academic literature. Firstly, most studies are located in either the United States or a single country. With an elaborate dataset on events and lending in Europe, I create a broad environment in which I study the impact of natural disasters on syndicate loans. By using name matching algorithms and manually identifying provinces within European countries, I am able to study impact on a regional level, extended with borrower information that is not directly linked to Dealscan data. Secondly, the main contribution to existing literature is that it uses natural disasters as a setting of high information asymmetry. Other papers recognize that after a natural disaster, information becomes more uncertain (Nguyen et al., 2023a) and that prior relationships become more important (Berg and Schrader, 2012). Other papers also study the role of information asymmetry on syndicated lending structure (Champagne and Coggins (2012), Sufi (2007), Blickle et al. (2020), (Dennis and Mullineaux, 2000)). However, to the extent of my knowledge, no paper has studied the direct impact of natural disasters as a setting of information asymmetry on syndicate structure. As bank lending plays an important role in recovery after disasters, it is worth studying how the structure and amount of loans differ from a regular setting without a natural disaster.

The following chapter of this thesis highlights the literature most relevant for this research. It is divided into theory on bank lending and natural disasters. Section 3 discusses the hypothesis, descriptive statistics, sample and methodology. Section 4 provides the results. Section 5 concerns the conclusion. Finally, the results will be discussed in Section 6.

2 Literature Review

2.1 Bank lending

2.1.1 Information asymmetry

Seminal work by Stiglitz and Weiss (1981) explains the role of information asymmetry in the interest charged on loans. Assuming a simplified setting where banks cannot perfectly observe borrower characteristics, two types of borrowers exist: safe and risky. Due to this information asymmetry, banks cannot differentiate between the two and set a single interest rate. This equilibrium rate reflects the average risk of the borrower pool. As a result, the interest rate is higher than what would be charged to safe borrowers alone, discouraging them from borrowing. This phenomenon, known as adverse selection, occurs because the higher interest rate attracts disproportionately more risky borrowers, driving out the safer ones. However, borrowers are able to overcome information asymmetry by providing credible signals: collateral would signal that the borrower is of better quality, and it reduces risk, which in turn should lower the interest rate charged. Pozzolo (2004) sheds light on the role of different types of guarantees, where an important distinction is made between real and personal guarantees. Real guarantees involve the pledging of securities or real estate as collateral, which are mostly internal. In a personal guarantee, which is external, an individual assumes responsibility for the repayment of the loan. Pozollo finds that both types of guarantees reduce credit risk, but differentiate in doing so as personal guarantees reduce moral hazard incentives, and real guarantees provide priority to the creditor in case of default. Ioannidou et al. (2022) underscore the importance of collateral, demonstrating that it reduces credit risk ex ante: borrowers with a high probability of default get less benefit from pledging collateral. Ex post, the authors show that collateral significantly reduces the probability of default. Similarly, maturity can also help reduce agency problems like asymmetric information and managerial risk incentives (Barnea et al., 1980). While the maturity of a loan is dependent on the financing needs of a borrower, the authors find that shorter maturities can force the borrower to focus more on short-term profitability. This aligns the values of the debt holders and shareholders within a firm. Ortiz-Molina and Penas (2007) find that in small business lending, maturity and collateral pose as a substitute for each other. Firstly, debt maturities are often shorter for firms with poor credit history and firms that are less opaque. Secondly, personal collateral is often associated with longer maturities. When a firm is able to reduce information asymmetry and pledge (personal) collateral, the maturities get longer. While these results suggest that maturity serves as a governing mechanism, this might not apply to firms of all sizes. The authors note that larger firms, which are subject to more disclosure requirements, face fewer problems in enforcing covenants and therefore have less need for this governing mechanism.

Another body of literature studies how information asymmetry is related to geographical proximity between the lender and borrower. Mian (2006) finds that when information asymmetry is high between a lender and a small business, the lender tends to lend to geographically close borrowers. Agarwal and Hauswald (2010) find that lender-borrower proximity enables soft information to be retrieved, which highlights a local informational competitive advantage. Cotugno et al. (2013) highlight another dimension of proximity in their paper. Instead of studying the geographical distance between a lender and borrower, they specify distance as the distance (in kilometres) between the branch responsible for the financing decision and the operating branch of the lender. They find that this hierarchical distance reduces the ability to transfer soft information, and in turn reduces the availability of credit for firms.

2.1.2 Syndicated lending

The previous section described how information asymmetry between borrowers and lenders influences the pricing and structure of loans. In syndicated lending, an additional dimension of asymmetric information plays a role. To understand these dynamics, it is essential to first define a syndicated loan. According to Moles and Terry (1997), a syndicated loan involves multiple lenders, including banks and other financial institutions. In this arrangement, one or more lead arrangers retain a portion of the loan while distributing the remainder to other lenders. This structure creates information asymmetry not only between lenders and borrowers, but also among the lenders themselves. Holmstrom and Tirole (1997) provide a framework of monitoring incentives in lending to businesses. In a setting with multiple lenders, the lead arranger lacks perfect incentives to monitor. Holding only a part of the loan, the lead arranger faces unobserved and costly monitoring responsibilities. They bear most of the costs for screening and monitoring but are entitled to only a fraction of the loan's benefits. When more intensive monitoring is required, the lead arranger may lack the motivation to monitor properly. In turn, this can create a moral hazard problem (Jensen and Meckling, 1976). Additionally, adverse selection can occur when the lead arranger has superior information to other lenders. The lead arranger will then be incentivized to keep larger shares of good-performing loans and smaller shares of poor-performing loans. Sufi (2007) finds that syndicates are more concentrated and a larger share is retained by the lead arranger, if their borrowers require more monitoring and more extensive due diligence. Similarly, Simons (1993) finds that the retained share by the lead arranger is generally bigger when the quality and quantity of borrower information is poor. It highlights that only lenders with a large enough stake in the borrower have the right incentives to properly monitor.

While the share retained by the lead arranger plays a key role in explaining or mitigating information asymmetry, there are multiple elements in the structure of a syndicate that play a role. As mentioned in the paper by Champagne and Coggins (2012), this structure contains elements like the reputation of the lead bank, the distribution of loan shares among lenders, syndicate geography, existing borrower relationships, the number of lenders, and the number of lead arrangers. The role of the different elements of syndicate structure can be explained with the private debt - public debt continuum by Diamond (1991). This continuum explains a firm's choice for acquiring debt. On one end of the spectrum, sole-bank loans are suitable for borrowers with no credit reputation. On the other hand, as firms build a credit reputation, they require little to no monitoring and will choose to place public debt. While this choice is simplified and is actually also dependent on other characteristics like interest rates, it does provide a good framework for syndicated loans. Dennis and Mullineaux (2000) propose that syndicate loans fall in the middle of the spectrum, right in between sole-lender loans and public debt. Sufi (2007) describes how borrowers with little or no credit reputation rely on syndicated loans with a larger lead arranger share and fewer participants, resembling almost a sole-lender loan. Lending to borrowers with a solid credit reputation closely resembles public debt: the share retained by the lead arranger is smaller, and the syndicate will contain more lenders. Dennis and Mullineaux (2000) find the same relationship between information quality and asymmetry and the number of lenders, and find that lead bank reputation and success in syndicating larger loan portions are positively related.

Blickle et al. (2020) find rather contrasting results. The authors form three hypotheses that should logically follow from information asymmetry theory. First, the lead arranger would not often sell its share, as this would create problems with moral hazard and adverse selection. Secondly, a lead arranger should have an information advantage above other lenders, due to its increased incentives to monitor and screen the loan, and therefore should be less likely to sell the loan than the other lenders. Lastly, loans that are entirely sold by the lead arranger should, on average, perform worse, as the lead arranger loses all exposure to the borrower and should therefore have no incentives to monitor any more. Blickle et al. (2020) find that for the first hypothesis, the results are contradictory: 13% of all loans are sold before maturity, and for some types of loans this percentage is higher. Moreover, lead arrangers are just as likely to sell off their entire share as other lenders, and retention of the share is negatively linked to loan performance.

Furthermore, the syndicate structure is not only determined by characteristics of asymmetric information, in its turn it can also determine loan terms. While structure and loan terms are often determined in an equilibrium, and are not exogenous per definition, academics have found some important relationships. The spread on a loan is influenced by two opposite effects related to the lead bank's share. A larger share held by the lead bank reduces the cost of asymmetric information, which lowers the premium demanded by other participating lenders. Conversely, a larger share also means the lead bank takes on more credit risk, which calls for a diversification premium demanded by the lead bank. This trade-off between monitoring incentives and diversification underscores that larger, well-diversified banks have a competitive advantage as they have less need to spread the credit risk among other lenders (Ivashina, 2009). In an out-of-sample test, Coleman et al. (2006) find that for banks, monitoring intensity is positively related to yield spread, and positively related to loan maturity.

2.1.3 Credit risk

In the previous subsections, much has been explained about screening and monitoring incentives. As screening and monitoring essentially concern credit risk, this subsection provides a deeper insight into the definition and types of credit risk, and drivers of this risk.

Credit risk refers to the possibility that a bank's borrower or counterparty may not fulfil their obligations as per the agreed terms. (BIS, n.d). Within the broader definition of credit risk, different types of risk can be defined. Firstly, concentration risk is the risk of great financial losses resulting from a concentrated risk exposure to a certain borrower, industry, or other homogenous group. Secondly, spread risk is the possibility of financial loss resulting from changes in the difference between yields of different financial instruments or interest rates. Thirdly, downgrade risk is the possibility of financial loss resulting from a credit rating agency reducing the credit rating of an issuer, which can cause a decline in the value of the issuer's securities. Lastly, default risk is the potential for financial loss due to a borrower failing to repay a loan or meet debt obligations as agreed (Crouhy et al., 2000).

Credit risk can be influenced by numerous factors. Firstly, collateral significantly impacts both ex-ante and ex-post credit risk (Ioannidou et al., 2022). However, many other determinants also play a crucial role. In a meta-study by Naili and Lahrichi (2020), various factors contributing to credit risk are highlighted. Systemic influences, such as GDP growth, negatively correlate with the amount of non-performing loans (NPLs), a common measure of credit risk (Carey, 1998). Additionally, higher interest rates are associated with increased loan losses (Shrieves and Dahl, 1992). Unemployment rates, reflecting either income levels (Lawrance, 1995) or broader macroeconomic conditions (Louzis et al., 2012), are positively correlated with loan defaults. On a bank-specific level, Naili and Lahrichi (2020) identify numerous non-systematic factors influencing credit risk. For instance, Laeven and Levine (2009) demonstrate that banks with more influential owners tend to take greater risks, with ownership affecting the relationship between bank regulation and risk. Other factors affecting credit risk include bank size, profitability, diversification, and loan growth, as noted by Naili and Lahrichi (2020). Common measures of credit risk include NPLs and Value at Risk. Other measure can consist of the Expected Shortfall or various accounting measured. Additionally, individual probability of default can be assessed using logit and probit models, which is beyond the scope of this research.

2.2 Climate risk

As natural disasters can be regarded as a materialisation of climate risk, this section provides more insight into the types of climate risk, and earlier literature on this topic. Climate risk is often divided into two categories: physical risk and transition risk. While this thesis primarily addresses the impacts of physical climate risk, both types are crucial for banks' risk management. De Nederlandsche Bank (2019) discusses how these risks can affect banks. Physical climate risks stem directly from severe climate events, covering both chronic and acute risks that drive conventional risk factors. Extreme weather events and long-term shifts in weather patterns can damage properties, increasing credit risk by raising the loss given default. Furthermore, extreme weather can directly affect bank branches and operating systems, which introduces operational risks. In foreign exchange or commodity markets, climate risks elevate market risk, and severe weather events can cause long-term macroeconomic shocks, potentially leading to liquidity issues. On the other hand, climate transition risks do not arise directly from climate change but from the shift towards a greener economy. Financial institutions encounter risks associated with emerging sustainable technologies, regulatory frameworks, carbon taxes, policy measures, and changes in market attitudes. Both physical and transition risk can be generalized and noted as an equation, which showcase the range of factors that drive climate risks.

Physical climate risk can be described by the following equation (Tankov and Tantet, 2019). Hazard refers to the weather pattern or climate event of interest, both the probability of it occurring and the physical intensity. Exposure refers to the geographical location or system that the event affects, and vulnerability to the propensity to be adversely affected.

$$\text{Physical risk} = f(\text{hazard, exposure, vulnerability}) \tag{1}$$

Transitional climate risk can be represented by the following equation (Semieniuk et al., 2021).

$$\text{Transitional risk} = f(\text{policy risk, technology risk, preference change}) \tag{2}$$

This equation highlights that transitional risks are often part of policy changes, technological advances or preference changes. These preference changes can be by consumers, and/or by investors: either by investing according to ethical standards or to hedge downside risk. Obviously, these three inputs interact with each other and are not necessarily mutually exclusive. Even more so, physical risk and transitional risk are not independent. For example, extreme weather events (physical risks) might call for new policies (transitional risks). It is generally believed that if transitional risk is higher now, by a quicker implementation of low-carbon policies, physical risks are mitigated in the future.

2.2.1 Climate transition risk

Recently, the European Central Bank conducted a climate risk stress test (ECB, 2022). The report examines the green transition through three potential scenarios. The first scenario involves accelerating green investments and policies, resulting in carbon emission reductions aligned with the Paris Agreement goals. In the second scenario, the Paris Agreements targets would be met, but efforts would only be intensified from 2026. In the third scenario, reduction efforts would begin in 2026, with the Paris Agreement goals not being achieved. The report indicates that firms, households, and banks would benefit the most from the first scenario. Although this approach requires higher costs upfront, it ultimately lowers expenses as the benefits are realized sooner. Delayed green investments would expose banks to increased credit risk, as they lend to firms that are not well-prepared. With no investments, physical risks would materialise and impact financial institutions severely. This not only highlights the trade-off between transition and physical risks but also emphasizes the need for banks to account for climate risks in their planning.

Roncoroni et al. (2021) underwrite the impact of climate change policies on banks and investment funds that are connected. The authors map out the connectedness between financial institutions and, via stress testing, quantify the effects of climate change policies. In a scenario with stringent climate policies or a disorderly transition, banks and funds with significant exposure to high-carbon sectors may incur substantial financial losses. Roncoroni et al. (2021) stress that because of the interconnectedness of these banks and investment funds, the risks can be a source of systemic instability. Therefore, the paper underwrites the findings by the ECB that a smooth transition to low-carbon minimizes disruptions in the financial system.

Nguyen et al. (2023b) examine climate transition risk for US loan portfolios. The authors implement a bottom-up approach to calculate the overall exposure to transition risk of a bank's loan portfolio. First, they predict carbon footprints for individual syndicated loans and aggregate these individual estimates to the overall loan portfolio of banks. A second measure for transition risk is captured by how much of the bank's loan portfolio is towards sectors sensitive to climate change, which are suppliers of electricity and fossil fuels. In their stress test, Nguyen et al. (2023b) find that in moderate climate scenarios, the losses to the bank are manageable. However, this is dependent on the severity of the climate change. If global warming is more serious, a considerable amount of tail risk can materialise, leading to great losses. The authors state that to prevent such losses, banks should adopt a green lending policy that extents beyond an exclusion of fossil-fuel producers. Instead, other sectors can be greatly exposed to carbon price liabilities. Overall, borrowers with weaker financials and less green policies form a great risk to a bank's lending portfolio, which highlights that traditional financial risk and climate risk are connected.

2.2.2 Physical climate risk

The impact of physical risks on financial institutions has been studied by exploring historical extreme weather events. Garbarino and Guin (2021) examine how floods affect mortgage lending. In a study of repeat mortgage lending after a severe flood in England in 2013/2014, the authors find that lenders tend to underestimate the long-term flood risk, and regard the flood as a one-time event. After the flood, lenders did not adjust the property valuations downwards to account for the damage, and this valuation bias is not offset with interest rates or loan amounts. Generally, their findings suggest that ex-post, lenders do not take into account these local risks, but rather look at a highly aggregated price indexes. With the aggregate index as the framework, some properties may be overvalued and some undervalued, and the net effect of a flood may be absorbed. However, the authors do mention that taking into account these flood risks may also negatively affect households. They will then have fewer possibilities to borrow to rebuild damaged properties or to deal with financial losses after such a flood. Blickle et al. (2024) have also studied flood risk. In the United States, the Federal Emergency Management Agency (FEMA) maps out regions that are more prone to flooding. While many studies focus on mortgage lending within these so-called flood-zones, Blickle et al. (2024) focus on flood risk not mapped by the FEMA. Mortgage lenders are less likely to grant mortgage loans to borrowers in these unmapped flood risk regions, and if they do so, against a higher interest rate and/or lower Loan-To-Value (LTV). This effect is stronger for larger, traditional banks, compared to small banks and non-banks. These findings not only highlight different risk-taking by different lenders, it also shows that lenders actually regard flood-risk, even if not reported by the FEMA, as a risk factor that needs to be mitigated.

