The impact of physical climate risks on a commercial real estate mortgage portfolio

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A thesis submitted in fulfillment of the requirements for the degree of Master of Science in Quantitative Finance and Actuarial Science

Tilburg School of Economics and Management
Tilburg University

June, 2024

Abstract

The physical climate risks of floods and droughts damage buildings, including those serving as collateral within mortgage portfolios. This study assesses the financial impact of eight flood and drought scenarios on the commercial real estate mortgage portfolio of de Volksbank. These scenarios are based on data from the Klimaateffectatlas (*Climate Impact Atlas*), which provides flood data accuracy of 25 square meters. For droughts, the study considers pile rot and settlement. Combined with damage functions specific to building categories and damage classes, direct damages are estimated, amounting to a maximum of 11.7% of the total collateral value. Regression analyses indicate that revenue loss and increase in loan to value due to direct damages have a limited impact on the probability of default. Cobb-Douglas functions moderately match de Volksbank's internal revenue figures, correlating at 28%. The findings show an increase in expected loss over exposure ratios ranging from 0.00279 to 1.53 for flood scenarios and 0.227 to 0.356 for drought scenarios.

Acknowledgements

This thesis is the final part of the master's program Quantitative Finance and Actuarial Science at Tilburg University. The research focuses on the commercial real estate mortgage portfolio of de Volksbank and is conducted in the name of Mount Analytics.

I would like to acknowledge those who have made the outcome of this thesis possible. Firstly, I thank Jurriaan Groot and Erwin Siegers for their external guidance from Mount Analytics, particularly concerning the general applicability of the methodology and Python programming. Furthermore, I express gratitude to Hans Jacobs for his valuable contribution from de Volksbank, especially in guiding and ensuring its applicability within the banking sector. Finally, I extend thanks to Lieske Coumans for her internal guidance from Tilburg University, actively assisting in maintaining the structure, clarity and scientific content of the thesis.

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Chapter 1

Introduction

1.1 Problem context

Over the last century, the notable increase in global temperatures has affected weather extremes across the globe. This has resulted in extensive negative effects, causing losses and damages to both the environment and human populations. Since the emissions in greenhouse gases sustain, there will be further escalation of global warming in the near future (IPCC, 2023). For the Netherlands, this includes the threat of increased floods due to rising sea levels, heightened vulnerability to droughts impacting agriculture and water supplies, and potential challenges associated with changing rainfall patterns.

These climate changes challenge governments to adapt and cope with the evolving situation, compelling them to draft new regulations. Among these regulations is the Environmental Social and Governance (ESG) framework and it refers to a set of criteria and guidelines to assess the sustainability of businesses. The EU law prescribes that all large companies, like insurance companies and pension funds, must report on these ESG criteria (Bank for International Settlements, 2022).

Reporting on ESG, and so on climate risks, is new for the financial sector, and the implementation leads to challenges (Chopra et al., 2024). Mount Consulting is a consultancy firm that is able to help with qualifying these risks. The expertise of Mount Consulting lies in data management, support in the design of ESG regulatory solutions and help with the implementation to an already existing regulatory landscape for the regular finance and risk reporting. Moreover, it gets increasingly important to quantify the climate related hazards too and this is why Mount Analytics is established. Mount Analytics provides the financial sector with analytical services in order to leverage the available data and this is in particular important for quantifying climate risks.

One of the banks subject to the innovated regulations is de Volksbank. De Volksbank serves more than three million customers and is characterized by customer friendliness. The bank provides mortgages for both private individuals and businesses. The portfolios consisting of these mortgages are exposed to climate change in various ways. Since previous research already provides insights into the impact of climate risks on the residential mortgage (Gerrits, 2022), this thesis focuses on the commercial real estate mortgage portfolio. The next section describes how the commercial real estate mortgage portfolio is affected by the climate risks and identifies a literature gap by discussing the available literature.

1.2 Core problem

One of the consequences of climate change for the Netherlands is an increased risk of flooding. This includes flooding of large parts of the country due to rising sea levels and flooding of rivers caused by heavy rainfalls. These potential floods cause different forms of damage, affecting among others micro and small enterprises. Flooding of a business can lead to both direct and indirect damages. Direct damage includes damage to the business building and inventory, while indirect damage consists of a reduction in revenue for a certain recovery period. Since there exists only partly insurance against this damage, it results in a loss of income, potentially making the business unable to repay its loan to the bank (Hamel et al., 2021). If this scenario occurs for multiple enterprises, what impact does it have on the bank's commercial real estate mortgage portfolio? The same question could be asked for droughts, another physical climate risk relevant for the Netherlands.

There is existing literature available for various elements of this question. Firstly, the Klimaateffectatlas (*Climate Impact Atlas*) provides various maps showing the likelihood of flooding at different depths and droughts of different severities up to 2050 (Klimaateffectatlas, 2024). Additionally, the Standaardmethode Schade en Slachtoffers (*Standard Method for Damage and Victims*) determines the victims and economic consequences of a flood (Vrisou van Eck and Kok, 2001). This method calculates the direct and indirect damage. Direct damage involves the physical damage to the business building and inventory. Indirect damage consists of the temporary loss of revenue for the affected business. However this method does not take into account the damages resulting from droughts such as pile rot and settlement (Costa, Kok, and Korff, 2020).

In addition to the Standaardmethode Schade en Slachtoffers there are models available that more extensively estimate this direct damage by determining for instance the Loss Given Default up to 2050 (Siegers, 2023). Notice that these models are focused on residential properties, but business buildings are different due to the machinery and inventory. Furthermore, the indirect damage of enterprises is completely ignored.

There are also studies estimating indirect damage. An important example is input-output models, these models illustrate the interdependence between different economic sectors and can be applied to natural disasters (Hallegatte, 2015). Another example is Computable General Equilibrium (CGE) models, these models are also used to measure the impact of a disaster on the economy (Okuyama and Santos, 2014). Another relevant study describes a flood risk model for Rotterdam, employing various methods such as Cobb-Douglas functions and input-output models, including Adaptive Regional Input-Output (ARIO) models. These models describe output shocks to an economy while taking into account changes in aggregate demand (Koks et al., 2015). It is worth noting however that all these studies lack a connection to a commercial real estate mortgage portfolio.