Ivanov et al. (2022) examine how banks and shadow banks propagate natural disasters via a study of syndicated lending. Firstly, the authors establish that after a natural disaster, demand for credit lines increases. The question arises how banks allow for this increase in demand. While banks deposit bases do increase, this is likely not a funding source. Instead, the deposits are concentrated in *affected* regions, likely due to an inflow of government funding programs. Banks do not raise deposits, but instead reduce credit to unaffected regions. This phenomenon, known as the network effect, is even more pronounced for banks with low regulatory capital. After a natural disaster, the demand for credit primarily comes in the form of credit lines issued by banks. However, shadow banks step in to fill the gap in regions where banks restrict lending, though this is only for borrowers reliant solely on term loans. These findings highlight the important role of shadow banks in lending after natural disasters.

In a study on the effects of volcanic eruptions on bank lending, Berg and Schrader (2012) find that credit is restricted. While their study uses volcanic eruptions mainly as a tool to examine exogenous credit shocks, their findings highlight the general effect that natural disasters have on bank lending. Additionally, the paper highlights important characteristics that determine how easy a firm has access to external finance, such as the enforceability of contracts, the availability of credit registries and the protection of property rights. In case a company has little hard information to present to a lender, the lender may rely more on soft information, by which relationship lending becomes important to grant access to credit. Hard information involves quantitive objective data, and soft information involves more subjective information like reputation and future business prospects. With proper access to credit, the negative aggregate affects may be diluted in case of an external shock. Generally, Berg and Schrader (2012) find that after a natural disaster, the demand for credit increases, indicating that there is an additional need for financing damages above what is insured. Secondly, when a borrower experiences a volcanic eruption, they are less likely to be awarded a loan. Lastly, these restrictions are less severe for repeat borrowers, as there is reduced information asymmetry. Their findings not only confirm that demand for credit increases after a natural disaster, it also sheds light on borrower-lender relationships.

Cortés and Strahan (2017) have studied how banks in the United States respond to natural disasters. The authors explore how demand shocks, which arise from a natural disaster, are transmitted. The study covers mortgage origination between 2001 and 2010 for multi-market banks, which are banks with branches in multiple locations. First, the authors establish that following a natural disaster, demand for mortgages increases. While the FEMA and insurers award some funds to homeowners to rebuild their homes, this does not cover total damages. From their event study, it becomes clear that 2 two 6 months after the natural disaster, a peak in mortgage loan origination follows. This abnormal level of originations disappears after 12 months. Then, Cortés and Strahan (2017) study how banks respond to this increased demand. They propose two conditions for the framework in which this happens. Firstly, bank credit needs to be constrained: they cannot gain enough additional liquidity to meet the credit demand. Secondly, banks need to be able to move credit from one branch to another. For these two assumptions to hold, the banks must provide service that cannot be substituted by other banks, such as monitoring. The authors find that larger banks face fewer credit constraints compared to smaller banks. Specifically, larger banks benefit from lower external financing costs, allowing them to obtain additional liquidity from the interbank market more cheaply. Small banks reallocate credit: they increase credit in regions affected by the disaster, and reduce credit elsewhere. The credit is rationed from regions where the banks have little competitive advantage, which are the regions where they lend without branches or have only a minor market share. In these regions, it is likely that other intermediaries pose as a good substitute. Additionally, these smaller banks do not just reduce credit, they increase mortgage securitization and increase deposit rates in connected markets. The results show that small banks respond effectively to these demand shocks, smoothing the effects without needing to access capital markets for additional liquidity.

3 Methodology

3.1 Hypothesis

Hypothesis 1: Following a natural disaster in Europe, syndicated loan volume increases

1.1 Number of loans
H_0: The occurrence of a natural disaster is not significantly related to the total number of loans in a province.
H_1: The occurrence of a natural disaster is positively related to the total number of loans in a province.

1.2 Deal Volume
H_0: The occurrence of a natural disaster is not significantly related to the total deal volume in a province.
H_1: The occurrence of a natural disaster is positively related to the total deal volume in a province.

1.3 Number of lead arrangers
H_0: The occurrence of a natural disaster is not significantly related to the total number of lead arrangers in a province.
H_1: The occurrence of a natural disaster is positively related to the total number of lead arrangers in a province.

It is clear that natural disasters have financial consequences. Even if corporations, governments and individuals perfectly try to mitigate damages ex-ante, disasters remain unpredictable in terms of their location, severity and timing. Even more so, it is likely that governments, individuals and corporations do not perfectly try to mitigate disaster damages. Individuals and governments display myopic behaviour: if the likelihood and impact of disasters is underestimated, individuals will underinvest now because the upfront costs seem high in comparison to potential future losses. Similarly, politicians might also favour short-term electoral gain by investing in short-term disaster reliefs than expensive long-term preventative measures (Neumayer et al., 2014).

While the assumption that disasters lead to economic losses is straightforward and follows from real-life observations, it is not directly clear how these losses are absorbed. While a large portion of losses is insured, a sizable portion that is uninsured remains (Howard, 2024). While companies have multiple sources of funding, like government aid programs, internal financing, or alternative sources, banks play an important role in credit supply. Not only do banks possess a large pool of available capital, they are often encouraged by governments to lend out money to support economic recovery (Cortés, 2014). Therefore, I propose that at least a sizable portion of funding for recovery after a natural disaster stems from banks, which implies an increase in syndicated loan volume following a natural disaster in these regions. While loan volume is measured in three different ways, I expect a positive relationship for all sub-hypotheses.

Hypothesis 2: The syndicate structure for loans affected by natural disaster differs from non-affected loans

2.1 Lead arranger share
H_0: The occurrence of a natural disaster is not significantly related to the share retained by the lead arranger(s).
H_1: The occurrence of a natural disaster is positively related to the share retained by the lead arranger(s).

2.2 Number of lenders
H_0: The occurrence of a natural disaster is not significantly related to the number of lenders per loan.
H_1: The occurrence of a natural disaster is negatively related to the number of lenders per loan.

Economic theory suggests that information asymmetry is related to the structure of syndicate loans. When one lender lends to one borrower, there is an information asymmetry between those two, where the borrower has superior information on their future repayment prospects and collateral value. When loans are syndicated, so undertaken by multiple lenders, an additional dimension of asymmetry follows: some lenders can have superior information to other lenders. In syndicated loans, it can be beneficial to attract more lenders, as this is an opportunity for diversification (Ivashina and Scharfstein, 2010). However, when information asymmetry is high, and borrower information is of poor quality or quantity, there needs to be more incentive to monitor. With more lenders, ownership becomes dispersed, and lenders have less "skin in the game", which reduces their monitoring incentives. Therefore, it is believed that information asymmetry is negatively related to the number of lenders (Dennis and Mullineaux, 2000). With that same reasoning, the share retained by the lead arranger is positively related to information asymmetry. With more asymmetric information, monitoring and screening becomes more important, for which lead arranger are incentivized by keeping a larger stake in the loan.

I propose that natural disasters are a natural setting with high asymmetry. Firstly, natural disasters can directly damage collateral value via damaged real estate, inventory, machinery and even accounts receivable. Collateral can provide a credible signal of borrower quality to the lender (Stiglitz and Weiss, 1981). When there is less opportunity to use collateral as a signal to mitigate information asymmetry, it is assumed that a larger share retained and fewer lenders and less co-arrangers will increase the incentives for monitoring and screening. More monitoring and screening is required in the absence of signalling opportunities. Secondly, natural disasters increase information uncertainty due to their impact on business. Hidden damages and uncertainty about future repayment abilities due to a potential disruption of business heighten information uncertainty and asymmetry, as the lender has even less insight into these matters.

Furthermore, I propose that the setting of information asymmetry is related to other loan characteristics: maturity, the presence of collateral and deal spread.

2.3 Collateral

H_0: The occurrence of a natural disaster is not significantly related to whether a loan is secured.
H_1: The occurrence of a natural disaster significantly decreases the likelihood that a loan is secured.

2.4 Maturity

H_0: The occurrence of a natural disaster is not significantly related to the maturity of a loan.
H_1: The occurrence of a natural disaster is positively related to the maturity of a loan.

2.5 Loan spread

H_0: The occurrence of a natural disaster is not significantly related to the spread on a loan.
H_1: The occurrence of a natural disaster is positively related to the spread on a loan.

As previously mentioned, collateral can be destroyed during natural disasters. Generally, collateral plays a great role in overcoming information asymmetries ((Stiglitz and Weiss, 1981), (Pozzolo, 2004), (Ioannidou et al., 2022)). However, I expect that borrowers have fewer assets available to pledge as collateral in the aftermath of a natural disaster, creating a negative relationship. The maturity of a loan is based on many factors, but in lending with high information asymmetry, shorter maturities can act as a measure to prevent credit risk and to ensure timely repayments of the loan ((Barnea et al., 1980), (Ortiz-Molina and Penas, 2007)). Therefore, I expect a negative relationship between the occurrence of a natural disaster and maturity. At last, I expect that due to the inherent (credit) risk of these disaster loans, that deal spread will be higher than for non-disaster loans (Stiglitz and Weiss, 1981).

Additionally, I propose that borrower - lender proximity acts as a moderating effect for hypothesis 2. Prior research ((Sufi, 2007), (Agarwal and Hauswald, 2010)) highlights that proximity enables soft information to be transferred more smoothly from borrower to lender. If this proximity matters, it should mitigate the effects of asymmetrical information. Therefore, I propose that lender-borrower proximity has a moderating effect on the relationship between the occurrence of a disaster and lender share, number of lenders and number of lead arrangers. In that relationship, it should not matter whether this proximity is intentional (a lead arranger chooses participants geographically close to the lender), or not.

3.2 Sample

This thesis aims to capture the effect of natural disasters on lending behaviour by lenders in the European syndicated loan market. The lenders include mostly European banks, but also some non-banks and Asian and North-American lenders. Natural disasters are identified from the EM-DAT database (CRED and UCLouvain, 2024). The database records events as 'hazards' if they meet at least one of three criteria: cause at least ten deaths, affect at least 100 people, and/or a call for international assistance or an emergency declaration was made. The sample period runs from 2010 to 2023, and contains 490 natural disasters in Europe. The database originally contained heatwaves, but these have been excluded. Typically, they span over a longer time, making it harder to interpret their consequences. Furthermore, heatwaves may have less direct and severe economic consequences, making their effects more noticeable in terms of number of deaths rather than economic damages. The second argument is supported by the data in the database. The remaining events can generally be classified into either geophysical, climatological, meteorological or hydrological events. A division of these disaster types is displayed in the summary statistics, in Table 4. Additionally, while the EM-DAT database allows for strong identification of natural disasters, it is not free of biases. The estimate of total damages and total insured damages may suffer from some accounting biases, as these are less frequently reported than the human impact variables, according to the creators of the database (EM-DAT, 2023). As these total damages are both prone to misreporting and often not reported at all, I opt out of using them as inputs in my regression model. Instead, I quantify the impact of a disaster with a binary variable, which only indicates whether a disaster occurs or not.

The information on lending practices following natural disasters, is obtained from multiple sources. Primary information on syndicated lending is obtained from Dealscan (Dealscan, n.d.). From Dealscan, I identify the lead arrangers, for which I obtain basic financial data from Bankscope focus (BankFocus, n.d.). Borrower information is obtained from Orbis (Orbis, n.d.). Both lender and borrower balance sheet information is on a yearly basis, due to the lack of quarterly data available from before 2016. Data from all three databases is merged into the main dataset. Since the Dealscan data is from European syndicated loans, there is no unique borrower ID to match the data. After standardizing the names in all datasets by removing uppercase letters and removing words that are common across many names (incorporation, company and llc), I implement a bigram matching algorithm (Raffo and Lhuillery, 2009). This algorithm divides all names into chunks of 2 characters, and compares them to the other dataset using a Jaccard index: $J(A, B) = \frac{|A \cap B|}{|A \cup B|}$. Here, $|A \cap B|$ represent the number of elements in the intersection of sets A and B, and $|A \cup B|$ represent the number of elements in the union of datasets A and B. Essentially, this Jaccard index assigns a similarity score, which enables string variables to be matched. As this matching can be imprecise, I manually scan for matches as well.

3.3 Variables

In Appendix A, Table 14 provides a comprehensive list of all the variables used in this analysis. The next section offers a detailed description of the control variables. While fixed effects address some unobserved variability in the data, control variables are included to explain additional relationships. These variables are expected to influence syndicate structure, information asymmetry, or both. For the borrower and lender control variables, I replaced values below the 1st percentile and above the 99th percentile with missing data. This way, the results are not as strongly impacted by the extreme outliers found in the original data.

Borrower characteristics
The first control variable concerns firm size, or the total assets of a borrower. Generally, it is believed that smaller firms experience more information asymmetry than larger firms. This is due to their available resources for financial reporting, and because they are less well known, they would receive less attention by analysts (Lean and Tucker, 2001). Secondly, the Return on Assets (ROA) is included. ROA, calculated as net income / total assets, is a measure of profitability that accounts for the size of the firm. Firm profitability is negatively related to default risk (Altman, 1983), and by including it as a control, it accounts for other risk factors that may influence the structure of a loan syndicate. Similarly, the solvency and liquidity ratio of a borrower control for the financial health of the company. The liquidity ratio reflects a company's cash position. Firms with higher liquidity have more internal funds and are less reliant on external financing, especially during natural disasters. This reduced dependence on external sources may affect the structure of syndicate loans (Ross, 1977). The D/E ratio of a borrower indicates the financing structure of a company and may also signal risk (as more debt may imply a higher risk of default). Lastly, interest coverage ratio, which is calculated as EBIT / interest expenses, accounts for a company's inherent ability to service debt, separate from any information asymmetry created by the natural disaster.

Lender characteristics The most important control variable for lender characteristics is the size of a lender, measured by total assets. The size of a bank (or any non-bank lender for that matter) determines the potential to participate in larger syndicates, risk tolerance and diversification and inherent lending capacity (Chu et al., 2018). In a similar manner, the lenders profit margin controls for inherent risk preferences, as more profitable lenders may have more capacity or willingness to undertake higher-risk loans.

Loan characteristics The deal amount, deal spread and maturity control for loan characteristics that can otherwise influence the structure of a syndicate loan. The deal amount may influence the number of lenders or lead arrangers. Maturity is related to the riskiness of a loan, which in turn influences the incentives the lender has to monitor. These incentives to monitor play an important role in the relationship between information asymmetry and loan structure. Deal spread is included because it interacts with maturity and the presence of collateral, making it a potential confounding factor.

3.4 Identification

As the goal of this analysis is to study loans originated after the occurrence of a natural disaster, it is important to dissect how exactly I identify these disaster loans. The loans in the Dealscan database do not indicate whether they are used for repairing damages from weather events, but I consider "disaster loans" as such if they occur within the same province within 6 or 12 months. From the available data, it is unobserved how long it takes to originate a syndicated loan after a natural disaster has occurred. Given that a loan is specifically awarded to repair damages, it remains unclear when the loan was applied for or how long it took to form a syndicate. However, Cortés and Strahan (2017) provide a reasonable timeframe. In their study, mortgage originations peak in the 2 to 6 months following a natural disaster, and this abnormal level of originations remains for 12 months after the disaster. Following that same reasoning, I specify a 12-month timeframe to capture all potential effects. For robustness, I also use a shorter timeframe of 6 months to see whether the effects are captured in a shorter time period. Those results are included in Appendix B.

Given this timeframe of 12 months, and 6 months in the alternative specification, I match natural disasters from the EM-DAT database with syndicated lending data from Dealscan. In the Dealscan database, information is available on the location of the loan, which consists of the city, country and zip-code. However, analysis on the level of either the country or city is not suitable to discover any effects. Analysing data at the country level might miss connections between loans and natural disasters if they occur far apart. On the other hand, city-level analysis presents practical challenges. First, there may not be enough data points for each city to ensure a reliable analysis. Second, many disasters are reported only at a regional level, which means they may not be identifiable at the city level. Even if disasters are reported at the city level, important connections between loans and nearby cities might be overlooked. Therefore, I choose a divisional level that is regional, most closely related to a county or province. In the analysis, they are called province. As the sample consists of different countries with different types of administrative divisions, this regional level is specific to each country to most closely match a province-like subdivision. It is consistent within a country, so that each regional subdivision can reliably be compared with itself, and such that cities are consistently assigned to their appropriate provinces.

From there, the identification continues. Having chosen a timeframe and regional division, I start my matching procedure. Firstly, I manually supply the Dealscan database with their consequent provinces, by the city and zip-code the syndicated loan is originated from. If a loan in Dealscan reports no location, I try to replace it with the location of the headquarters of the borrowing firm, found in Orbis. Some loans have contrasting information on city and country and seem to have been misreported, these are removed. Now, from the EM-DAT database, I can assign values to the 6-month and 12-month disaster dummy variable. From the EM-DAT database, I identify disasters, and their corresponding date and location. If the Deal Active Date of a syndicated loan is within 6 or 12 months of the disaster date, and the loan is originated in the same province, I assign a value 1, and 0 otherwise. With this process, I have created the dummy variable that indicates whether loans are a "disaster loan" or not.

3.5 Methodological considerations

In the analysis, I employ different types of models. Ordinary Least Squares (OLS) models are used and reported for every sub-hypothesis. As OLS is generally well-understood and often used in financial research, it allows for easy comparison. However, for some of the analyses, other econometric models are more appropriate. This applies when the values of the dependent variable do not follow a continuous distribution. The number of loans, number of lead arrangers and number of lenders, are all dependent variables that have a count distribution. In these instances, it is common practice to employ a Poisson model or Negative Binomial model. While the models serve a similar purpose, a Poisson model requires that the mean and variance of the count variable are equal. The Negative Binomial model relaxes this assumption (Long, 1997). When the data is overdispersed (variance is greater than the mean), the Negative Binomial model captures this by an additional parameter α. Similarly, the Pearson Estimator, noted as $\tilde{\phi} = X^2/(n\text{-}p)$, captures overdispersion in a Negative Binomial model compared to a Poisson model (Cameron and Trivedi, 1986). The reported values in the robustness checks, in subsection 3.7, highlight that the data displays overdispersion. Therefore, I employ a Negative Binomial model. Additionally, I analyse the relationship between the occurrence of a natural disaster and the presence of collateral. The presence of collateral, in other words whether a loan is secured or not, follows a binary outcome: yes or no. This analysis uses a logistic regression model. While the assumption underlying a logit model are similar to OLS, it requires a larger sample than linear regression models to produce stable parameters. This requirement limits the use of some specific fixed effects for the logit models, as it would reduce the number of observations too much to produce any regression coefficients.

Besides the types of regression models, it is important to understand the research design used to estimate the coefficients. I analyse loans that are marked as a disaster loan, which could be seen as "treated". Typically, an event study or difference-in-difference study would provide a useful setting for this type of analysis. However, due to many disasters that follow closely in time, there would be many overlapping events and the possibility to retrieve estimates from an estimation window disappears. A simple difference-in-difference is also not suitable for the study. This begins at the fact that there are multiple disasters at different times. A two-way difference-in-differences analysis studies a control group and a treated group, where at one moment a treatment (like a disaster, regulation, policy, etc) is introduced. It requires parallel trends: if the treatment had not occurred, both the treated and control group would have had a similar trend in their outcome variable. While it is clear that a two-way difference in difference does not apply to the setting of my data, other more advanced techniques are also not applicable. Callaway and Sant'Anna (2021) propose a measure for diff-in-diff with multiple time periods. One of the useful properties is that it imposes a less stringent parallel trends assumption. When using either "never-treated" or "not-yet-treated" groups as control groups, it allows for a parallel trend assumption after controlling for covariates. In my research specifically, I would be able to use provinces where a natural disaster does not occur at all according to the EM-DAT database as a control group. After controlling for covariates such as economic growth and other factors, I could establish a conditional parallel trend assumption. However, the estimator by Callaway and Sant'Anna (2021) requires that treated groups remain treated. This is problematic, as treated groups get treated again (a province where one natural disaster occurs experiences a new disaster later), and because the effects of a natural disaster are not expected to last, but only be temporary. The estimator by Goodman-Bacon (2021) also allows for different time periods in a staggered difference-in-difference analysis, but requires some assumptions that my data does not fulfil. Similar to Goodman-Bacon (2021), it allows for flexible control groups. However, it still imposes a parallel trend assumption which is not likely to hold for my data, and it generally requires a constant average treatment effect. To conclude, the scope of my analysis is limited to studying effects of treated (=disaster) loans, but cannot make reliable causal claims, as it has no statistically sound way to exclude a treatment effect from other effects.

While a difference-in-difference analysis is not applicable, fixed effects and control variables account for other potentially confounding factors. The control variables capture various loan, lender, and borrower characteristics, as described in subsection 3.3. Different fixed effects are employed for Hypotheses 1 and 2. For the first hypothesis, the data is aggregated at the provincial level, with province and month fixed effects to capture local and time-specific influences. For the second hypothesis, analysed at the individual loan level, country and yearly fixed effects are used. Loan fixed effects are excluded due to the lack of repeated loans, and instead, loan characteristics are included to account for loan-specific properties. The same applies to lender and borrower fixed effects. As they have a limited number of observations, I include lender and borrower key financial data as control variables instead. Industry fixed effects were considered but found unsuitable due to high multicollinearity, introducing unnecessary noise. Therefore, I employ country and yearly fixed effects: country fixed effects capture time-invariant characteristics specific to a country, while yearly fixed effects account for time-variant characteristics consistent across all observations. The more granular analysis requires yearly effects to capture broader European developments and country fixed effects to describe broader lending environment characteristics like institutional settings, financial market development, and cultural differences. To implement these fixed effects, I use the "reghdfe" command in STATA, which captures high-dimensional fixed effects and absorbs them. Essentially, the algorithm creates a separate dummy variable for each level of country and each level of year, but does not display all these individual effects in the regression output. Instead, it demeans the dependent and independent variable of these country and year fixed effects before estimating the model.

3.6 Regression models

Hypothesis 1 At first, I hypothesize that the occurrence of a disaster is positively related to loan volume. For loan volume, I use 3 different specifications: the number of loans within a province, the total deal volume within a province, and the total number of lead arrangers within a province. The dataset is collapsed by aggregating all values to a provincial-month level. All borrower, lender and deal characteristics control variables are aggregated to the provincial level by their mean, while the deal volume is the total sum of deal amount and the number of loans and lead arrangers are counted. As each province is a string variable, I encode a numbered value that provides the input to one dimension of the panel data set. The other dimension of the panel dataset is month, which is month combined with its year.

1.1 Number of Lead Arrangers

$$\text{Number of Lead Arrangers}_{p,t} = \alpha + \gamma_p + \delta_t + \beta_1 \text{Disaster(m)}_{p,t} + \mathbf{X}_{p,t} + \epsilon_{p,t} \tag{3}$$

In this model, Number of Lead Arrangers$_{p,t}$ represents the total number of lead arrangers in province p at month t. α is the intercept, γ_p represents province fixed effects, and δ_t represents monthly fixed effects. Disaster(m)$_{p,t}$ is a dummy variable indicating whether a natural disaster occurred in the same province within the previous m months, where m can be either 6 or 12 months. Finally, $\mathbf{X}_{p,t}$ is the vector of control variables, including lender, loan, and borrower characteristics averaged per province-month pair, and $\epsilon_{p,t}$ represents the error term.

1.2 Deal Volume

$$\text{Deal Volume}_{p,t} = \alpha + \gamma_p + \delta_t + \beta_1 \text{Disaster(m)}_{p,t} + \mathbf{X}_{p,t} + \epsilon_{p,t} \tag{4}$$

In this model, Deal Volume$_{p,t}$ represents the sum of all deal amounts, the total deal volume, in province p at month t. α is the intercept, γ_p represents province fixed effects, and δ_t represents monthly fixed effects. Disaster(m)$_{p,t}$ is a dummy variable indicating whether a natural disaster occurred in the same province within the previous m months, where m can be either 6 or 12 months. Finally, $\mathbf{X}_{p,t}$ is the vector of control variables, including lender, loan, and borrower characteristics averaged per province-month pair, and $\epsilon_{p,t}$ represents the error term.

1.3 Number of loans

$$\text{Number of loans}_{p,t} = \alpha + \gamma_p + \delta_t + \beta_1 \text{Disaster(m)}_{p,t} + \mathbf{X}_{p,t} + \epsilon_{p,t} \tag{5}$$

In this model, Number of loans$_{p,t}$ represents the number of loans counted in province p at month t. α is the intercept, γ_p represents province fixed effects, and δ_t represents monthly fixed effects. Disaster(m)$_{p,t}$ is a dummy variable indicating whether a natural disaster occurred in the same province within the previous m months, where m can be either 6 or 12 months. Finally, $\mathbf{X}_{p,t}$ is the vector of control variables, including lender, loan, and borrower characteristics averaged per province-month pair, and $\epsilon_{p,t}$ represents the error term.

Hypothesis 2 Secondly, it is proposed that the syndicate structure is different for loans following a natural disaster. Syndicate structure[1] is decomposed into the number of lenders, maturity, the share

[1] Initially, covenants were considered as an additional unit of measurement. However, it is left out due to the highly

retained by the lead arranger, whether the loan is secured or not, and the deal spread.

2.1 Number of Lenders

$$\text{Number of Lenders}_{i,t} = \alpha + \gamma_c + \delta_y + \beta_1 \text{Disaster(m)}_{p,t} + \mathbf{X}_{i,t} + \epsilon_{i,t} \tag{6}$$

In this model, the unit of observation is a single loan, therefore Number of Lenders$_{i,t}$ represents the number of lenders for a loan i at time t, where time represents the deal active date. α is the intercept, γ_c represents country fixed effects, and δ_y represents yearly fixed effects. Disaster(m)$_{p,t}$ is a dummy variable indicating whether a natural disaster occurred in the same province within the previous m months, where m can be either 6 or 12 months. Finally, $\mathbf{X}_{i,t}$ is the vector of control variables, including lender, loan, and borrower characteristics, and $\epsilon_{i,t}$ represents the error term.

2.2 Maturity

$$\text{Maturity}_{i,t} = \alpha + \gamma_c + \delta_y + \beta_1 \text{Disaster(m)}_{p,t} + \mathbf{X}_{i,t} + \epsilon_{i,t} \tag{7}$$

In this model, the unit of observation is a single loan, therefore Maturity$_{i,t}$ represents the loan maturity in months for a loan i at time t, where time is the deal active date. α is the intercept, γ_c represents country fixed effects, and δ_y represents yearly fixed effects. Disaster(m)$_{p,t}$ is a dummy variable indicating whether a natural disaster occurred in the same province within the previous m months, where m can be either 6 or 12 months. Finally, $\mathbf{X}_{i,t}$ is the vector of control variables, including lender, loan, and borrower characteristics, and $\epsilon_{i,t}$ represents the error term.

2.3 Lead Arranger Share The models for hypothesis 2.3, which concern the relationship between Lead Arranger Share and the occurrence of a disaster, require some more attention. I use a model to predict lender share. I specify a model with the data directly from Dealscan and in an alternative model I attempt to address some issues, as the reported data in Dealscan may be unreliable. First, there are many missing observations, and these are non-randomly distributed, which presents a potential bias. Secondly, shares are often sold to institutional investors after origination. Syndicate structure can change rapidly after origination, but Dealscan only reports this structure as it is formed at the origination of the loan. This implies that the reported data can be an inaccurate representation of real-life loan characteristics (Blickle et al., 2020). However, there are some ways to overcome this problem. In the same article, Blickle et al. (2020) propose a weighting scheme to approximate lender share, and the authors compare two other approximations. The most simple approximation for loan ownership is assuming an equal share across all lenders, but this method has poor prediction power, especially for term B loans, as these are often originated to be sold to institutional investors. Another method involves using average values from certain subgroups of lenders, which are then used as input for missing values (Chodorow-Reich, 2014). While this method is useful for missing values, it assumes that ultimate loan holdings are reflected by syndicate structure at origination. This assumption seems to be unrealistic, as this method comes with poor prediction power. The third option is to use the method developed by Blickle et al. (2020), as described in equation 8. $X_{i,t}$ and X_t are vectors of lender loan-characteristics, observable for nearly all loans in Dealscan.

$$\text{Imputed Lender Share}_{i,t} = \beta_0 + \beta_1 X_{i,t} + \beta_2 X_{i,t-1} + \varepsilon_{i,t} \tag{8}$$

The regression coefficients from this model are used as inputs for the ownership approximation. As this

skewed distribution of covenant versus non-covenant loans, where only 4% of the loans contains a covenant.

model has better predictive properties than the other two models, it is most suited to deal with lead arranger share for this research[2]. In my analysis, I use this imputed lender share to replace the lender share from Dealscan. For completeness, the regression output with the original lender share variable is reported in Appendix D.

$$\text{Imputed Lender Share}_{i,t} = \alpha + \gamma_c + \delta_y + \beta_1 \text{Disaster(m)}_{p,t} + \mathbf{X}_{i,t} + \epsilon_{i,t} \tag{9}$$

In this model, the unit of observation is a single loan, therefore Imputed Lender Share$_{i,t}$ represents the loan maturity in months for a loan i at time t, where time is the deal active date. α is the intercept, γ_c represents country fixed effects, and δ_y represents yearly fixed effects. Disaster(m)$_{p,t}$ is a dummy variable indicating whether a natural disaster occurred in the same province within the previous m months, where m can be either 6 or 12 months. Finally, $\mathbf{X}_{i,t}$ is the vector of control variables, including lender, loan, and borrower characteristics, and $\epsilon_{i,t}$ represents the error term.

2.4 Secured loans

$$\text{Secured}_{i,t} = \alpha + \gamma_c + \delta_y + \beta_1 \text{Disaster(m)}_{p,t} + \mathbf{X}_{i,t} + \epsilon_{i,t} \tag{10}$$

In this model, the unit of observation is a single loan, therefore Secured$_{i,t}$ is a binary variable that indicates whether a loan i at time t has collateral (= secured) or not, where time is the deal active date. α is the intercept, γ_c represents country fixed effects, and δ_y represents yearly fixed effects. Disaster(m)$_{p,t}$ is a dummy variable indicating whether a natural disaster occurred in the same province within the previous m months, where m can be either 6 or 12 months. Finally, $\mathbf{X}_{i,t}$ is the vector of control variables, including lender, loan, and borrower characteristics, and $\epsilon_{i,t}$ represents the error term.

2.5 Loan spread

$$\text{Loan spread}_{i,t} = \alpha + \gamma_c + \delta_y + \beta_1 \text{Disaster(m)}_{p,t} + \mathbf{X}_{i,t} + \epsilon_{i,t} \tag{11}$$

In this model, the unit of observation is a single loan, therefore Loan Spread$_{i,t}$ represents the spread in basis points for loan i at time t, where time t is the deal active date. α is the intercept, γ_c represents country fixed effects, and δ_y represents yearly fixed effects. Disaster(m)$_{p,t}$ is a dummy variable indicating whether a natural disaster occurred in the same province within the previous m months, where m can be either 6 or 12 months. Finally, $\mathbf{X}_{i,t}$ is the vector of control variables, including lender, loan, and borrower characteristics, and $\epsilon_{i,t}$ represents the error term.

Moderator model As a moderating effect of borrower-lending proximity is expected, separate regressions are run with the inclusion of the interaction variable disaster and proximity. The proximity variable is a dummy variable that assigns a 1 to borrowers and lenders located in the same country, and a 0 otherwise. For sole-lender loans to small business (assuming they only have one location), it makes more sense to use the actual physical distance in kilometres or miles. This is what other academics have done who studied proximity ((Agarwal and Hauswald, 2010), (Mian, 2006)). While the actual distance might be more precise, it is less suitable for applications in syndicate loans. As these loans concern multiple lenders and because the businesses (the borrowers) may have multiple operating branches, I opt for a simplified classification that only looks at the country level. As the proximity dummy is interacted with the occurrence of a disaster in the previous 12 months (6 months in the robustness model), it helps explain

[2] To implement the model of Blickle et al. (2020), I use the provided STATA code from their Internet Appendix.

whether the effect of a disaster on syndicate structure is equally strong for close-by borrower-lender relationships. The regressions are performed with fixed effects to account for unobserved characteristics in the data, whenever possible. Equation 12 till 16 in Appendix B show the extended model specifications. To account for potential heteroskedasticity in the data, these are all run with robust standard errors.