There are also studies describing the link between climate change and credit ratings, such as Li, Zhang, and Zhao (2022a) and Bonacorsi et al. (2022). In all these studies, the focus is on stock traded companies in large countries like the United States or China, and direct and indirect damage are not calculated. However, the impact of climate change on stock traded companies might differ from the impact on micro and small sized enterprises that are incorporated in the commercial real estate mortgage portfolio of de Volksbank.

As a result, a gap in the literature becomes clear. There is in the literature no integration available of the physical climate risks of droughts and floods, direct and indirect damage, and the implication for a commercial real estate mortgage portfolio for micro and small-sized enterprises. Furthermore, it is striking that a combination of direct and indirect damage for micro and small enterprises is only determined for the area of Rotterdam, not for the whole Netherlands. Lastly, the impact of floods and droughts is only determined for a residential mortgage portfolio and not for a portfolio consisting of commercial real estate loans.

1.3 Research objective

The aim of this thesis is to fill the gap identified in the literature discussed in the previous section. For this purpose, the following research question is addressed:

What implications does the predicted financial impact, resulting from floods and droughts on micro and small enterprises up to 2050, have on the expected loss of a commercial real estate mortgage portfolio?

The thesis applies the research question to the commercial real estate mortgage portfolio of de Volksbank. The outcome of this study quantifies the impact of floods and droughts on this portfolio, providing valuable insights for reporting on ESG criteria. Notice that the time frame of 2050 is mentioned, because governments are working towards achieving the objectives outlined in the Paris Agreement by 2050, aiming for a zero-carbon emission (European Union, 2021). Subsequently, the Klimaateffectatlas has integrated the data with scenarios from this year into the maps as well.

Besides, the objective of the thesis is to develop a method that can potentially be applied more broadly. In order to keep the scope of the thesis limited, the research method only addresses floods and droughts. However, the idea of reasoning of the thesis can be applied for other physical climate risks as well, which might be relevant in case of for example more frequent natural fires and storms. In this way, this methodology can be utilized by Mount Analytics for assessing other companies beyond de Volksbank and de Volksbank is able to easily expand the existing model.

1.4 Research approach

As indicated before, the thesis builds upon a dataset provided by de Volksbank. This dataset contains around seven thousand commercial real estate loans to micro and small enterprises (i.e. less than 50 employees and a turnover or balance sheet total less than 10 million euros (European Union, 2024)) with various Standaard BedrijfsIndelingscodes (*Standard Business Classification codes*) and address information. Using this data, the thesis can estimate which companies are prone to floods and droughts and can differentiate between various business categories.

The thesis consists of several steps to apply the data to the research question, where an overview of these steps is shown in Figure 4.1. Firstly, the physical climate risks of floods and droughts are determined with the business addresses and the Klimaateffectatlas by using European Petroleum Survey Group (EPSG) data. The thesis creates various climate scenarios for this by using the specified flood and drought scenarios of the Klimaateffectatlas. Afterwards, the businesses are identified that are affected for the different scenarios.

The subsequent step is calculating the direct damage to the affected businesses. The Standaardmethode Schade en Slachtoffers and Siegers' model can be used for this purpose. Distinctions between businesses from different categories must also be made, which can be done using the Standaard BedrijfsIndelingscodes. The Standaardmethode Schade en Slachtoffers allows for differentiating between business categories.

The following step is determining the indirect damage for the affected businesses. Besides internal data from de Volksbank, the thesis uses Cobb-Douglas functions in order to estimate the turnover of the businesses and consequently the indirect impact. The direct and indirect damages together constitute the total damage. Notice that the results will be aggregated to ensure the privacy of the companies is not violated.

In the final step, the impact of this total damage on the commercial real estate mortgage portfolio can be determined. The thesis proposes a method to determine both the increase of the probability of default and loss given default of the affected businesses to estimate the potential corresponding losses. As a result, the thesis determines the effect of potential climate scenarios on the commercial real estate mortgage portfolio of de Volksbank.

In order to arrive at the result, the thesis is structured as follows. Chapter 2 provides an overview of the available literature and identifies gaps in the existing research. Chapter 3 describes the variables and their respective data sources. The implementation of these variables within the mathematical model is detailed in Chapter 4. The findings relating to the main research question are presented in Chapter 5, followed by conclusions in Chapter 6 and a discussion in Chapter 7.

Chapter 2

Literature Review

This chapter provides an overview of the literature, where the structure of the chapter corresponds with the framework outlined in Figure 2.1. The first section delves into the global climate change scenario, narrowing its focus to the specific context of the Netherlands. Following this, the second section explores the two central climate risks addressed in this thesis, floods and droughts, along with their associated physical impacts. The third section defines the characteristics of micro and small enterprises and provides an overview of the methods used to describe climate impacts on firms. Subsequently, the fourth section investigates a commercial real estate mortgage portfolio and outlines methods for stress testing and measuring portfolio losses. The chapter concludes by phrasing the literature gap addressed by this thesis.

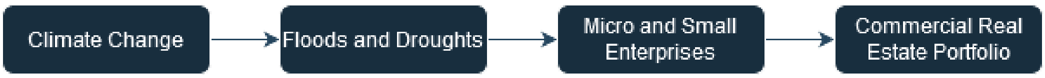


FIGURE 2.1: Outline of the Literature Review.

2.1 Climate change

Climate change is an important challenge of the 21st century. As it is a global problem, there is worldwide attention focused on it. However, since not every country faces the same challenges, a tailored approach for each nation is required. This section first highlights some of the global climate statements, and afterwards, these statements are specifically addressed in the context of the Netherlands.

The Intergovernmental Panel on Climate Change (IPCC) provides governments with scientific information about climate change. The key content of the latest IPCC report includes the expectation that global temperatures will continue to rise in the future. Therefore, a likely scenario is a further sea level rise of 0.15-0.23 meters by 2050. Additionally, droughts are expected to become more recurrent (IPCC, 2023).

These statements from the IPCC are adapted for the Netherlands by the Koninklijk Nederlands Meteorologisch Instituut (*Royal Netherlands Meteorological Institute*). The Koninklijk Nederlands Meteorologisch Instituut (KNMI) develops climate scenarios based on the IPCC to guide policymakers in making informed decisions. Due to uncertainties in future greenhouse gas emissions and variations in climate models, KNMI has produced four different scenarios. These scenarios distinguish between high (H) and low (L) pollution levels and between wet (w) and dry (d) conditions, resulting in the set S which is defined as follows,

$$S := \{Hw, Hd, Lw, Ld\}. \tag{2.1}$$

This set S serves as the foundation for models used in the Netherlands concerning floods and droughts (Stuurgroep Water, 2018), examples where this set is used include (Huijgevoort et al., 2020), (Nazar et al., 2023) and (Bosdijk et al., 2023). From the scenarios becomes clear that both extreme summer rainfalls and droughts will occur more often, where the severity depends on the different scenarios (KNMI, 2023).