3.7 Robustness checks

To ensure the reliability and validity of the model's estimates, a series of diagnostic checks were performed. These included assessments for multicollinearity using the Variance Inflation Factor (VIF), along with standard checks for normality, homoskedasticity, and zero mean residuals. Given the count nature of certain dependent variables, negative binomial models were employed here to accommodate overdispersion. The Pearson chi-square statistic, calculated as $\tilde{\phi} = X^2/(n\text{-}p)$ was used to formally test for deviations from the Poisson assumption that the mean and variance are equal. The results of these diagnostic tests are presented in Table 1.

Table 1: Summary of robustness checks

DV	Months	Multicollinearity VIF	Homoskedasticity Breush-Pagan		Mean residual = 0 t-test	Normality Jarque-Bera		Overdispersion Pearson estimator
Lead Arrangers	12	1.24	52.26	✗	✓	174	✗	72.235
	6	1.23	59.70	✗	✓	145.7	✗	65.992
Deal Volume	12	1.24	270.12	✗	✓	4651	✗	
	6	1.23	282.56	✗	✓	4174	✗	
Number Loans	12	1.24	63.27	✗	✓	1429	✗	46.243
	12	1.23	73.82	✗	✓	1273	✗	43.456
Number Lenders	12	4.91	71.44	✗	✓	42.09	✗	3.045
	6	4.37	112.69	✗	✓	146.8	✗	4.016
Maturity	12	5.17	47.05	✗	✓	52000	✗	
	6	5.20	59.42	✗	✓	39000	✗	
Lender Share	12	11.26	35.31	✗	✓	39000	✗	
	6	11.64	100.26	✗	✓	8370	✗	
Secured	12	4.91	135.73	✗	✓	46.07	✗	
	6	4.95	54.60	✗	✓	100.8	✗	
Loan Spread	12	5.13	17.55	✗	✓	898.9	✗	
	6	5.16	57.24	✗	✓	884.5	✗	

[1] DV represents the dependent variable

[2] Months represents the timeframe for the classification of disaster loans

3.8 Descriptive Statistics

Table 2 displays the most important summary statistics: the mean, standard deviation, median, minimum value, maximum value and the number of observations. It can be noted that for number of loans, the data is quite skewed. The mean differs strongly from the median, and the standard deviation. The number of lenders and lead arrangers all fall within a relatively small range, but the maximum amount of lenders and lead arrangers is quite high. From the table, it can be noted that lender share displays quite extreme values, which is not the case for predicted lender share. From the table, it can also be noted some borrowers display quite negative profitability, indicated by the negative profitability ratio and interest coverage ratio. Lastly, maturity has a mean and median of 60, which indicates that loans in the sample have an average maturity of 5 years.

Table 3 displays the distribution of natural disasters across the countries in the sample, over the period 2010-2023. This table shows that France and the Russian Federation have by far the most amount of disasters, followed by France. The majority of countries have relatively few disasters, and few disasters occurred in Scandinavian Europe.

Table 2: Descriptive Statistics

Variable	Mean	SD	p50	Min	Max	N
Loan Count	120.563	297.725	12	0	1887	305698
No. Lenders	12.783	12.609	8	1	94	258850
No. Lead Arrangers	8.055	6.576	6	1	58	258850
Lender Share	28.715	291.185	11.06	0	10885	39561
Imputed Lender Share	8.032	11.142	4.477	0	100	30079
Total Assets (Borrower)	8168494	29.8m	299608.5	0	777m	35446
Profitability Ratio (Borrower)	231.470	30745.73	0.008	-1016287	3656759	15418
Solvency Ratio (Borrower)	43.601	27.543	39.17	0	100	21667
Liquidity Ratio (Borrower)	2.300	5.715	1.05	0	100	35947
D/E Ratio (Borrower)	100.565	121.838	65.75	0	990.955	30874
Interest Coverage Ratio (Borrower)	8.226	43.754	1.362	-99.423	3704.79	36364
Profit Margin (Lender)	29.010	27.739	28.632	-98.964	100	25311
Total Assets (Lender)	441m	858m	182m	282.953	2.66b	26367
Deal Amount	1889.118	5476.32	585.5	0	200000	258464
Tenor Maturity	60.458	43.692	60	0	540	250222

[1] Mean represents the average value, SD the standard deviation, p50 the median, Min and Max the minimum and maximum values and N the number of observations

Table 3: Number of Disasters per Country

Country	Number of Disasters		
France	64	Norway	4
Germany	29	Poland	27
Greece	26	Portugal	18
Hungary	10	Romania	19
Iceland	2	Russian Federation	47
Ireland	7	Serbia	27
Isle of Man	1	Slovakia	10
Italy	60	Slovenia	7
Latvia	3	Spain	34
Lithuania	6	Sweden	4
Luxembourg	3	Switzerland	17
Montenegro	4	Ukraine	15
The Netherlands	11	United Kingdom	26
North Macedonia	9		

Table 4: Summary of Disaster Types

Disaster Type	Freq.	Percent	Cum.
Drought	13	2.65	2.65
Earthquake	21	4.29	6.94
Extreme temperature	61	12.45	19.39
Flood	183	37.35	56.73
Glacial lake outburst flood	1	0.20	56.94
Mass movement (dry)	1	0.20	57.14
Mass movement (wet)	9	1.84	58.98
Storm	164	33.47	92.45
Volcanic activity	2	0.41	92.86
Wildfire	35	7.14	100.00
Total	490	100.00	

Table 4 summarizes the different types of disaster across the sample. Floods and storms account for most of the types of disasters, while dry mass movements and glacial lake outburst floods only occur once.

4 Results

The following section presents the regression outputs and provides a detailed description of the results. In this section, the main explanatory variable is the 12 months disaster dummy, where loans are marked as a disaster loan if they are originated within 12 months of the occurrence of a natural disaster. In an alternative specification, loans are marked as such within 6 months. The results for that specification are included in Appendix B.

4.1 Number of loans

Table 5 displays the results for the regression model that includes number of loans and the occurrence of a disaster within one year. As the data is aggregated to a provincial - month level, the number of loans represents the average number of loans per province per month. For the Negative Binomial model in Column (5), the coefficients are not directly interpretable as a one-to-one unit association because they are on a log scale. Instead, interpretation is simplified using the Incidence Rate Ratio (IRR), where IRR $= e^{\beta}$. The IRR shows how the expected count of the outcome variable changes for the treated group (dummy = 1) compared to the non-treated group (dummy = 0). Specifically, the count outcome for the treated group is multiplied by the IRR relative to the non-treated group. Furthermore, the model in Column (5) includes no control variables, as it disables the model to reach convergence.

Table 5: Loan count (1 year disaster)

	(1) Loan Count	(2) Loan Count	(3) Loan Count	(4) Loan Count	(5) Loan Count
Disaster_1y	6.622^{***}	7.183	5.093^{***}	13.536	0.286
	(0.767)	(16.703)	(0.873)	(22.111)	(0.185)
Size (borrower)		7.141^{*}		3.630	0.033
		(3.679)		(5.989)	(0.047)
Profitability (borrower)		0.368		0.175	0.004
		(0.339)		(0.427)	(0.003)
Solvency ratio (borrower)		−0.371		-0.930^{*}	-0.010^{**}
		(0.326)		(0.503)	(0.005)
Liquidity ratio (borrower)		−1.444		9.613	−0.002
		(6.078)		(17.718)	(0.134)
D/E ratio (borrower)		0.004		0.134	0.003^{*}
		(0.080)		(0.183)	(0.002)
Interest Coverage ratio (borrower)		−0.690		−0.805	0.005
		(1.017)		(2.110)	(0.017)
Profit Margin (lender)		0.720		−0.611	0.001
		(0.563)		(1.086)	(0.007)
Size (lender)		-19.950^{***}		-31.342^{***}	-0.438^{***}
		(6.974)		(11.134)	(0.103)
Deal Amount		14.634^{*}		16.171	0.264^{***}
		(7.657)		(11.268)	(0.100)
Maturity		0.583		0.933	0.008
		(0.440)		(0.653)	(0.005)
Loan spread		0.037		0.046	−0.000
		(0.064)		(0.098)	(0.001)
Constant	3.535^{***}	199.017	3.992^{***}	455.303^{*}	6.298^{***}
	(0.409)	(140.394)	(0.426)	(264.670)	(2.156)
Fixed Effects	No	No	Yes	Yes	No
Observations	7232	82	7195	82	66
R-squared	0.010	0.264	0.005	0.350	

[1] Column (1) represents the most basic model, column (2) the model with control variables, column (3) adds province and month fixed effects, and column (4) represents the complete model. Column (5) represents the Negative Binomial Model.

[2] The R-squared in column (5) presents the Pseudo R-Squared.

[3] Robust standard errors are in parentheses.

[4] * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

As displayed in the table, the coefficient for disaster is significant and positive in Column (1) and (3).

When a loan is marked as a disaster loan, it is associated with an increase in number of loans of 6.622 and 5.093 respectively. When control variables are included, it is not significant, just like when the model is fit to a negative binomial model. The inclusion of fixed effects reduces the magnitude of the disaster coefficient, which implies that it accounts for some of the variability otherwise attributed to the disaster variable. Interestingly, the average lender size is significant for all model specifications, and negative. This implies that on a provincial-month level, the average lender size is negatively related to the number of loans. While aggregating the data leads to a reduction in the number of observations, this applies even more to the models with control variables. Due to missing values for these variables, the number of observations is reduced even further, although the R^2 does improve with the inclusion of those variables. For the model in Column (1), (3) (4) and (5), depending on the confidence level, the constant is significant. In Column (5), the coefficient is not directly interpretable. Instead, the Incidence Rate Ratio (IRR) can be computed as: $IRR = e^{6.298} \approx 543.48$.

4.2 Deal Volume

Table 6 displays the regression results for deal volume, where the occurrence of a disaster within the previous 12 months is defined in the disaster dummy. The data is aggregated to a provincial-month level, so the deal volume represents the average (logarithm of) deal volume per province per month. Therefore, the coefficients can be interpreted as a percentage change by exponentiating the coefficient.

Table 6: Deal Volume (1 year disaster)

	(1) Deal Volume	(2) Deal Volume	(3) Deal Volume	(4) Deal Volume
Disaster_1y	-0.303^{***}	0.057	-0.089^{**}	-0.063
	(0.037)	(0.261)	(0.036)	(0.310)
Size (borrower)		0.116^{**}		0.091
		(0.056)		(0.083)
Profitability (borrower)		0.005		0.003
		(0.005)		(0.006)
Solvency ratio (borrower)		-0.001		-0.006
		(0.005)		(0.007)
Liquidity ratio (borrower)		0.011		-0.059
		(0.095)		(0.248)
D/E ratio (borrower)		-0.000		0.004
		(0.001)		(0.002)
Interest Coverage ratio (borrower)		-0.009		-0.029
		(0.016)		(0.029)
Profit Margin (lender)		0.017^{*}		0.004
		(0.009)		(0.015)
Size (lender)		-0.023		-0.126
		(0.109)		(0.155)
Maturity		-0.018^{***}		-0.015
		(0.007)		(0.009)
Loan spread		-0.001		-0.002
		(0.001)		(0.001)
Constant	5.647^{***}	5.970^{***}	5.586^{***}	8.518^{**}
	(0.020)	(2.072)	(0.018)	(3.461)
Fixed Effects	No	No	Yes	Yes
Observations	7166	82	7166	82
R-squared	0.009	0.219	0.001	0.276

[1] Column (1) represents the most basic model, column (2) the model with control variables, column (3) adds province and month fixed effects, and column (4) represents the complete model.

[2] Robust standard errors are in parentheses.

[3] * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

From Table 6, it is observed that the occurrence of a disaster is negatively related to deal volume, but this significance varies across models. In Column (1), the coefficient for Disaster_1y is -0.303 and is significant, indicating that the occurrence of a natural disaster is associated with a $(1 - e^{-0.303}) \approx 26.14\%$ decrease in deal volume. In Column (3), the coefficient for Disaster_1y is -0.089 and is significant, suggesting an 8.52% decrease in deal volume. The reduction in the coefficient magnitude when fixed effects are included implies that fixed effects account for some of the variability, as the size of the coefficient decreases. In contrast, the coefficients in Columns (2) and (4) are 0.057 and -0.063, respectively, and are not statistically significant. This suggests that the deal volume is better explained by the control variables included in these models, such as borrower size and loan maturity. These models also exhibit higher R^2 values compared to those in Columns (1) and (3). The constant term is significant in all model specifications. Overall, the regressions present mixed results regarding the relationship between natural disasters and deal volume.

4.3 Number of Lead Arrangers

Table 7 displays the results for the regression of the disaster dummy on the number of lead arrangers. Similar as for deal volume and number of loans, the data is aggregated to a provincial-month level. The disaster dummy indicates whether a natural disaster has taken place in that province within the previous 12 months. The number of lead arrangers represents the total umber of lead arrangers per province-month.

Table 7: No. Lead Arrangers (1 year disaster)

	(1) Lead Arrangers	(2) Lead Arrangers	(3) Lead Arrangers	(4) Lead Arrangers	(5) Lead Arrangers
Disaster_1y	1.416	−26.570	4.295**	−13.565	0.114
	(1.749)	(31.167)	(1.837)	(43.645)	(0.172)
Size (borrower)		6.018		5.769	0.010
		(6.865)		(11.821)	(0.043)
Profitability (borrower)		0.413		0.282	0.002
		(0.632)		(0.842)	(0.003)
Solvency ratio (borrower)		−0.684		−0.578	−0.002
		(0.608)		(0.992)	(0.004)
Liquidity ratio (borrower)		−15.368		0.606	−0.112
		(11.341)		(34.974)	(0.123)
D/E ratio (borrower)		−0.093		0.191	0.002**
		(0.149)		(0.362)	(0.001)
Interest Coverage ratio (borrower)		−0.944		−4.602	−0.028*
		(1.898)		(4.166)	(0.015)
Profit Margin (lender)		−0.438		−1.679	−0.010
		(1.050)		(2.143)	(0.008)
Size (lender)		−38.201***		−39.207*	−0.268***
		(13.013)		(21.977)	(0.083)
Deal Amount		41.844***		43.992*	0.135
		(14.287)		(22.243)	(0.089)
Maturity		1.466*		1.299	0.002
		(0.820)		(1.290)	(0.005)
Loan spread		−0.086		−0.081	−0.001
		(0.120)		(0.194)	(0.001)
Constant	35.389***	548.703**	34.747***	547.317	5.359***
	(0.933)	(261.970)	(0.895)	(522.437)	(1.869)
Fixed Effects	No	No	Yes	Yes	No
Observations	7232	82	7195	82	66
R-squared	0.000	0.290	0.001	0.287	

[1] Column (1) represents the most basic model, column (2) the model with control variables, column (3) adds province and month fixed effects, and column (4) represents the complete model. Column (5) represents the Negative Binomial Model.

[2] The R-squared in column (5) presents the Pseudo R-Squared.

[3] Robust standard errors are in parentheses.

[4] * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In Column (3), which includes fixed effects, the coefficient for Disaster_1y is 4.295 and statistically significant, suggesting that disaster loans are associated with an increase of approximately 4.295 lead arrangers. However, the low R-squared value in this model indicates that it explains little of the variability in lead arrangers. In other specifications, including Columns (1), (2), (4), and (5), the coefficient for Disaster_1y is not statistically significant, showing no clear relationship between natural disasters and the number of lead arrangers. Columns (2) and (4) show that control variables such as lender size and deal amount better explain the number of lead arrangers. The Negative Binomial Model in Column (5) shows significant associations between some borrower characteristics and lead arrangers, but disaster loans themselves do not have a significant effect. Additionally, the constant term in Column (5) has an incidence rate ratio (IRR) of approximately 212.51. Overall, the findings indicate a mixed and inconsistent relationship between natural disasters and the number of lead arrangers, where control variables play a more important role than the occurrence of natural disasters.

4.4 Lead arranger Share

Table 8 displays the relationship between the share retained by the lead arranger and the occurrence of a natural disaster within the past 12 months. The lender share is imputed based on the model by Blickle et al. (2024), as described in the methodology section. While previous regressions are conducted at an aggregated level, the regressions here are performed at the loan level. The fixed effects applied in this analysis include yearly and country-specific dummies. These fixed effects are not shown as individual coefficients in the table, but instead are absorbed.