These KNMI scenarios serve as the foundation for the climate models used in the Netherlands. The following section specifies the existing knowledge on floods and droughts.

2.2 Floods and droughts

This paragraph discusses the flood and drought types that are relevant for the Netherlands. Droughts and floods are inherently linked, amongst others because warm air leads to more intense rainfall. An example is the Dutch summer of 2018, which resulted in significant economic damage (Philips et al., 2020). It holds for both natural phenomena that the causes are initially identified, followed by the specification of various types along with their corresponding physical consequences. Both subsections conclude with a description of the Klimaateffectatlas, which appears to be an important tool and often used in literature.

2.2.1 Floods

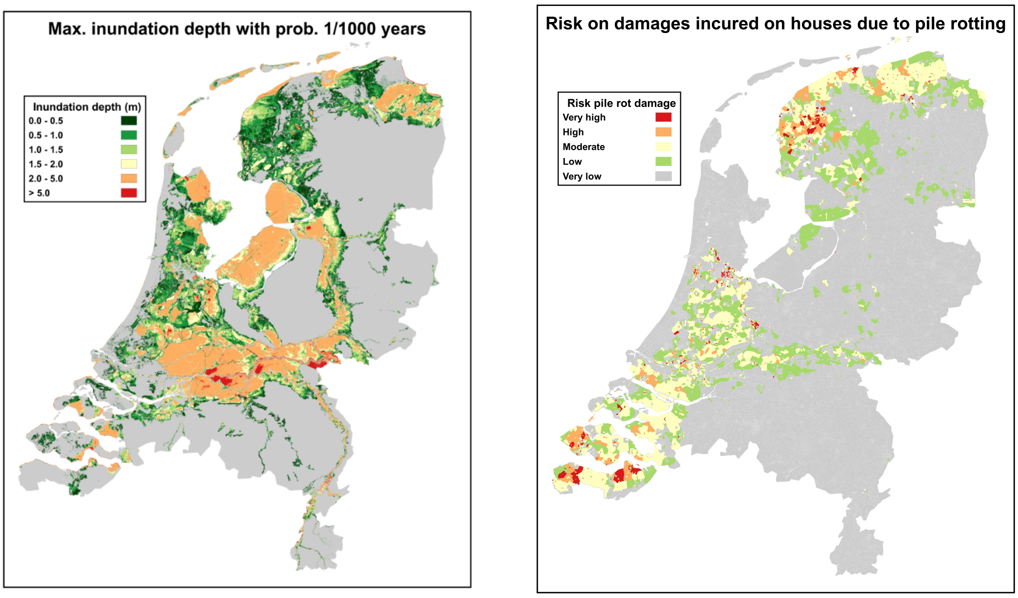
In the Netherlands, approximately 59% of the land is susceptible to flooding, with 26% of that area situated below sea level. This vulnerability has historically resulted in devastating floods, with a major example being the North Sea flood of 1953 (Planbureau voor de Leefomgeving, 2024). In response to these challenges, various laws and institutions have been established for water management, including the Richtlijn Overstromingsrisico's (*Guideline Flood Risks*).

The Richtlijn Overstromingsrisico's (ROR) is a European guideline designed in 2007 to mitigate the impact of potential flood scenarios in the Netherlands. The ROR mandates the assessment of the most destructive scenarios with probabilities of occurrence at 1/10, 1/100, and 1/1,000 years. Therefore, the Landelijk Informatiesysteem Water en Overstromingen (*National Water and Flood Information System*) assessed the water levels within the Netherlands for these scenarios (Watermanagementcentrum Nederland, 2024; Landelijk Informatiesysteem Water en Overstromingen, 2022).

The outcomes of these assessments are represented by the Klimaateffectatlas (*Climate Impact Atlas*). The Klimaateffectatlas is an online map that combines various flood types. This atlas presents the physical risks of five climate topics applied to the Netherlands in 2050. It serves as a basis for stress testing, and among the devised themes are coastal and river floods (combined) and pluvial floods. Users can select different climate scenarios and various physical impacts on the Klimaateffectatlas (Klimaateffectatlas, 2024).

The flood intensity can be approached from two perspectives. On one hand, one can fix the flood probability and investigate the depth of flooding across the Netherlands. On the other hand, it is possible to display the flood probability by keeping the flood depth constant. We will use the scenarios where the flood probability is held constant (See Chapter 4 for the motivation) and for one of the probabilities a map is shown in Figure 2.2a.

Notice that the **inundation depth** in these figures refers to the depth of water



(A) Inundation depth with fixed probability (B) Pile rot risk with severe climate change

FIGURE 2.2: Data from the Klimaateffectatlas (Siegers, 2023).

covering a location due to flooding. It is the measurement of how deep the floodwater is at a specific point. The Klimaateffectatlas allows the user to select four different probability levels. Furthermore, the atlas distinguishes three different climate scenarios: the current situation, limited climate change, and severe climate change, respectively. These scenarios are based on the KNMI scenarios as described in the previous subsection. Unfortunately, the Klimaateffectatlas does not provide detailed information about the derivation of these probabilities. The atlas refers to the Landelijk Informatiesysteem Water en Overstromingen as the author of the flood probabilities, however this system does not provide a derivation of the results.

In addition to floods, the Klimaateffectatlas also addresses the theme of droughts. The following subsection describes the different types of droughts and concludes with a characterization of the information about droughts displayed by this atlas.

2.2.2 Droughts

The Klimaateffectatlas indicates that droughts arise from two different sources: a shortage of rainfall for an extended period and an increase in water evaporation (Klimaateffectatlas, 2024). (In addition to the Klimaateffectatlas, one could consider factors such as reduced water supply by the main water systems and increased water demand, which are currently not taken into account.) These sources are expected to occur more often. The KNMI scenarios S, described in Equation (2.1), predict a global temperature rise, resulting in increased evaporation. Additionally, the dry scenarios Hd and Ld involve longer periods of absence of rainfall. Even for the wet scenarios Hw and Lw, the KNMI anticipates an increase in drought periods, although limited (KNMI, 2023).

These droughts have several consequences. Firstly, they lead to a decrease in surface water, resulting in lower water levels in both the main and regional water systems. This might seem in contrast with the previous paragraph, however the KNMI indicates that both cases will alternate in the future. Secondly, droughts increase the probability of a natural fire (Kennisportaal Klimaatadaptie, 2024; Kok and Angelova, 2020).

Thirdly, droughts cause a lower groundwater level, leading to a shortage. The groundwater shortage has significant consequences for foundations built on wooden piles. These foundations are designed to remain underwater, preventing air from reaching the piles. If the wood comes into contact with oxygen, it can lead to rotting, resulting in a damaged foundation. This process is known as 'paalrot' (**pile rot**) and the Kennis Centrum Aanpak Funderingsproblematiek (*Knowledge Center for Foundation Issues*) indicates that 750,000 buildings in the Netherlands have a pile foundation prone to pile rot (Rijksdienst voor Ondernemend Nederland, 2019).

Another negative consequence of groundwater shortage is **settlement**. Settlement of the soil affects both buildings with pile foundations and those with a foundation directly on the ground, known as an 'op staal' foundation. In the case of a pile foundation, the building remains supported by the piles even as the ground beneath it sinks. For buildings with an 'op staal' foundation, settlement results in an overall sinking of the entire structure, leading to subsidence and cracks in walls (Kennis Centrum Aanpak Funderingsproblematiek, 2022a).

Kennis Centrum Aanpak Funderingsproblematiek (KCAF) (*Knowledge Center for Handling of Foundation Problems*) has mapped out the issues surrounding foundations. Buildings constructed before 1970 almost always have a wooden pile foundation (Appendix B.2). KCAF displays, by postal code area, the percentage of homes built before 1970 (Kennis Centrum Aanpak Funderingsproblematiek, 2022b). In addition to KCAF, the Klimaateffectatlas has also charted the consequences of droughts.

The Klimaateffectatlas displays the physical effects of drought through various maps. Similar to floods, it is possible to distinguish between different climate scenarios. The maps show the risks of pile rot and settlement for both limited and severe climate change. The risk of pile rot in the case of severe climate change is displayed in Figure 2.2b (Klimaateffectatlas, 2024).

For both floods and droughts, the physical consequences have an impact on enterprises. The following section describes micro and small enterprises and gives an overview of the methods used to model climate damages.

2.3 Micro and small enterprises

This section describes the method performed by this thesis to measure the damages to micro and small enterprises caused by floods and droughts. The method is uses parts of the modelling framework of Koks et al. (2015). The whole modelling structure of Koks et al. (2015) is described in Appendix B.1, this section describes the components used in this thesis. Notice that direct impact in this thesis is defined as the damage to buildings that serve as collateral within the mortgage portfolio of de Volksbank. In addition, indirect impact refers to the decrease in turnover after a natural disaster and consequently to the increase in Probability of Default (PD). The direct damage, decrease in turnover and impact on the PD are discussed in the first, second and third subsection respectively. In the literature definitions of damages and losses considerably differ (Okuyama, 2003), (Rose, 2004), but these definitions correspond to the ones in Bočkarjova, Steenge, and Hoekstra (2010) and Vrisou van Eck and Kok (2001).

2.3.1 Direct loss assessment

For the calculation of direct damage, various models are used in the literature and they differ for floods and droughts. For floods, many methods are based on so-called damage functions, while damage classes are used for droughts (Smith, 1994; Jonkman et al., 2008; Jongman et al., 2012; Costa, Kok, and Korff, 2020). This subsection addresses damage functions and damage classes successively, ultimately arriving at a direct damage D^{dir} for both methods.

An important reason why damage functions are used for flood risk assessment is due to the limited number of variables that are required. Once a **damage function** α is developed, it is solely dependent on the **inundation depth** h. The value of the function $\alpha(h)$ then represents the fraction of the **maximum value at risk** $D^{\mathbf{max}}$ affected by a flood with depth h (Moel, Vliet, and Aerts, 2014). The Standaardmethode Schade en Slachtoffers (*Standard Method for Damage and Victims*) defines this value D^{max} as the replacement value of an identical object (Vrisou van Eck and Kok, 2001). In the case of enterprises, the value D^{max} might represent the appraisal value of a business building or the inventory value.

In the literature, damage functions are often specified for various categories, including business categories (Briene et al., 2002). These damage functions are presented in Appendix A.1. Additionally, Koks et al. (2015) divides a map into cells to differentiate between different inundation depths. Consequently, the damage function is expressed as $\alpha_i(h_j)$ for category i and cell j. The direct damage D^{dir} for a specific area is then defined as the sum of individual damages where each damage is the multiplication of the damage function with the maximum value at risk. Although the concept of these functions is straightforward, they can provide an accurate estimate (Amadio et al., 2019).

Unlike flood risk modeling, there is limited literature available for estimating the damage caused by droughts. In the Netherlands, the only available methods are those proposed by Costa, Kok, and Korff (2020) and Kok and Angelova (2020), both of which build on the same set of damage classes.

A damage class represents the damage of a building due to a drought. The set of damage classes D consists of five different categories, where *D1* reflects a building with little cracks and *D5* signifies severe damage, including extensive cracks, a reduction in the carrying capacity of the walls, broken windows and a risk of instability. Each class i is associated with a specific repair cost C^i, which has been specifically estimated for the Netherlands by Salerno (2017) and the results are shown in Appendix A.3.

To determine the relevant damage class, a distinction is made between pile rot and settlement. For pile rot, the damage class $C^{i,p}$ is determined based on the duration of the dry setting of the foundation and the age of the building. Conversely, the settlement damage class $C^{i,s}$ takes into account the settlement rate. It is important to note that both pile rot and settlement increase linearly over time, considering the drought duration and settlement rate respectively. Additionally, these factors are influenced by the soil type, as discussed by Burland and Wroth (1975).

After all, the direct damage D^{dir} to a certain area is then the sum of the individual damage for both pile rot and settlement ($C_j^{i,p} + C_j^{i,s}$), where $C_j^{i,k}$ is the repair cost belonging to damage class i for building j and damage type $k \in \{p, s\}$.