Table 8: Imputed Lender Share (1 year disaster)

	(1) Lender Share	(2) Lender Share	(3) Lender Share	(4) Lender Share
Disaster_1y	2.092***	17.015***	1.241***	20.227***
	(0.127)	(1.943)	(0.127)	(2.657)
Size (borrower)		1.949		7.051*
		(1.329)		(4.023)
Profitability (borrower)		0.210**		5.445***
		(0.103)		(1.857)
Solvency ratio (borrower)		−0.002		−0.137
		(0.092)		(0.208)
Liquidity ratio (borrower)		−3.145		5.982
		(2.350)		(3.919)
D/E ratio (borrower)		0.016		0.000
		(0.034)		(0.031)
Interest Coverage ratio (borrower)		−0.371		−5.473***
		(0.266)		(1.776)
Profit Margin (lender)		−0.011		−0.012
		(0.016)		(0.014)
Size (lender)		0.227		0.276
		(0.232)		(0.222)
Deal Amount		−6.407***		−11.581**
		(2.211)		(5.172)
Maturity		−0.290***		−0.271***
		(0.048)		(0.057)
Loan spread		0.010		0.028*
		(0.010)		(0.015)
Constant	6.942***	28.215	7.385***	−70.425
	(0.082)	(20.398)	(0.084)	(54.333)
Fixed Effects	No	No	Yes	Yes
Observations	30079	352	30079	350
R-squared	0.009	0.505	0.128	0.550

[1] Column (1) represents the most basic model, column (2) the model with control variables, column (3) adds country and year fixed effects, and column (4) represents the complete model.

[2] Robust standard errors are in parentheses.

[3] * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The results indicate a significant positive relationship between a disaster and the lender's share, regardless of the model specification. Specifically, in Column (1), the coefficient for Disaster_1y is 2.092, and in Column (2), it increases to 17.015, both significant at the 1% level. This shows that a natural disaster is associated with a higher retained lead share. Columns (3) and (4) include fixed effects, with significant coefficients for Disaster_1y of 1.241 and 20.227, respectively, which display a positive relationship as well. The impact of maturity and deal amount on the lender share are significant in both control variable models. Both variables are negatively related to the lender share, with coefficients of -6.407 and -11.581 for deal amount, and -0.290 and -0.271 for maturity, significant in Columns (2) and (4). This indicates that larger deal amounts and longer maturities are associated with a smaller share retained by the lead arranger. The variation in the disaster coefficient between models with and without fixed effects suggests that fixed effects account for some of the variability that would otherwise be attributed to the disaster variable. Consequently, the magnitude of the disaster coefficient decreases when fixed effects are included. Finally, the R-squared value is notably low in Column (1), while the models in Columns (2) and (4) show higher R-squared values but have fewer observations due to missing values for the control variables. Overall, the table demonstrates a consistent positive association between natural disasters and the lender share, with other factors like deal amount and maturity also playing significant roles.

4.5 Number of Lenders

Table 9 displays the relationship between the occurrence of a disaster within the past 12 months and the number of lenders in a syndicated loan. The regression is performed at the individual loan level, with country and year fixed effects included as categorical dummy variables that are absorbed into the model. Column (5) features control variables but does not include fixed effects, as these cannot be directly absorbed in this model specification. Consequently, the coefficients in Column (5) cannot be interpreted directly, and important results will be presented with their incidence rate ratio (IRR) for interpretation.

Table 9: Number of lenders (1 year disaster)

	(1) No. Lenders	(2) No. Lenders	(3) No. Lenders	(4) No. Lenders	(5) No. Lenders
Disaster_1y	1.006***	−19.668***	0.630***	−20.958***	−1.416***
	(0.060)	(1.767)	(0.054)	(1.778)	(0.125)
Size (borrower)		−2.175*		−0.572	−0.249***
		(1.213)		(3.005)	(0.092)
Profitability (borrower)		−0.038		0.974	−0.014*
		(0.099)		(1.798)	(0.008)
Solvency ratio (borrower)		0.078		0.153	−0.000
		(0.144)		(0.190)	(0.007)
Liquidity ratio (borrower)		−1.103		0.756	−0.114**
		(0.839)		(1.370)	(0.052)
D/E ratio (borrower)		−0.014		−0.010	−0.002**
		(0.012)		(0.014)	(0.001)
Interest Coverage ratio (borrower)		−0.114		−1.295	−0.015
		(0.189)		(1.880)	(0.013)
Profit Margin (lender)		−0.027		−0.015	−0.000
		(0.022)		(0.019)	(0.001)
Size (lender)		0.028		0.008	−0.000
		(0.270)		(0.245)	(0.010)
Deal Amount		11.812***		17.988***	0.969***
		(2.142)		(2.858)	(0.212)
Maturity		0.240***		0.228***	0.013***
		(0.066)		(0.061)	(0.003)
Loan spread		0.078***		0.084***	0.003***
		(0.008)		(0.008)	(0.000)
Constant	12.499***	−67.018***	12.605***	−157.312**	−1.232*
	(0.027)	(14.547)	(0.026)	(64.212)	(0.647)
Fixed Effects	No	No	Yes	Yes	No
Observations	258850	364	258849	362	364
R-squared	0.001	0.725	0.222	0.773	0.175

[1] Column (1) represents the most basic model, column (2) the model with control variables, column (3) adds country and year fixed effects, and column (4) represents the complete model. Column (5) represents the Negative Binomial Model.

[2] The R-squared in column (5) presents the Pseudo R-Squared.

[3] Robust standard errors are in parentheses.

[4] * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In Table 9, Column (1) shows the basic model without control variables or fixed effects, with a coefficient for Disaster_1y of 1.006, indicating a positive but not significant association. In contrast, Column (2) includes control variables, showing a significant negative coefficient of -19.668 for Disaster_1y, which displays a decrease in the number of lenders associated with disaster loans. Column (3) incorporates fixed effects, and the coefficient for Disaster_1y decreases to 0.630, still significant, indicating a smaller positive association when accounting for year and country fixed effects. Column (4) presents the complete model with both control variables and fixed effects, showing a coefficient of -20.958 for Disaster_1y, which suggests a significant negative relationship between disaster loans and the number of lenders. Finally, Column (5) employs a Negative Binomial Model and yields a coefficient of -1.416, which translates to an incidence rate ratio (IRR) of approximately 0.24 $IRR = e^{-1.416}$. This suggests that disaster loans have about 0.24 times the number of lenders as non-disaster loans. Across Columns (2), (4), and (5), loan characteristics such as deal amount, maturity, and deal spread are positively associated with the number of lenders. Conversely, the size of the borrower is negatively related to the number of lenders, as seen in Columns (2) and (5). The Negative Binomial Model highlights significant effects for many borrower and lender control variables. The results demonstrate a generally negative and significant relationship between disasters and the number of lenders, where control variables affect the size of this relationship. The models incorporating control variables (Columns (2), (4), and (5)) show stronger explanatory power compared to the basic model in Column (1), which has a low R-squared value. The number of observations is reduced in models with control variables due to missing data.

4.6 Collateral

Table 10 presents the relationship between collateral (secured loans) and the occurrence of a natural disaster. The analysis is conducted at the individual loan level, incorporating fixed effects for country and year, which are absorbed into the model. In Column (5), a logit model is used that includes control variables but excludes deal spread. The exclusion of deal spread is due to a high number of missing values, which would significantly reduce the number of observations and prevent the model from achieving convergence. Additionally, fixed effects are not incorporated in the logit model of Column (5), due to their inability to be absorbed in the model.

Table 10: Secured / Unsecured (1 year disaster)

	(1) Secured	(2) Secured	(3) Secured	(4) Secured	(5) Secured
Disaster_1y	-0.044^{***}	0.358^{***}	-0.016^{***}	0.203^{**}	1.798^{***}
	(0.002)	(0.081)	(0.002)	(0.090)	(0.286)
Size (borrower)		0.114^{**}		0.043	0.359^{**}
		(0.054)		(0.126)	(0.159)
Profitability (borrower)		0.004		0.025	0.013
		(0.005)		(0.080)	(0.013)
Solvency ratio (borrower)		0.001		-0.009	-0.013
		(0.006)		(0.012)	(0.009)
Liquidity ratio (borrower)		-0.029		-0.137^{**}	0.264^{*}
		(0.043)		(0.069)	(0.155)
D/E ratio (borrower)		0.001		0.000	-0.005^{*}
		(0.001)		(0.001)	(0.003)
Interest Coverage ratio (borrower)		-0.010		-0.005	-0.032^{*}
		(0.008)		(0.092)	(0.019)
Profit Margin (lender)		-0.001		-0.001	0.008^{*}
		(0.001)		(0.001)	(0.004)
Size (lender)		-0.010		-0.008	0.136^{*}
		(0.011)		(0.010)	(0.073)
Deal Amount		-0.365^{***}		-0.471^{***}	-0.503^{***}
		(0.115)		(0.115)	(0.190)
Maturity		-0.000		0.001	0.015^{**}
		(0.002)		(0.002)	(0.007)
Loan spread		-0.002^{***}		-0.003^{***}	
		(0.000)		(0.000)	
Constant	0.434^{***}	1.700^{***}	0.428^{***}	4.427	-6.639^{***}
	(0.001)	(0.612)	(0.001)	(2.792)	(1.809)
Fixed Effects	No	No	Yes	Yes	No
Observations	260305	364	258849	362	567
R-squared	0.002	0.358	0.071	0.473	0.228

[1] Column (1) represents the most basic model, column (2) the model with control variables, column (3) adds country and year fixed effects, and column (4) represents the complete model. Column (5) represents the Logit Model.

[2] The R-squared in column (5) presents the Pseudo R-Squared.

[3] Robust standard errors are in parentheses.

[4] * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 10 presents the relationship between collateral (secured loans) and the occurrence of a natural disaster within the past year. In Column (5), the disaster coefficient is 1.798, which can be interpreted using the odds ratio. Computed as $e^{1.798} \approx 6.03$ suggests that loans classified as "disaster loans" are approximately 6.03 times more likely to be secured compared to loans that are not disaster loans, a result that is highly significant and economically relevant. This strong positive association is also observed in Columns (2) and (4), which include control variables and fixed effects, respectively. In contrast, Column (1) and (3) report a negative coefficient of -0.044 and -0.016 respectively for the disaster variable, but the model from Column (1) has low explanatory power, with an R^2 of 0.002. Significant control variables across the models include borrower size, with a positive coefficient of 0.114 in Column (1) and 0.359 in Column (3); liquidity ratio, showing a positive effect in Column (4) with a coefficient of 0.264; and deal amount, which consistently has a negative impact across Columns (1), (2), and (3) with coefficients of -0.365, -0.471, and -0.503, respectively. Loan spread is significant in Columns (1) and (2), with negative coefficients of -0.002 and -0.003. The inclusion of these control variables reduces the number of observations per model but increases the R^2.

4.7 Maturity

Table 11 displays the results of the regression analysis examining the relationship between loan maturity and the occurrence of a natural disaster within the past 12 months. The OLS regressions are at the individual loan level, with fixed effects for country and year absorbed into the model.

Table 11: Maturity (1 year disaster)

	(1) Maturity	(2) Maturity	(3) Maturity	(4) Maturity
Disaster_1y	-4.445^{***}	19.358^{***}	-4.028^{***}	14.564^{***}
	(0.172)	(2.719)	(0.194)	(2.782)
Size (borrower)		1.233		-14.947^{**}
		(2.492)		(6.910)
Profitability (borrower)		-0.018		-9.033^{**}
		(0.252)		(4.021)
Solvency ratio (borrower)		0.076		1.071^{***}
		(0.216)		(0.406)
Liquidity ratio (borrower)		0.965		-9.607^{***}
		(1.744)		(3.708)
D/E ratio (borrower)		0.012		0.145^{***}
		(0.015)		(0.037)
Interest Coverage ratio (borrower)		-0.649		8.357^{**}
		(0.430)		(4.049)
Profit Margin (lender)		-0.048		-0.017
		(0.031)		(0.028)
Size (lender)		-0.329		-0.227
		(0.368)		(0.357)
Deal Amount		0.282		10.331^{**}
		(3.837)		(4.525)
Loan spread		0.003		-0.002
		(0.014)		(0.016)
Constant	61.710^{***}	38.650	61.593^{***}	272.942^{**}
	(0.110)	(25.291)	(0.108)	(129.018)
Fixed Effects	No	No	Yes	Yes
Observations	250222	364	250221	362
R-squared	0.002	0.285	0.072	0.549

[1] Column (1) represents the most basic model, column (2) the model with control variables, column (3) adds country and year fixed effects, and column (4) represents the complete model.

[2] Robust standard errors are in parentheses.

[3] * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The results vary across models: in Column (1), without control variables, the disaster coefficient is significantly negative (4.445), which shows that loans affected by disasters are associated with maturity that is 4.445 months shorter on average. When control variables are included in Column (2), the relationship shifts to a positive and significant value of 19.358, indicating that disaster loans are associated with longer maturities. This positive association is also shown in the complete model of Column (4), which includes both control variables and fixed effects, showing a coefficient of 14.564 that is significant. The R^2 values increase with model complexity, and is 0.549 in Column (4), reflecting a stronger explanatory power when accounting for additional factors. Overall, the results show that the occurrence of a natural disaster is correlated with a higher maturity.

4.8 Deal spread

In the models in Table 12, deal spread is regressed on the occurrence of a natural disaster within the previous year. The country and year fixed effects are absorbed into these models, which means that this group-level variation is subtracted from the error term, leaving the model with only the residual variation. The results indicate a clear negative association between disasters and deal spread. In Column (1), without control variables, the disaster coefficient is significantly negative at 6.549, suggesting that loans

Table 12: Deal spread (1 year disaster)

	(1) Deal spread	(2) Deal spread	(3) Deal spread	(4) Deal spread
Disaster_1y	-6.549^{***}	-66.988^{***}	-5.249^{***}	-98.319^{***}
	(1.087)	(10.454)	(1.177)	(8.513)
Size (borrower)		1.269		16.075
		(5.128)		(12.421)
Profitability (borrower)		-1.386^{***}		39.876^{***}
		(0.454)		(10.467)
Solvency ratio (borrower)		-1.640^{***}		0.753
		(0.519)		(1.148)
Liquidity ratio (borrower)		-9.173		-16.387
		(7.612)		(11.101)
D/E ratio (borrower)		-0.179^{*}		-0.354^{**}
		(0.099)		(0.141)
Interest Coverage ratio (borrower)		-0.355		-41.992^{***}
		(1.065)		(12.160)
Profit Margin (lender)		-0.215		-0.110
		(0.187)		(0.147)
Size (lender)		-1.028		0.895
		(2.347)		(1.824)
Deal Amount		-31.066^{***}		28.908^{***}
		(8.956)		(10.431)
Maturity		0.074		-0.044
		(0.256)		(0.250)
Constant	266.736^{***}	701.047^{***}	266.380^{***}	-376.115
	(0.569)	(81.210)	(0.555)	(280.167)
Fixed Effects	No	Yes	No	Yes
Observations	101197	364	101197	362
R-squared	0.000	0.394	0.134	0.661

[1] Column (1) represents the most basic model, column (2) the model with control variables, column (3) adds country and year fixed effects, and column (4) represents the complete model.

[2] Robust standard errors are in parentheses.

[3] * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

affected by disasters have lower spreads, -6.549 basis points on average. This relationship is even stronger in Column (4), where the model accounts for lender, borrower, and loan characteristics, as well as country and year fixed effects, showing a coefficient of 98.319. This Column also highlights significant relationships between deal spread and factors such as deal amount, size, profitability, debt-to-equity (D/E) ratio, and interest coverage ratio. The inclusion of control variables and fixed effects improves the R^2, reaching 0.661 in Column (4), but reduces the number of observations. Despite this, the constant in Column (4) is not significant, contrasting with the significant constants in Columns (1) to (3). Overall, these results show that disaster loans are associated with significantly lower spreads, particularly when accounting for additional variables.

4.9 Proximity

Table 13 presents the results for proximity. For the dependent variables Number of Lenders, Maturity, Lender Share, Loan Spread and Secured, an extended model includes the interaction term proximity. Proximity is a binary variable indicating whether the lead arranger and borrower are located in the same country. It is interacted with the disaster dummy. All OLS models, so maturity, lender share and deal spread in Column (2) to (4), are run with absorbed fixed effects of country and year. The number of lenders is fit to a negative binomial model, and the model for "secured" is fit to a logit model, as these models suit the distributions of the dependent variable best. Due to issues with convergence, the models in Column (1) and (5) do not include fixed effects.