2.3.2 Decrease in turnover

After the direct impact D^{dir} is determined, it is possible to measure the corresponding indirect damage, where this section focuses on the decrease in turnover. An appropriate function for this purpose is the Cobb-Douglas function, which is a function Y returning the value of produced goods for a certain capital K and labor L (Cobb and Douglas, 1928). The function is given by

$$Y(K, L) = bK^{\alpha}L^{\beta} \tag{2.2}$$

where b is a scaling factor and α and β are output elasticities. An output elasticity measures the percentage change in value added divided by the percentage change in input and thus measures the sensitivity of Y with respect to either capital or labor (Charnes, Cooper, and Schinnar, 1976). The Cobb-Douglas function differentiates between different industries by using different parameters b_i, α_i and β_i for a business industry i.

It is assumed that labor is unaffected by a flood or drought. However, the direct impact D^{dir} is considered a loss in capital, resulting in remaining capital $K - D^{\text{dir}}$. As a result, the loss in value added is the difference of the value Y calculated with capital K and $K - D^{\text{dir}}$.

2.3.3 Impact PD

Lastly, the impact of floods and droughts on the PD of a firm is assessed. The literature extensively explores the connection between ESG factors and the default risk of stock-listed firms. The consensus suggests that companies whose returns are more closely associated with carbon emissions tend to face higher credit risks (Bonacorsi et al., 2022). Additionally, research indicates that firms with higher ESG ratings tend to have lower default risks and enjoy higher stock prices (Mendiratta, Varsani, and Giese, 2021; Li, Zhang, and Zhao, 2022b; Devalle, Fiandrino, and Cantino, 2017). Moreover, there is evidence suggesting that improved management of ESG factors is associated with better overall risk management practices (Henisz and McGlinch, 2019).

However, there is an essential difference between listed on the stock-market and non-listed companies. Firstly, the financial conditions of non-listed firms are weaker as they generally have higher debt-to-equity ratios and a lower return on assets (Intrisano, Micheli, and Calce, 2020; Fuertes and Serena, 2014). Secondly, the impact of a disaster for quoted companies can be weaker because these companies have easier access to financial markets. Therefore, listed companies can better mitigate the shock by borrowing money, allowing them to recover from the disaster (Demirgüç-Kunt, Peria, and Tressel, 2020). Thirdly, asset prices are influenced by market perception and investor confidence, leading to a carbon and transition risk premium, which is not applicable for non-traded companies (Hambel and Ploeg, 2024).

There is also literature describing the impact of a natural disaster on the PD of micro and small enterprises. Most companies are not prepared for a flood or drought, but if precautions are taken, they do not significantly help businesses in general to survive (Kreibich et al., 2007). Moreover, given that business owners typically leverage their resources and make considerable efforts to avoid bankruptcy, the majority of businesses do not collapse immediately after such an event (Alesch et al., 2001).

There is research too indicating that certain business characteristics influence the

PD. Zhang, Lindell, and Prater (2009) indicate that the capacity to manage a disaster varies across industry sectors. Sectors like services and essential goods generally have a greater post-disaster survival potential, while retail and entertainment industries tend to be more vulnerable. Industries where the company clients are affected by the flood or drought also have a weaker position. In addition, businesses with more buildings are less exposed than companies located at one specific location (Alesch et al., 2001).

These enterprise characteristics can be converted to a PD with a dynamic regression approach. This methodology uses historical data of a set of firms, including default rates, to quantify the impact on business failure. The PD is then estimated as a function where the company feature parameters are estimated with a regression. The approach is called dynamic because it takes the changes of these features over time into account (Gupta, Gregoriou, and Healy, 2015).

In the context of a mortgage portfolio, one of the outcomes of this method is that the Loan to Value (LtV) has a significant impact on the default risk. The LtV describes the ratio of the loan amount to the appraised value of the collateral. This ratio and the PD are positively correlated (Saha, Rooj, and Sengupta, 2023). Next to the LtV, the approach also indicates that macroeconomic factors like interest and unemployment rates both affect the PD (Wong et al., 2004).

In summary, the PD is influenced by many different characteristics, where the impact of each characteristic can be assessed with a dynamic regression approach. For this thesis, it is therefore relevant to know for which business features there is data available within de Volksbank. Consequently, the next chapter describes the available data for the firms included in the commercial real estate mortgage portfolio, but first a conclusion on the literature gap is given.

2.4 Conclusion

The previous sections have described the literature available, after which the literature contribution of this thesis is displayed. The thesis's contribution includes the use of data, the calculation of damages to buildings and the impact on the creditworthiness of companies with consequently the expected loss of a mortgage portfolio. The red blocks in Figure 4.1 also indicate a contribution to existing literature.

First of all, it is worth noting that the analysis is performed on an existing commercial mortgage portfolio with properties spread across the Netherlands. This contrasts with Siegers (2023), who used fictional buildings. Secondly, it is an addition that the building categories are analyzed using data from the Kadaster, de Volksbank and Google Maps. This allows for the application of damage functions as described in Section 2.3.1.

Another important addition lies in the use of the data. While previous analyses were based on flood data at the postcode level or per hundred square meters, the current accuracy of the Klimaateffectatlas has improved to 25 square meters. This is significant because, for a flood, the location of a building relative to a dike can make a substantial difference. From Figure 2.2a it can be inferred that inundation depths can vary greatly per area, therefore a higher accuracy leads to more reliable results.

Furthermore, this thesis adds adds significant value regarding indirect damage. While other studies stop at calculating direct damage to buildings, this thesis goes further by analyzing the impact on turnover. This turnover decline resulting from a flood or drought is then used to estimate the new PD for micro and small enterprises. This is an addition not yet seen in the literature. The Cobb-Douglas function is used as a substitute for revenue data. Since Volksbank also has real revenue figures of companies within the portfolio, a comparison between the results based on Cobb-Douglas and actual data is possible.

Lastly, note that the combination of the aforementioned elements is unique. This thesis begins by analyzing the direct damage of floods and droughts on buildings, followed by determining the effect on the repayment ability of businesses. In this way, the thesis can conclude by determining the losses of a mortgage portfolio where these buildings serve as collateral for the loans.

Chapter 3

Data Description

This chapter contains a description of data used to answer the research question. The first section describes the data sources, while the vulnerability of the mortgage portfolio of de Volksbank to the data is analysed in the second section. For the implementation of the variables is referred to the next chapter.