Table 13: Borrower - Lender proximity (1 year disaster)

	(1) No. Lenders	(2) Maturity	(3) Lender Share	(4) Loan spread	(5) Secured
Disaster_1y	0.276^{***}	-4.676^{***}	0.558^{***}	-9.426^{***}	-0.083^{***}
	(0.005)	(0.226)	(0.138)	(1.363)	(0.011)
Proximity*Disaster_1y	-0.571^{***}	1.581^{***}	2.045^{***}	15.009^{***}	-0.241^{***}
	(0.008)	(0.272)	(0.197)	(1.983)	(0.016)
Fixed Effects	No	Yes	Yes	Yes	No
Observations	258848	250219	30079	101197	260303
R-squared	0.005	0.072	0.131	0.135	0.002

[1] The R-squared in column (1) (5) present the Pseudo R-Squared.

[2] Robust standard errors are in parentheses.

[3] * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In Column (1), the disaster coefficient is significantly positive, with a coefficient of 0.276, which shows an incidence rate ratio (IRR) of $e^{0.276} \approx 1.32$. This suggests that disaster loans are associated with a 32% increase in the number of lenders. Column (2) shows that disaster loans have a significantly shorter maturity by 4.676 months, while the interaction term in Column (2) indicates that proximity amplifies this effect, increasing maturity by 1.581 months when both the lender and borrower are in the same country. In Column (3), the disaster coefficient positively impacts lender share with a coefficient of 0.558, and the interaction term further increases lender share by 2.045 when proximity is considered. Column (4) shows a negative association between disaster and deal spread with a coefficient of -9.426, indicating that disaster loans tend to have a lower spread. The proximity interaction term significantly increases deal spread by 15.009 when the lender and borrower are in the same country. Finally, Column (5) shows a negative coefficient of -0.083 for the disaster variable in the logit model, suggesting that the likelihood of a loan being secured decreases during a disaster. The interaction term shows an additional reduction in the likelihood of being secured by -0.241 when the lender and borrower are in the same country. Interpreting these coefficients using odds ratios, the effect of a disaster on the likelihood of a loan being secured decreases by a factor of $e^{-0.083} \approx 0.92$, and the proximity interaction term further reduces this likelihood by a factor of $e^{-0.241} \approx 0.79$. Generally, these models are challenging to interpret because the coefficients for disasters show different directions compared to earlier results, and many contradictory relationships are present.

5 Conclusion

In this thesis, research has been conducted to investigate European syndicated loans succeeding a natural disaster. The research poses two central questions:
1. Is a natural disaster followed by an increased loan volume in the European syndicated lending market?
2. What impact does the occurrence of a natural disaster have on the syndicate structure of a loan?

In the analysis, loan volume is measured by three different metrics: the total number of lead arrangers, the total deal volume and the total number of loans, all on a provincial-month level. First, the total number of lead arrangers is not related to whether a disaster has occurred within the previous 12 months. Secondly, while there appears to be a negative correlation between total deal volume and the occurrence of natural disasters, this effect does not remain when a broader set of loan, lender, and borrower characteristics are accounted for: the observed 8.52% decrease in deal volume does not persist. Thirdly, the total number of loans is positively correlated with the occurrence of a natural disaster, where the occurrence of a natural disaster is associated with an increase of 5.093 in the number of loans. However, similar to deal volume, this effect does not remain when lender, borrower and loan characteristics are taken into account. Generally, there is no conclusive evidence to support the hypothesis that a natural disaster is followed by an increased loan volume in that same province. This also applies to the more strict timeframe of disaster loans, where the associated reduction in deal volume is 10.8% and the associated increase in number of loans is 3.882.

To measure how the occurrence of a natural disaster impacts the syndicate structure of a loan, I studied a set of loan characteristics. The first two loan characteristics, the share retained by the lead arranger and the number of lenders, are specific to syndicated loans, contrary to deal spread, maturity and collateral which also apply to sole-lender loans. The results show that loans following a natural disaster are more concentrated: they have fewer lenders and the lead arranger retains a larger share, which is in line with the hypothesis. Loans that are originated in the aftermath of a natural disaster are associated with an increase in lender share of 20.227, and 0.24 the amount of lenders of a non-disaster loan. Within a shorter time-frame of 6 months, loans originated following a natural disaster are associated with an increase in lender share of only 0.541, and this positive significant effect does not withstand the inclusion of control variables. Within this same 6-month framework, disaster loans have 0.59 times the amount of lenders of a non-disaster loan. The other loan characteristics (maturity, deal spread and collateral) are all related to the occurrence of a natural disaster, but in a direction opposite of the hypothesis. On average, for loans following a natural disaster, maturity is 14.564 months longer and the deal spread is 98.319 basis points lower. Additionally, these loans are 6.03 times more likely to be secured than non-disaster loans. This relationship is more complex than initially proposed, and is strongly impacted by lender, borrower and other loan characteristics. When the analysis marks loans if they follow within 6 months of a disaster, these disaster loans are associated with an increase in maturity of 34.690 months, a reduction in deal spread of 178.759 basis points, and these loans are 5.88 times more likely to be secured than non-disaster loans. Finally, this level of complexity is highlighted by the analysis of lender-borrower proximity, which shows no moderating effect on these relationships, independent of the 6 or 12-month framework.

6 Discussion

The outcomes of this research have provided insight into syndicated lending following a natural disaster, in terms of loan volume and loan characteristics. This chapter provides a reflection on the research process. It interprets the results, relates it to previous academic research, and highlights potential limitations. At last, this chapter discusses opportunities for future research.

The results show that there is no direct relationship between the occurrence of a natural disaster and the total loan volume in a province on a monthly basis. The syndicate structure is related to the occurrence of a natural disaster, but this relationship differs for different components of this structure. Loans following a natural disaster do seem to be more concentrated with fewer lenders and a larger share retained by the lead arranger, which is in line with the hypothesis. The other components, maturity, deal spread and collateral are related to the occurrence of a natural disaster, but have an effect contrary to what is hypothesized. The expected moderating effect of borrower-lender proximity does not hold.

The fact that there is no clear relationship between natural disasters and loan volume is somewhat surprising at first. I hypothesised that in the aftermath of a disaster, firms rely on bank funding to some degree at least, as not all damages are insured (Howard, 2024) and because banks are often encouraged to aid in recovery (Cortés, 2014). However, loan volume does not fully capture that effect. Even when those two statements hold, loan volume is an equilibrium outcome of syndicated loan supply and demand. Loan demand may increase, but if supply is constrained, this may not lead to an actual increase in loan volume. A constrained supply is quite plausible, as is shown in earlier research ((Cortés and Strahan, 2017), (Berg and Schrader, 2012), (Ivanov et al., 2022)). It may be that in my analysis, lenders are constrained and have no means to gain the additional liquidity needed to lend. Alternatively, even if disasters would increase both demand and supply for bank funding, the scope of this research does not exceed syndicated loans. Instead, smaller sole-lender loans could possibly capture the effects of a natural disaster.While the exact underlying mechanisms have not yet been observed, my research indicates that the importance of the syndicated loan market may vary between Europe and the United States, with the latter being the focus of much prior research on this topic.

Interestingly, my research does show that loans originated in the aftermath of a natural disaster tend to be more concentrated. This closely follows the private - public debt continuum by Diamond (1991), which states that the placement of debt on this spectrum depends on credit reputation and information quality. Generally, when credit information is hard to observe (asymmetric) and of poor quality, loans tend to resemble sole-lender loans more closely ((Dennis and Mullineaux, 2000), (Sufi, 2007)). Assuming that natural disasters increase information asymmetry, my results demonstrate that higher information asymmetry makes a loan more similar to a sole-lender loan. With fewer lenders and a larger share retained by the lead arranger, the lenders have stronger incentives to monitor. For other loan characteristics less specific to syndicated loans, being deal spread, maturity and collateral, the relationship is more complicated. Contrary to expectations, loans issued following natural disasters are more likely to be collateralized (secured). While intuition suggests that disaster-related property damage would reduce the availability of collateral, the results indicate otherwise. It remains possible that some collateral is destroyed, but loans are secured with the remaining collateral value. The role of collateral could be influenced by the information asymmetry that a natural disaster can bring. If syndicated loans are awarded to borrowers who did not borrow before but only in the aftermath of the disaster, information asymmetry may be stronger due to a lack of prior relationships (Berg and Schrader, 2012). In such cases, collateral plays an even more important role. Additionally, loans that are originated in the aftermath of a natural disaster have longer maturities. In this scenario, shorter maturities may not be used as a disciplinary mechanism to force timely repayments (Barnea et al., 1980). This may be due to collateral that acts as a substitute for maturity (Ortiz-Molina and Penas, 2007), or because the disciplinary effect of maturity does not apply to larger loans where covenants are easier to enforce. Alternatively, the longer maturity may simply reflect the borrowers need for long-term loans to assist in recovery. Furthermore, the lower interest spreads observed on disaster loans challenge the assumption of increased risk. This relates back to the presence of collateral: I find a negative association between collateral and deal spread. If more loans are collateralized, lenders may justify a similar or lower fee for disaster loans compared to non-disaster loans. Overall, maturity, deal spread and collateral are significantly correlated with many borrower, lender and loan characteristics. My research highlights that natural disasters are likely not the explanatory factor behind loan characteristics like maturity, spread and collateral, but that they are well-explained by indicators of borrower financial health in general. Even more so, maturity, collateral and spread are all interdependent, and cannot be dissected easily. In the origination of a syndicated loan, all these factors jointly determine loan pricing and contracts. Lastly, the fact that borrower-lender proximity yields no conclusive results can be because information asymmetry is not the main explanation for this relationship. It could be that geographical proximity is not a big factor of information asymmetry, especially in syndicated loans. These loans are generally bigger than sole-lender loans, and are often allocated to larger borrowers. These borrowers may have more resources to signal soft information, also digitally. Even when proximity is a source of heightened information asymmetry, loan characteristics may be influenced more by the borrowers specific needs after a disaster, rather than asymmetrical information. The results show that in a setting of disasters and larger loans, this relationship is more nuanced than found in other literature, possibly because the role of soft information is different for large syndicated loans.

However, this research has several important limitations. First and foremost, it lacks the ability to establish causal effects. While it identifies relationships between disaster loans, loan characteristics, and loan volume, it cannot single out an effect that is only attributable to loans issued following a natural disaster. The research design and setting, and the frequent occurrence of disasters, limit the ability to provide causal evidence. Additionally, one of the novel aspects of the study—the European context—introduces several complications. Obtaining the required data is more challenging due to the lack of a standardized borrower ID between Dealscan and databases that include borrower financial data. As a result, data matching relies on string variables, which may be less reliable and can reduce the number of data points when matches cannot be made. Furthermore, accounting information on borrowers is not as widely available as it is for US firms, further reducing the number of data points and complicating the introduction of control variables. Assigning regions within Europe also poses difficulties, as the regions are over different countries with diverse geographical divisions. Although the regression models account for regional effects, comparing regions is problematic due to differences in size and constitution. A small but noteworthy limitation is the lender share, which is unreliable in its raw form and is predicted using loan characteristics. While this method is generally reliable, it introduces a predicted dependent variable into the model, potentially affecting the validity of the results. Moreover, the complex setting of natural disasters involves numerous factors influencing loan volume and syndicate structure. While it is reasonable to assume that natural disasters heighten information asymmetry, it remains uncertain whether this presents a distinct information problem that is different from in regular loan settings. This issue is further complicated by the scope of the thesis, which only covers loans that are actually syndicated and does not include loan applications that were not awarded.

These limitations pose many possibilities for future research. While natural disasters and syndicate loans have often been studied, more research is needed to understand what kind of information problems arise when a natural disaster occurs. It is highlighted in earlier research that firms rely on bank credit to rebuild after a natural disaster, and disasters are expected to occur more frequently. Therefore, it is important to understand how informational problems specific to natural disasters influence loan decisions. In a broader setting, with information available on loan applications, sole-lender loans and syndicate loans, it can be better understood how natural disasters influence loan characteristics and lending decisions. With a more specific focus on loan applications, the mechanisms of informational asymmetry can extend beyond only the loans that are actually awarded.

Appendix A List of variables

Table 14: List of variables

Variable	Explanation
Disaster_1y	Dummy variable, indicating a loan in the same region where a natural disaster was present up to 12 months prior (1) or not (0)
Disaster_6m	Dummy variable, indicating a loan in the same region where a natural disaster was present up to 6 months prior (1) or not (0)
Loan Count	Number of loans for a province at time t
No. Lenders	The number of lenders (participants) in a syndicated loan from Dealscan
No. Lead Arrangers	The number of lead arrangers in a province at time t.
Secured	Dummy variable indicating whether a loan is secured (1) or unsecured (0)
Lender Share	The share retained by the lead arranger at the moment of syndication
Imputed Lender Share	The lead arranger share, predicted with the method of Blickle et al. (2020)
Size (Borrower)	Logarithm of the total assets of the borrower, at t_{-1}. Reported on yearly basis
Profitability ratio (Borrower)	Logarithm of yearly net income over total assets of the borrower, at t_{-1}.
Solvency ratio (Borrower)	Logarithm of $\frac{\text{Shareholders' funds}}{\text{Non-current liabilities+Current liabilities}} \times 100$, 1-year lagged
Liquidity ratio (Borrower)	Logarithm of $\frac{(\text{Current assets}-\text{Stocks})}{\text{Current liabilities}}$, 1-year lagged
D/E ratio (Borrower)	Logarithm of 1-year lagged: $\left(\frac{\text{Non current liabilities+Loans}}{\text{Shareholders' funds}}\right) \times 100$
Interest Coverage ratio (Borrower)	$\frac{\text{Operating profit}}{\text{Interest paid}}$, 1-year lagged and log-transformed
Profit margin (Lender)	$\left(\frac{\text{Profit before tax}}{\text{Operating revenue}}\right) \times 100$, log-transformed, at t_{-1}
Size (Lender)	The logarithm of total assets of the lender, reported on yearly basis, at t_{-1}
Deal Amount	Total (log-tranformed) size of a loan, consisting of all proportions offered by the participants.
Loan Volume	Consists of the sum of the deal amounts, at an aggregated provincial level
Maturity	Tenor maturity, number of months for which the loan is outstanding
Loan Spread	The spread in basis points over the reference rate, over the used portion of the syndicated loan
Proximity	Dummy variable indicating whether the borrower and lead arranger are headquartered in the same country (1) or not (0)
Province	A regional division of countries
Province_Numbered	Encoded variable of Province, where each province gets a unique number

Appendix B 6-month disaster timeframe

The following section provides the regression results, where a disaster loan is earmarked if it is originated within 6 months of a disaster occurring. This shorter time frame is added for robustness, to show whether the effects remain in a shorter timeframe. The following section presents the regression results and briefly highlights the key findings. The focus lies on the results that differ significantly from the 12-month timeframe.

B.1 Number of loans

Table 15 displays the results for the regression model of number of loans and the occurrence of a disaster within the previous 6 months. Number of loans represents the number of loans per province per month, and all the control variables are aggregated to their average level per province-month. The model is extended with province-month fixed effects.

Table 15: Loan count (6 months disaster)

	(1) Loan Count	(2) Loan Count	(3) Loan Count	(4) Loan Count	(5) Loan Count
Disaster_6m	3.882***	−13.224	0.940	−25.351	−0.154
	(0.988)	(16.978)	(1.068)	(28.433)	(0.246)
Size (borrower)		6.691*		3.920	0.036
		(3.689)		(5.958)	(0.047)
Profitability (borrower)		0.336		0.131	0.005
		(0.341)		(0.429)	(0.003)
Solvency ratio (borrower)		−0.392		−1.045**	−0.010**
		(0.325)		(0.512)	(0.005)
Liquidity ratio (borrower)		−1.670		10.834	0.019
		(6.022)		(17.586)	(0.132)
D/E ratio (borrower)		0.002		0.135	0.003**
		(0.080)		(0.182)	(0.001)
Interest Coverage ratio (borrower)		−0.783		−0.713	0.001
		(0.994)		(2.090)	(0.017)
Profit Margin (lender)		0.701		−0.651	−0.001
		(0.560)		(1.080)	(0.007)
Size (lender)		−19.642***		−31.264***	−0.424***
		(6.969)		(11.068)	(0.108)
Deal Amount		15.239*		16.244	0.256**
		(7.660)		(11.208)	(0.102)
Maturity		0.632		1.023	0.010*
		(0.437)		(0.647)	(0.006)
Loan spread		0.028		0.026	−0.000
		(0.063)		(0.096)	(0.001)
Constant	4.860***	206.046	5.313***	470.697*	6.201***
	(0.376)	(138.383)	(0.379)	(263.487)	(2.281)
Fixed Effects	No	No	Yes	Yes	No
Observations	7232	82	7195	82	66
R-squared	0.002	0.268	0.000	0.357	

[1] Column (1) represents the most basic model, column (2) the model with control variables, column (3) adds province and month fixed effects, and column (4) represents the complete model. Column (5) represents the Negative Binomial Model.