3.1 Data sources

The data comes from four different sources: Klimaateffectatlas (*Climate Impact Atlas*), de Volksbank, Kadaster and Centraal Bureau voor Statistiek (*Statistics Netherlands*), which are outlined in succession. Each subsection includes an overview of the variables together with an explanation.

3.1.1 Klimaateffectatlas

The data from the Klimaateffectatlas is divided in the categories floods and droughts. Regarding floods, only the current situation in the Netherlands is accessible. This situation is divided into four cases, each corresponding to probabilities of occurring once in 10, 100, 1,000, and 100,000 years respectively. (Table 3.1 shows the four cases where the statistics are applicable to the mortgage portfolio of de Volksbank.) Each of the four files corresponding to a probability contains 10,921 by 12,523 inundation depths. This means the Netherlands is divided in 10,921 times 12,523 squares. Notice this corresponds to an accuracy of 25 square meters, which is significantly more precise than analyses based on 100 square meters or even postal codes. To match a collateral building with an inundation depth, EPSG 28992 coordinates are utilized, which is the same coordinate system employed by the Kadaster.

However, for droughts, the neighborhoods of the Netherlands are utilized. The Klimaateffectatlas provides for each of the 14.221 neighbourhoods the variables as shown in Table 3.1. The limited climate change scenarios correspond to the wet scenarios Hw and Lw from Equation (2.1), while the strong climate change scenarios are the dry cases Hd and Ld from the same set S.

3.1.2 De Volksbank

Table 3.2 shows the variables that are available from de Volksbank and used in the mathematical model. The Basisregistratie Addressen en Gebouwen (BAG), *Register Addresses and Building*) is an unique number for each building and is employed to receive data from Kadaster (Section 3.1.3). Notice that the collateral and business addresses are not necessarily the same, but we have categorized each of the 109 possible combinations in seven categories as described in Appendix A.2. The collateral address is utilized for the direct damage calculation, while the indirect damage and

Variable	Explanation	Mean	Max
Flood 1/10	Inundation depth (m) with probability of occurring once in 10 years	0.0013	2.96
Flood 1/100	Inundation depth (m) with probability of occurring once in 100 years	0.14	6.50
Flood 1/1,000	Inundation depth (m) with probability of occurring once in 1,000 years	0.51	10.92
Flood 1/100,000	Inundation depth (m) with probability of occurring once in 100,000 years	0.80	11.40
Pile rot 2050 low	The pile rot risk of 2050 with limited climate change	0.39	9.07
Pile rot 2050 high	The pile rot risk of 2050 with severe climate change	0.41	9.56
Settlement 2050 low	The settlement risk of 2050 with limited climate change	1.27	9.85
Settlement 2050 low	The settlement risk of 2050 with severe climate change	1.43	9.91

TABLE 3.1: Variables regarding the impact of a flood for each 25 square meters or drought for each neighbourhood code where the minimum is zero for each variable (Klimaateffectatlas, 2024)

the PD are assessed with the business address. The Standard Industrial Classification (SIC) code categorizes each company within an industry sector. Regarding credit risk, the PD is provided and reflects the probability a business will not (fully) pay the mortgage payments within the next year. In addition, the LtV is given for the moment where the loan is provided, where the LtV is defined as the amount at the moment of granting the loan divided by the taxation value of the collateral. For 2024, the liability is given too, where the liability is the unpaid amount of the loan and hence the maximum loss for the bank.

Variable	Explanation
Overall ID	Identification number for each loan
BAG ID	Register Addresses and Building's number for each collateral
Collateral address	Address of the collateral
Taxation	Taxation value for the collateral with the taxation date
Building type	Type of the collateral building
Business address	Address of the business
SIC description	Industry sector of the business
PD	Probability of default
LtV	Loan to value
Liability	Unpaid amount of the loan

TABLE 3.2: Available data from de Volksbank

3.1.3 Kadaster

The Kadaster is a register that contains information regarding buildings in the Netherlands with the BAG number as key identification number (Kadaster, 2024). For each collateral building, the following variables are requested from the Kadaster. First, the surface area reflecting the aggregate surface of the building floors. Second, the building type is retrieved, which is different from de Volksbank's building type. Last, EPSG coordinates are given for each collateral building.

3.1.4 Centraal Bureau voor Statistiek

The Centraal Bureau voor Statistiek (*Statistics Netherlands*) provides data on the Dutch economy, which we have used for two calculations. First, a building value index is used to estimate collateral values for the year 2023 (Centraal Bureau voor de Statistiek, 2024a). Second, national growth numbers on the value added, capital investments and labor expenses per industry sector are retreived for the period 2010-2020 in order to calibrate the Cobb-Douglas function (Centraal Bureau voor de Statistiek, 2024c).

3.2 Vulnerability analysis

The commercial real estate mortgage portfolio of de Volksbank consists of $6,841$ loans with unique collateral buildings. However, not every building is vulnerable to floods and droughts. Therefore, this section first highlights the fraction of buildings prone to floods and droughts. Second, the distribution of the building types is provided. The direct damage to the collateral buildings for each of the flood and drought scenarios is presented in Chapter 5.

As described in Section 4.1, we first match the data from the Klimaateffectatlas with the addresses of the collateral buildings. From this, it becomes clear that not every building is susceptible to floods and droughts. The results are presented in Table 3.3.

Probability (years)	Inundation depth > 0m	Inundation depth ≥ 1m	Inundation depth ≥ 2m
$1/10$	16	3	1
$1/100$	871	396	154
$1/1{,}000$	2,372	1,417	705
$1/100{,}000$	3,313	2,170	1,153

TABLE 3.3: Fraction of collateral buildings susceptible to floods where the total amount of buildings is $6,841$. The buildings may be counted several times as the buildings within the second and third column are also included in the first and second column respectively.

From Table 3.3 we derive that for the flood scenario with a high probability (i.e., occurring once in ten years), only sixteen buildings are prone to flood risk according to the data from the Klimaateffectatlas. For the flood scenario with a probability ten times smaller, this number increases significantly to 871.