[2] The R-squared in column (5) presents the Pseudo R-Squared.

[3] Robust standard errors are in parentheses.

[4] * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The coefficient for Disaster_6m is significantly positive in Column (1) (3.882), which indicates a positive correlation between the occurrence of a natural disaster and the number of loans in a province-month. However, this effect turns significantly negative in Column (4) (25.351), which includes fixed effects and control variables, suggesting a substantial decrease in loans once these factors are accounted for. Additionally, in Column (5), the coefficient for Size (lender) is significantly negative (0.424), indicating that larger lenders are associated with fewer loans, contrasting with other models. The constant in Column (5) is also significant (6.201), with an Incidence Rate Ratio (IRR) of approximately 493.24. The results differ slightly from the 12-month analysis. The disaster coefficient in Column (1) is larger, and the coefficient in Column (3) is significant, whereas in the 6-month timeframe, the coefficient is not significant in Column (3) and is notably smaller in Column (1).

B.2 Deal volume

Table 16 displays the regression results for deal volume, where the occurrence of a disaster within the previous 6 months is defined in the disaster dummy. Deal volume represents the logarithm of the sum of deal amount per province-month combination, and fixed effects are included at the province-month level.

Table 16: Deal Volume (6 months disaster)

	(1) Deal Volume	(2) Deal Volume	(3) Deal Volume	(4) Deal Volume
Disaster_6m	-0.291^{***}	0.193	-0.114^{***}	0.075
	(0.047)	(0.264)	(0.044)	(0.401)
Size (borrower)		0.120^{**}		0.090
		(0.056)		(0.083)
Profitability (borrower)		0.006		0.003
		(0.005)		(0.006)
Solvency ratio (borrower)		-0.001		-0.005
		(0.005)		(0.007)
Liquidity ratio (borrower)		0.008		-0.064
		(0.094)		(0.248)
D/E ratio (borrower)		-0.000		0.004
		(0.001)		(0.002)
Interest Coverage ratio (borrower)		-0.009		-0.029
		(0.015)		(0.029)
Profit Margin (lender)		0.017^{*}		0.004
		(0.008)		(0.015)
Size (lender)		-0.030		-0.126
		(0.109)		(0.155)
Maturity		-0.018^{***}		-0.015^{*}
		(0.006)		(0.009)
Loan spread		-0.001		-0.002
		(0.001)		(0.001)
Constant	5.603^{***}	6.031^{***}	5.577^{***}	8.467^{**}
	(0.018)	(2.035)	(0.016)	(3.468)
Fixed Effects	No	No	Yes	Yes
Observations	7166	82	7166	82
R-squared	0.005	0.224	0.001	0.276

[1] Column (1) represents the most basic model, column (2) the model with control variables, column (3) adds province and month fixed effects, and column (4) represents the complete model.

[2] Robust standard errors are in parentheses.

[3] * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In Column (1), the disaster coefficient is significantly negative (0.291), suggesting that the occurrence of a disaster within the past 6 months is associated with a decrease in deal volume by approximately 25.3%, calculated as $(1 - e^{-0.291})$. This negative effect remains significant in Column (3), with a coefficient of 0.114, indicating a reduction of about 10.8% in deal volume. However, the effect becomes insignificant in Columns (2) and (4) once control variables and fixed effects are included, suggesting that the initial significant impact may be decreased when accounting for other factors. Additionally, in the complete model, the size of the borrower is positively related to deal volume, and maturity is negatively related, with both effects being statistically significant. The R^2 values increase with model complexity, reaching 0.276 in the complete model. Compared to the 12-month specification, the disaster coefficient in Column (1) is smaller, while the disaster coefficient in (3) is larger (more negative).

B.3 Number of lead arrangers

The regression output for the relationship between the number of lead arrangers and the occurrence of a disaster within 6 months is displayed in Table 17. The number of lead arrangers represents the total number of lead arrangers per province-month, as the data is aggregated to a provincial-month level.

Table 17: No. Lead Arrangers (6 months disaster)

	(1) Lead Arrangers	(2) Lead Arrangers	(3) Lead Arrangers	(4) Lead Arrangers	(5) Lead Arrangers
Disaster_6m	−2.068	−52.323*	−1.156	−63.243	−0.039
	(2.243)	(31.317)	(2.242)	(55.578)	(0.219)
Size (borrower)		4.991		6.135	0.015
		(6.804)		(11.647)	(0.042)
Profitability (borrower)		0.218		0.075	0.002
		(0.629)		(0.839)	(0.003)
Solvency ratio (borrower)		−0.720		−0.816	−0.003
		(0.600)		(1.001)	(0.004)
Liquidity ratio (borrower)		−14.036		0.945	−0.107
		(11.108)		(34.376)	(0.122)
D/E ratio (borrower)		−0.106		0.173	0.002**
		(0.147)		(0.356)	(0.001)
Interest Coverage ratio (borrower)		−0.653		−3.366	−0.027*
		(1.834)		(4.086)	(0.015)
Profit Margin (lender)		−0.390		−1.709	−0.011
		(1.032)		(2.110)	(0.008)
Size (lender)		−36.061***		−39.944*	−0.270***
		(12.854)		(21.635)	(0.085)
Deal Amount		43.583***		44.945**	0.137
		(14.129)		(21.908)	(0.089)
Maturity		1.505*		1.355	0.003
		(0.806)		(1.264)	(0.005)
Loan spread		−0.076		−0.091	−0.001
		(0.115)		(0.188)	(0.001)
Constant	36.092***	506.573*	36.145***	571.296	5.409***
	(0.854)	(255.252)	(0.795)	(515.037)	(1.921)
Fixed Effects	No	No	Yes	Yes	No
Observations	7232	82	7195	82	66
R-squared	0.000	0.311	0.000	0.309	

[1] Column (1) represents the most basic model, column (2) the model with control variables, column (3) adds province and month fixed effects, and column (4) represents the complete model. Column (5) represents the Negative Binomial Model.

[2] The R-squared in column (5) presents the Pseudo R-Squared.

[3] Robust standard errors are in parentheses.

[4] * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The results in Table 17 indicate a negative and weakly significant association between the occurrence of a disaster and the number of lead arrangers, as shown in Column (2). In Columns (1) and (3), the disaster variable does not significantly explain the variation in the number of lead arrangers, with R^2 values of 0 and only the constant term being significant. Generally, some variation in the number of lead arrangers is explained by average lender size and deal amount. In Column (5), which uses a Negative Binomial Model, significant relationships are found between the number of lead arrangers and the borrower's debt-to-equity (D/E) ratio and interest coverage ratio. In this 6-month timeframe specification, the model with control variables but without fixed effects shows a weakly significant disaster coefficient. In contrast, the 12-month timeframe specification displays a significant disaster coefficient in the model that excludes control variables but includes fixed effects.

B.4 Lead arranger share

The results in Table 18 show the regression output for the lender share model, when disaster is specified as occurring within the 6 previous months, and the regression is conducted on an individual loan level. The country and year fixed effects are absorbed into the model.

Table 18: Imputed Lender Share (6 months disaster)

	(1) Lender Share	(2) Lender Share	(3) Lender Share	(4) Lender Share
Disaster_6m	2.248***	2.331	0.541***	−6.460
	(0.168)	(3.820)	(0.176)	(4.822)
Size (borrower)		−0.243		−7.739**
		(0.977)		(3.554)
Profitability (borrower)		0.040		−0.367
		(0.080)		(1.821)
Solvency ratio (borrower)		−0.117		−0.695***
		(0.103)		(0.262)
Liquidity ratio (borrower)		2.460		11.436**
		(2.618)		(5.243)
D/E ratio (borrower)		0.009		0.102***
		(0.043)		(0.030)
Interest Coverage ratio (borrower)		−0.087		−0.109
		(0.256)		(1.810)
Profit Margin (lender)		−0.024		−0.023
		(0.021)		(0.020)
Size (lender)		0.356		0.264
		(0.298)		(0.292)
Deal Amount		−6.204**		−6.576
		(2.742)		(5.284)
Maturity		−0.039		0.038
		(0.072)		(0.093)
Loan spread		−0.034***		−0.063***
		(0.011)		(0.013)
Constant	7.575***	67.254***	7.922***	201.848***
	(0.070)	(16.358)	(0.069)	(46.936)
Fixed Effects	No	No	Yes	Yes
Observations	30079	352	30079	350
R-squared	0.007	0.346	0.125	0.402

[1] Column (1) represents the most basic model, column (2) the model with control variables, column (3) adds country and year fixed effects, and column (4) represents the complete model.

[2] Robust standard errors are in parentheses.

[3] * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

From Table 18, it can be noted that the relationship between the occurrence of a disaster and the share retained by the lead arranger is positive and significant, in Column (1) and (3). When control variables are included, the coefficients are insignificant. Some of the control variables themselves are significant: deal spread and deal amount are negatively related to the retained lender share. A significant association between solvency ratio, D/E ratio, borrower size and profit margin of the lender exists as well, depending on the confidence level. For every model, the constant is significant. At last, it should be mentioned that the number of observations is greatly reduced by introducing control variables, and the R^2 for the first model is limited. Overall, the results for the 6-month timeframe differ from those for the 12-month timeframe. In the 12-month specification, the disaster coefficient is consistently statistically significant and positive. In contrast, for the 6-month models, the disaster coefficient is only statistically significant when control variables are excluded.

B.5 Number of lenders

Table 19 presents the relationship between the occurrence of a natural disaster within the 6 previous months and the number of lenders, on an individual loan level. The country and year fixed effects are absorbed into the model.

Table 19: Number of lenders (6 months disaster)

	(1) No. Lenders	(2) No. Lenders	(3) No. Lenders	(4) No. Lenders	(5) No. Lenders
Disaster_6m	0.318***	−10.068***	0.298***	−1.403	−0.534**
	(0.086)	(3.326)	(0.076)	(4.245)	(0.248)
Size (borrower)		−1.750		−2.671	−0.169*
		(1.257)		(3.315)	(0.101)
Profitability (borrower)		−0.052		−3.105	−0.007
		(0.116)		(2.478)	(0.008)
Solvency ratio (borrower)		0.126		0.206	0.007
		(0.156)		(0.319)	(0.011)
Liquidity ratio (borrower)		−0.479		0.766	−0.073
		(0.897)		(2.047)	(0.063)
D/E ratio (borrower)		−0.001		0.038*	−0.000
		(0.013)		(0.023)	(0.001)
Interest Coverage ratio (borrower)		−0.192		2.919	−0.034**
		(0.207)		(2.821)	(0.014)
Profit Margin (lender)		−0.010		0.002	−0.000
		(0.027)		(0.026)	(0.001)
Size (lender)		0.005		−0.023	−0.000
		(0.348)		(0.344)	(0.015)
Deal Amount		12.053***		14.617***	0.857***
		(2.375)		(3.423)	(0.220)
Maturity		0.120**		0.052	0.004
		(0.047)		(0.076)	(0.003)
Loan spread		0.100***		0.142***	0.005***
		(0.013)		(0.014)	(0.001)
Constant	12.741***	−83.627***	12.198***	−86.883	−2.525**
	(0.026)	(20.740)	(0.198)	(71.161)	(1.265)
Fixed Effects	No	No	Yes	Yes	No
Observations	258850	364	258850	362	364
R-squared	0.000	0.575	0.222	0.638	0.097

[1] Column (1) represents the most basic model, column (2) the model with control variables, column (3) adds country and year fixed effects, and column (4) represents the complete model. Column (5) represents the Negative Binomial Model.

[2] The R-squared in column (5) presents the Pseudo R-Squared.

[3] Robust standard errors are in parentheses.

[4] * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The relationship between the occurrence of a disaster and the number of lenders varies across different model specifications. In Column (2), the disaster coefficient is significantly negative, indicating that loans marked as a disaster loan are associated with a lower number of lenders. Column (5) also shows a significant negative coefficient. The coefficient in Column (1) is significant but has almost no explanatory power, as shown by an R^2 of 0. The coefficient in Column (5) can be interpreted using the Incidence Rate Ratio (IRR): $IRR = e^{-0.534} \approx 0.59$. This suggests that "disaster loans" are associated with approximately 41% fewer lenders compared to "non-disaster loans." Additionally, the deal amount is strongly positively correlated with the number of lenders. Other significant factors include lender profitability, borrower size, debt-to-equity ratio, maturity, and deal spread, with varying levels of statistical significance across the models. The results do not differ drastically from the 12-month models. The magnitude of the coefficients is generally smaller for the 6-month specification. Additionally, the disaster coefficient in Column (4) is only significant in the 12-month specification.

B.6 Collateral

Table 20 displays the regression output for collateral and the occurrence of a disaster within 6 months. Similarly, the regressions are run on an individual loan level, with fixed effects for country and year absorbed in the model. The model in Column (5) also includes control variables, but it does not include deal spread. Similar as for the previous regressions, this would make the model be unable to reach convergence. It also does not include fixed effects, as they are unable to be absorbed in the model.

Table 20: Secured / Unsecured (6 months disaster)

	(1) Secured	(2) Secured	(3) Secured	(4) Secured	(5) Secured
Disaster_6m	-0.047^{***}	0.702^{***}	-0.042^{***}	0.580^{***}	1.773^{***}
	(0.003)	(0.114)	(0.003)	(0.135)	(0.374)
Size (borrower)		0.106^{**}		0.011	0.359^{**}
		(0.053)		(0.123)	(0.183)
Profitability (borrower)		0.006		-0.005	0.024
		(0.004)		(0.076)	(0.015)
Solvency ratio (borrower)		0.002		-0.002	-0.026^{**}
		(0.006)		(0.010)	(0.011)
Liquidity ratio (borrower)		-0.051		-0.156^{**}	0.327^{*}
		(0.042)		(0.065)	(0.179)
D/E ratio (borrower)		0.001		0.001	-0.004
		(0.001)		(0.001)	(0.003)
Interest Coverage ratio (borrower)		-0.013		0.021	-0.037
		(0.008)		(0.085)	(0.026)
Profit Margin (lender)		-0.000		-0.001	0.006
		(0.001)		(0.001)	(0.004)
Size (lender)		-0.002		-0.002	0.131^{*}
		(0.011)		(0.010)	(0.068)
Deal Amount		-0.303^{***}		-0.448^{***}	-0.794^{***}
		(0.110)		(0.116)	(0.239)
Maturity		-0.002		-0.002	0.018^{**}
		(0.002)		(0.002)	(0.008)
Loan spread		-0.002^{***}		-0.003^{***}	
		(0.000)		(0.001)	
Constant	0.427^{***}	1.291^{**}	0.429^{***}	4.683^{*}	-4.222^{*}
	(0.001)	(0.633)	(0.001)	(2.675)	(2.169)
Fixed Effects	No	No	Yes	Yes	No
Observations	260305	364	258849	362	567
R-squared	0.001	0.402	0.071	0.496	0.215

[1] Column (1) represents the most basic model, column (2) the model with control variables, column (3) adds country and year fixed effects, and column (4) represents the complete model. Column (5) represents the Logit Model.

[2] The R-squared in column (5) presents the Pseudo R-Squared.

[3] Robust standard errors are in parentheses.

[4] * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The coefficient for the disaster variable is significant and positive in Column (5), suggesting that loans issued during a disaster are significantly more likely to be secured compared to those issued in non-disaster periods. Specifically, the Logit model (Column (5)) indicates that disaster loans are approximately $e^{1.773} \approx 5.88$ times more likely to be secured than non-disaster loans. In contrast, the OLS models in columns (1) and (3) show a negative disaster coefficient, but these models are limited by their lack of control variables and their unsuitability for binary outcomes. The inclusion of control variables in columns (2) and (4) improves the model fit, as reflected by increased R^2 values, but this also results in a reduction in the number of observations due to missing data. Furthermore, borrower size, deal amount, and deal spread exhibit strong significant relationships with the likelihood of a loan being secured. While borrower profitability, solvency ratio, liquidity ratio, and maturity also show varying levels of significance, their impact is less consistent. Overall, the model with control variables and fixed effects (Column (4)) provides the most comprehensive understanding, though it still only has a limited number of observations due to missing values. While the significance and direction of the relationships is quite similar to the 12-month specification, some of the coefficients are larger in magnitude for the 6-month timeframe, which indicates a stronger effect over a shorter timeframe.

B.7 Maturity

In Table 21, the results are displayed for the relationship between maturity and the occurrence of a disaster within 6 months. Again, the OLS regressions are run on an individual loan level, with country and year fixed effects absorbed into the model.

Table 21: Maturity (6 months disaster)

	(1) Maturity	(2) Maturity	(3) Maturity	(4) Maturity
Disaster_6m	-3.507^{***}	32.658^{***}	-3.231^{***}	34.690^{***}
	(0.211)	(5.143)	(0.220)	(2.624)
Size (borrower)		0.756		-14.136^{**}
		(2.549)		(6.140)
Profitability (borrower)		0.062		-9.177^{**}
		(0.238)		(3.930)
Solvency ratio (borrower)		0.153		1.332^{***}
		(0.248)		(0.385)
Liquidity ratio (borrower)		-0.178		-8.955^{***}
		(1.888)		(3.445)
D/E ratio (borrower)		0.011		0.159^{***}
		(0.019)		(0.037)
Interest Coverage ratio (borrower)		-0.707^{*}		8.460^{**}
		(0.405)		(4.031)
Profit Margin (lender)		-0.032		-0.008
		(0.030)		(0.024)
Size (lender)		0.062		0.147
		(0.387)		(0.320)
Deal Amount		3.072		9.769^{**}
		(4.416)		(4.208)
Loan spread		0.002		0.025^{*}
		(0.012)		(0.013)
Constant	60.919^{***}	17.380	60.882^{***}	238.810^{**}
	(0.096)	(23.584)	(0.092)	(115.501)
Fixed Effects	No	No	No	Yes
Observations	250222	364	250221	362
R-squared	0.001	0.352	0.071	0.632

[1] Column (1) represents the most basic model, column (2) the model with control variables, column (3) adds country and year fixed effects, and column (4) represents the complete model.

[2] Robust standard errors are in parentheses.

[3] * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The results show that the disaster coefficient is consistently significant across all models. Specifically, the disaster coefficient is positive when control variables are included (columns (2) and (4)) and negative when they are not (columns (1) and (3)). The most notable results are found in Column (4), which includes both control variables and fixed effects. In this specification, the disaster coefficient is positive and highly significant, indicating a strong association between a disaster and increased loan maturity.

The inclusion of control variables significantly reduces the number of observations due to missing data. Overall, the findings show that loans issued in the aftermath of a natural disaster are associated with longer maturities. The control variables, including borrower size, profitability, and liquidity, as well as deal amount and deal spread, also display varying degrees of significance. Column (4) provides the most comprehensive results, reflecting the relationship between the occurrence of natural disaster and loan maturity while controlling for various factors. Compared to the 12-month regression output, the effects for 6 months tend to be more positive: in Column (2) and (4), the disaster coefficient is more positive, and it is less negative in Column (1) and (3).

B.8 Deal spread

Table 22 presents the regression results for deal spread and the occurrence of a disaster within 6 months on an individual loan level. The country and year fixed effects are absorbed into these models.

Table 22: Deal spread (6 months disaster)

	(1) Deal spread	(2) Deal spread	(3) Deal spread	(4) Deal spread
Disaster_6m	-10.703^{***}	-82.745^{***}	-9.579^{***}	-178.759^{***}
	(1.575)	(26.223)	(1.641)	(13.512)
Size (borrower)		2.795		21.950
		(10.829)		(23.508)
Profitability (borrower)		-1.626		40.841^{*}
		(1.065)		(21.618)
Solvency ratio (borrower)		-1.789		-1.530
		(1.241)		(2.896)
Liquidity ratio (borrower)		-6.360		-9.943
		(10.147)		(18.529)
D/E ratio (borrower)		-0.163		-0.470^{**}
		(0.151)		(0.194)
Interest Coverage ratio (borrower)		-0.273		-41.801^{*}
		(1.693)		(25.084)
Profit Margin (lender)		-0.218		-0.108
		(0.199)		(0.139)
Size (lender)		-1.827		-0.884
		(2.225)		(1.695)
Deal Amount		-37.539^{**}		15.381
		(18.546)		(13.244)
Maturity		0.050		0.616^{*}
		(0.320)		(0.362)
Constant	266.248^{***}	736.091^{***}	266.111^{***}	-329.928
	(0.512)	(166.386)	(0.477)	(548.147)
Fixed Effects	No	No	Yes	Yes
Observations	101197	364	101197	362
R-squared	0.001	0.369	0.135	0.676

[1] Column (1) represents the most basic model, column (2) the model with control variables, column (3) adds country and year fixed effects, and column (4) represents the complete model.

[2] Robust standard errors are in parentheses.

[3] * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Column (4), which incorporates both control variables and fixed effects, provides the most comprehensive results. In this specification, the disaster coefficient is highly significant and negative, with a substantial decrease in deal spread. While many control variables are significant, some, such as the solvency and liquidity ratios and lender size, do not show significant effects. The inclusion of control variables improves the R^2 in the models, indicating a better fit, but reduces the number of observations due to missing data. Overall, the results suggest that disaster loans tend to have lower spreads. This is also indicated by the 12-month models, while the association is even more negative for the 6-month specification.

B.9 Proximity

Table 23 presents the results for proximity. For the dependent variables Number of Lenders, Maturity, Lender Share, Loan Spread and Secured, an extended model includes the interaction term proximity. Proximity is a binary variable indicating whether the lead arranger and borrower are located in the same country. It is interacted with the disaster dummy. All OLS models, so maturity, lender share and deal spread in Column (2) to (4), are run with absorbed fixed effects of country and year. The number of lenders is fit to a negative binomial model, and the model for "secured" is fit to a logit model. These models are best suited for their respective distributions.

Table 23: Borrower - Lender proximity (6 months disaster)

	(1) No. Lenders	(2) Maturity	(3) Lender Share	(4) Loan spread	(5) Secured
Disaster_6m	0.112^{***}	-2.950^{***}	0.074	-11.568^{***}	-0.107^{***}
	(0.007)	(0.230)	(0.181)	(1.663)	(0.013)
Proximity*Disaster_6m	-0.385^{***}	-0.979^{***}	2.357^{***}	11.684^{***}	-0.270^{***}
	(0.007)	(0.246)	(0.186)	(1.785)	(0.013)
Constant	2.572^{***}	60.960^{***}	7.547^{***}	265.519^{***}	-0.273^{***}
	(0.002)	(0.096)	(0.071)	(0.490)	(0.004)
Fixed Effects	No	Yes	Yes	Yes	No
Observations	258848	250219	30079	101197	260303
R-squared	0.003	0.071	0.131	0.135	0.002

[1] The R-squared in column (1) (5) present the Pseudo R-Squared.

[2] Robust standard errors are in parentheses.

[3] * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The results show that the disaster coefficient is consistently significant across all model specifications. In Column (1), where the analysis uses the Incident Rate Ratio (IRR), the coefficient indicates that the number of lenders increases by a factor of $e^{0.112} \approx 1.12$ if a loan is originated in the aftermath of a natural disaster, suggesting a moderate increase in the number of lenders. In Column (5), the disaster coefficient is negative and significant, with an odds ratio of $e^{-0.107} \approx 0.90$. This implies that disaster loans are less likely to be secured compared to those in non-disaster periods. The interaction term, Proximity*Disaster_6m, is significant across all models. While the interaction terms for proximity show significant effects, the conflicting directions of these relationships, along with the disaster coefficients in this model, leave little room for interpretation in regard to the hypothesis. This finding is in line with the 12-month specification of disaster loans.

Appendix C Extended model specifications

The equations below show the extended model specifications for hypothesis 2.1, 2.2, 2.3, and 2.4, and 2.5, where borrower-lender proximity is interacted with Disaster to capture potential moderating effects.

$$\text{Number of Lenders}_{i,t} = \alpha + \gamma_c + \delta_y + \beta_1 \text{Disaster(m)}_{p,t} + \beta_2 \text{Disaster(m)*Proximity}_{i,t} + \mathbf{X}_{i,t} + \epsilon_{i,t} \quad (12)$$

In this model, the unit of observation is a single loan, so Number of $\text{Lenders}_{p,t}$ represents the number of lenders for loan i at time t, where t denotes the deal's active date.α is the intercept, γ_c represents country fixed effects, and δ_y represents yearly fixed effects. $\text{Disaster(m)}_{p,t}$ is a dummy variable indicating whether a natural disaster occurred in the same province within the previous m months, where m can be either 6 or 12 months. $\text{Disaster(m)*Proximity}_{i,t}$ is an interaction term between the disaster dummy and a proximity dummy, which equals 1 if the borrower and lender are in the same country and 0 otherwise. Finally, $\mathbf{X}_{i,t}$ is the vector of control variables, including lender, loan, and borrower characteristics specific to each loan, and $\epsilon_{i,t}$ represents the error term.

$$\text{Maturity}_{i,t} = \alpha + \gamma_c + \delta_y + \beta_1 \text{Disaster(m)}_{p,t} + \beta_2 \text{Disaster(m)*Proximity}_{i,t} + \mathbf{X}_{i,t} + \epsilon_{i,t} \quad (13)$$

In this model, the unit of observation is a single loan, therefore the $\text{Maturity}_{i,t}$ represents the loan maturity in months for a loan i at time t, where time denotes the deal active date. α is the intercept, γ_c represents country fixed effects, and δ_y represents yearly fixed effects. $\text{Disaster(m)}_{p,t}$ is a dummy variable indicating whether a natural disaster occurred in the same province within the previous m months, where m can be either 6 or 12 months. $\text{Disaster(m)*Proximity}_{i,t}$ is an interaction term between the disaster dummy and a proximity dummy, which equals 1 if the borrower and lender are in the same country and 0 otherwise. Finally, $\mathbf{X}_{i,t}$ is the vector of control variables, including lender, loan, and borrower characteristics specific to each loan, and $\epsilon_{i,t}$ represents the error term.

$$\text{Imputed Lender Share}_{i,t} = \alpha + \gamma_c + \delta_y + \beta_1 \text{Disaster(m)}_{p,t} + \beta_2 \text{Disaster(m)*Proximity}_{i,t} + \mathbf{X}_{i,t} + \epsilon_{i,t} \quad (14)$$

In this model, the unit of observation is a single loan, therefore the Imputed Lender $\text{Share}_{i,t}$ represents the loan maturity in months for a loan i at time t, where time is the deal active date. α is the intercept, γ_c represents country fixed effects, and δ_y represents yearly fixed effects. $\text{Disaster(m)}_{p,t}$ is a dummy variable indicating whether a natural disaster occurred in the same province within the previous m months, where m can be either 6 or 12 months. $\text{Disaster(m)*Proximity}_{i,t}$ is an interaction term between the disaster dummy and a proximity dummy, which equals 1 if the borrower and lender are in the same country and 0 otherwise. Finally, $\mathbf{X}_{i,t}$ is the vector of control variables, including lender, loan, and borrower characteristics specific to each loan, and $\epsilon_{i,t}$ represents the error term.

$$\text{Secured}_{i,t} = \alpha + \gamma_c + \delta_y + \beta_1 \text{Disaster(m)}_{p,t} + \beta_2 \text{Disaster(m)*Proximity}_{i,t} + \mathbf{X}_{i,t} + \epsilon_{i,t} \quad (15)$$

In this model, the unit of observation is a single loan, therefore $\text{Secured}_{i,t}$ is a binary variable that indicates whether a loan i at time t has collateral (= secured) or not, where time is the deal active date. α is the intercept, γ_c represents country fixed effects, and δ_y represents yearly fixed effects. $\text{Disaster(m)}_{p,t}$ is a dummy variable indicating whether a natural disaster occurred in the same province within the previous m months, where m can be either 6 or 12 months. Disaster(m)*Proximity$_{i,t}$ is an interaction term between the disaster dummy and a proximity dummy, which equals 1 if the borrower and lender are in the same country and 0 otherwise. Finally, $\mathbf{X}_{i,t}$ is the vector of control variables, including lender, loan, and borrower characteristics specific to each loan, and $\epsilon_{i,t}$ represents the error term.

$$\text{Loan spread}_{i,t} = \alpha + \gamma_c + \delta_y + \beta_1 \text{Disaster(m)}_{p,t} + \beta_2 \text{Disaster(m)*Proximity}_{i,t} + \mathbf{X}_{i,t} + \epsilon_{i,t} \qquad (16)$$

In this model, the unit of observation is a single loan, therefore Loan Spread$_{i,t}$ represents the spread in basis points for loan i at time t, where time t is the deal active date. α is the intercept, γ_c represents country fixed effects, and δ_y represents yearly fixed effects. Disaster(m)$_{p,t}$ is a dummy variable indicating whether a natural disaster occurred in the same province within the previous m months, where m can be either 6 or 12 months. Disaster(m)*Proximity$_{i,t}$ is an interaction term between the disaster dummy and a proximity dummy, which equals 1 if the borrower and lender are in the same country and 0 otherwise. Finally, $\mathbf{X}_{i,t}$ is the vector of control variables, including lender, loan, and borrower characteristics specific to each loan, and $\epsilon_{i,t}$ represents the error term.

Appendix D Lender Share

$$\text{Lead Arranger Share}_{i,t} = \alpha + \gamma_i + \beta_1 \text{Disaster(m)}_{p,t} + \mathbf{X}_{i,t} + \epsilon_{i,t} \tag{17}$$

In this model, the unit of observation is a single loan, therefore Lead Arranger Share$_{i,t}$ represents the share retained by the lead arranger for loan i at time t, where time t is the deal active date. α is the intercept, γ_c represents country fixed effects, and δ_y represents yearly fixed effects. Disaster(m)$_{p,t}$ is a dummy variable indicating whether a natural disaster occurred in the same province within the previous m months, where m can be either 6 or 12 months. Finally, $\mathbf{X}_{i,t}$ is the vector of control variables, including lender, loan, and borrower characteristics specific to each loan, and $\epsilon_{i,t}$ represents the error term.

Table 24: Lender Share (1 year disaster)

	(1) Lender Share	(2) Lender Share	(3) Lender Share	(4) Lender Share
Disaster_1y	7.315*	0.000	10.904***	0.000
	(3.854)	(.)	(3.990)	(.)
Size (borrower)		0.000		0.000
		(.)		(.)
Profitability (borrower)		−0.345***		0.000
		(0.000)		(.)
Solvency ratio (borrower)		0.000		0.000
		(.)		(.)
Liquidity ratio (borrower)		0.000		0.000
		(.)		(.)
D/E ratio (borrower)		−0.131***		0.000
		(0.000)		(.)
Interest Coverage ratio (borrower)		0.000		0.000
		(.)		(.)
Profit Margin (lender)		−0.577***		−0.577***
		(0.000)		(0.000)
Size (lender)		−0.314***		−0.314***
		(0.000)		(0.000)
Deal Amount		0.000		0.000
		(.)		(.)
Maturity		0.000		0.000
		(.)		(.)
Loan spread		−0.047***		0.000
		(0.000)		(.)
Constant	27.397***	72.944***	26.719***	26.342***
	(1.640)	(0.000)	(1.609)	(0.000)
Fixed Effects	No	No	Yes	Yes
Observations	39020	7	38995	4
R-squared	0.000	1.000	0.034	1.000

[1] Column (1) represents the most basic model, column (2) the model with control variables, column (3) adds country and year fixed effects, and column (4) represents the complete model.

[2] Robust standard errors are in parentheses.

[3] * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 25: Lender share (6 months disaster)

	(1) Lender Share	(2) Lender Share	(3) Lender Share	(4) Lender Share
Disaster_6m	24.265***	0.000	28.763***	0.000
	(6.583)	(.)	(6.727)	(.)
Size (borrower)		0.000		0.000
		(.)		(.)
Profitability (borrower)		−0.345***		0.000
		(0.000)		(.)
Solvency ratio (borrower)		0.000		0.000
		(.)		(.)
Liquidity ratio (borrower)		0.000		0.000
		(.)		(.)
D/E ratio (borrower)		−0.131***		0.000
		(0.000)		(.)
Interest Coverage ratio (borrower)		0.000		0.000
		(.)		(.)
Profit Margin (lender)		−0.577***		−0.577***
		(0.000)		(0.000)
Size (lender)		−0.314***		−0.314***
		(0.000)		(0.000)
Deal Amount		0.000		0.000
		(.)		(.)
Maturity		0.000		0.000
		(.)		(.)
Loan spread		−0.047***		0.000
		(0.000)		(.)
Constant	26.334***	72.944***	25.881***	26.342***
	(1.485)	(0.000)	(1.471)	(0.000)
Fixed Effects	No	No	Yes	Yes
Observations	39020	7	38995	4
R-squared	0.001	1.000	0.035	1.000

[1] Column (1) represents the most basic model, column (2) the model with control variables, column (3) adds country and year fixed effects, and column (4) represents the complete model.

[2] Robust standard errors are in parentheses.

[3] * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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