For droughts, the risks of pile rot and settlement are relevant for a larger portion of the collateral buildings compared to floods, as reflected in Table 3.4. We see that five out of six buildings are prone to settlement and three out of seven buildings are vulnerable to pile rot. Notice that the risks from the Klimaateffectatlas data vary between zero and ten, while Koks et al. (2015) only distinguishes between five damage classes, as given in Appendix A.3. Since only a small part exceeds the fifth risk category of the Klimaateffectatlas and there is no explanation of the different classes available, we assume the numbers of the risk categories of the Klimaateffectatlas correspond to the values of the classes proposed by Koks et al. (2015).

Scenario (2050)	Risk > 0	Risk ≥ 2	Risk ≥ 5
Pile rot low	2,967	315	48
Pile rot high	2,967	330	51
Settlement low	5,666	732	210
Settlement high	5,666	844	320

TABLE 3.4: Fraction of collateral buildings susceptible to droughts where the total amount of buildings is $6,841$. The buildings may be counted several times as the buildings within the second and third column are also included in the first and second column respectively.

To assess the damage to the collateral buildings from floods, we differentiate between various building categories as detailed in Appendix A.2. For the commercial real estate mortgage portfolio of de Volksbank, the distribution of building categories is provided in Table 3.5. Note that the amounts do not add up to $6,841$ because land is used as collateral for 45 loans. Since we assume the value of land is invulnerable to floods and droughts, the collateral for these loans is not included in one of the seven building categories.

Building category j	Number	Amount
Office	1	608
Retail	2	748
Industry	3	3,052
House	4	1,777
Apartment ground floor	5	281
Apartment first floor	6	310
Agriculture	7	20

TABLE 3.5: Building category distribution portfolio

In addition to the building category, the surface area is used for the direct damage assessment of both floods and droughts. The surface area is retrieved from the Kadaster using the BAG identification number for each collateral building (Section 3.1.3). Unfortunately, not every BAG number is recognized by Kadaster, resulting in the surface area of $1,537$ buildings being missing. As a result, these buildings are excluded from the calculation of the direct damage.

To summarize, by matching collateral building addresses with Klimaateffectatlas data, it is clear that the portfolio's vulnerability to floods increases significantly for lower probability scenarios. In contrast, the susceptibility to pile rot and settlement remains relatively consistent across different climate scenarios. The collateral buildings in the portfolio vary significantly in type, with the majority categorized as either industrial buildings or houses. Unfortunately, a portion of the collateral is excluded from the damage calculation because not all building identification numbers are recognized by Kadaster.

Chapter 4

Model Description

This chapter describes the model used to determine losses in the commercial real estate mortgage portfolio. An overview of the modelling structure is presented in Figure 4.1 where the red blocks indicate a contribution to existing literature. Section describes the calculation of the direct damage. Based on the direct damage, the indirect damage is assessed in Section 4.2. Finally, the impact of the total damage for de Volksbank is evaluated in Section 4.3.

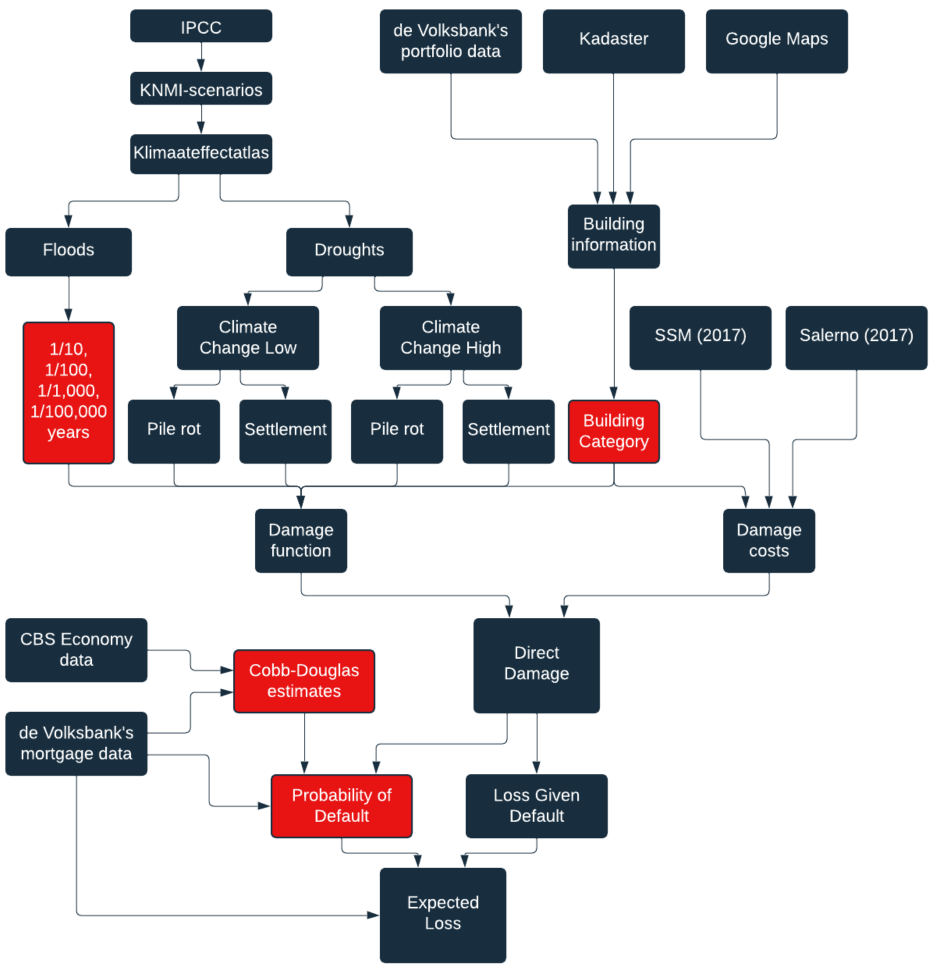


FIGURE 4.1: Model overview with red blocks indicating a contribution to existing literature

4.1 Direct damage

The direct damage is defined as damage to business collateral caused by floods or droughts. Section 2.3.1 describes that direct loss can also be evaluated for business inventory such as machinery. The business inventory is neglected in the calculation of the direct impact because it is on the one hand difficult to estimate since there is not much data about the business inventory. On the other hand, for a commercial real estate mortgage portfolio consisting of loans for business buildings, the damage to inventory is less relevant. In contrast, damage to business inventory is relevant for indirect damage because it affects the daily turnover and is therefore taken into account in the estimation of the PD, as will be described in the next section.

Since the direct damage is calculated differently for floods and droughts, the section is divided into three subsections. The first two subsections highlight the climate scenarios used and assess afterwards the calculation of the direct damage for the specific disaster. The last subsection describes how the damage up to 2050 is calculated. The variables on which the calculation is based are motivated in Chapter 3.

4.1.1 Floods

The direct damage resulting from floods is calculated using the three components: the inundation depth h_i, a damage function α_j and the maximum value at risk $D_{i,j}^{\max}$ where $i = 1, \ldots, n_j$ for n_j the amount of business buildings in the portfolio within building category j and $j = 1, \ldots, m$ for m the total of different building categories. These three components are successively addressed in this subsection. (Notice that Figure 4.1 also indicates the usage of these components.)

The climate scenarios for both floods and droughts are taken from the Klimaateffectatlas. As Subsection 2.2.1 points out, the flood intensity can be approached from the perspective of either fixing the flood probability or fixing the inundation depth. We have chosen to keep the flood probabilities constant and evaluate the corresponding inundation depths for several reasons. First, by considering the probability, the model aligns with European guidelines to assess the most destructive scenarios with probabilities occurring at 1/10, 1/100, and 1/1,000 years (Subsection 2.2.1, Stuurgroep Water, 2018). In addition, keeping the probability constant allows for having a larger damage compared to keeping the inundation depth constant (Siegers, 2023), because the maximum inundation depth is 2.00 meter, while the most extreme fixed probability scenarios include flood depths of more than 5.00 meter. Besides the 1/10, 1/100, and 1/1,000 year scenarios, we also determine the direct damage for the 1/100,000 scenario in order to evaluate how an extreme scenario would look like.

Besides different probabilities, the Klimaateffectatlas also distinguishes between different climate scenarios corresponding to the set S as indicated in Section 2.1. Unfortunately, there is only data made available for the current situation in the Netherlands, that is why the different wet and dry cases, as described in Section 2.1, are not included.

The four flood scenarios, i.e. probabilities of 1/10, 1/100, 1/1,000 and 1/100,000 year, correspond to different inundation depths h with an accuracy of 25 square meters. In order to determine the matching flood depth h_i to a building, the EPSG 28992 coordinate system is utilized. This coordinate system is utilized by both the Klimaateffectatlas and the Kadaster. The Kadaster is responsible in the Netherlands for providing data about real estate and supplies unique EPSG coordinates for each building.

In addition to coordinates, the Kadaster also provides the building's purpose of use. This is useful for determining the relevant damage category and corresponding damage function. Taking into account the data of both Kadaster and de Volksbank, we distinguish between seven building categories: Office, Retail, Industry, House, Apartment ground floor, Apartment first floor and Agriculture. Each building category $j = 1, \ldots, 7$ belongs to a damage function α_j and these functions are provided by Berg et al. (2000) and shown in Appendix A.1. The decisions made on the building category for each building's purpose of use are outlined in Appendix A.2.

Last, the maximum value at risk $D_{i,j}^{\max}$ for each collateral $i = 1, \ldots, n_j$ and each building category $j = 1, \ldots, 7$ is determined with repair costs provided by Slager and Wagenaar (2017) and shown in Appendix A.2. Since the repair costs C_j are square meter values, the surface area A_i of building i is used too. The Kadaster provides these surface values and the repair costs C_j are different for each building type j. As the damage for the Volksbank never exceeds the market value of the collateral, taxation values provided by the Volksbank are taken into account as well. Since the taxation years date from the range of 30 years ago until now, an indexation is used provided by the Statistics Netherlands (Centraal Bureau voor de Statistiek, 2024a). The maximum value at risk $D_{i,j}^{\max}$ is then the minimum of the repair costs $C_j A_i$ and the taxation value.

Finally, the direct damage D^{dir} resulting from a flood with a certain probability is calculated as

$$D^{\text{dir}} = \sum_{j=1}^{7} \sum_{i=1}^{n_j} \alpha_j(h_i) D_{i,j}^{\max} \tag{4.1}$$

where j indicates the business building's category and the total amount of collateral in the portfolio n equals $n_1 + \cdots + n_7$.

4.1.2 Droughts

The methodology of determining direct damage for droughts is on one hand comparable to the method for calculating the direct damage of floods. There is namely a function based on data from the Klimaateffectatlas that is multiplied with building characteristics. On the other hand however, for droughts the damage results from both pile rot and settlement and the calculation is described below.

As described in Section 2.2.2, the type of foundation, together with the groundwater level, wood type and top of foundation layer are relevant for determining the exposure of a building to pile rot and settlement. Consequently, the risk of pile rot and settlement varies per building. The Klimaateffectatlas has estimated the risk category for both pile rot r_i^p and settlement r_i^s for each building i separately, based on all the mentioned indicators and where the values r_i^p and r_i^s are between zero and five. Unlike floods, the Klimaateffectatlas distinguishes between these risks for two climate scenarios, namely the wet and dry scenarios as defined in Section 2.1.

Based on the risk r_i^k, the corresponding damage costs $c(r_i^k)$ are calculated for damage type $k \in \{p, s\}$. The cost $c(r_i^k)$ can take six different values, each belonging to a damage category. Hence, c is a step function mapping a risk $r_i^k \in \{0, 1, \ldots, 5\}$ to a damage value. The damage categories are introduced in Section 2.2.2, and a description of each category with the matching damage cost is contained in Appendix A.3.

Since the damage costs are values per cubic meter, the size of the building is also necessary to determine the direct damage. Since the floor height is not available, an average floor height H of three meters is used (Rijksoverheid Bouwbesluit Online, 2012). This value is based on Dutch construction regulations and multiplied with the same surface values A_i as from the previous subsection. Notice that the direct damage of droughts grows linear with this average floor height as becomes clear from Equation (4.2).

Taking the components: risk of pile rot r_i^p, risk of settlement r_i^s, cost function c, surface area A_i and floor height H together yields the formula for the direct damage of droughts for a specific climate scenario:

$$D^{\text{dir}} = \sum_{i=1}^{n} \left(c(r_i^p) + c(r_i^s) \right) A_i H \tag{4.2}$$

where n is the total amount of collateral buildings in the portfolio.

4.1.3 Damage up to 2050

Until this point, time has been ignored in calculating the direct damage. However, to address the research question, we aim to calculate the damage from 2023 to 2050. Therefore, this subsection focuses on calculating the damage up to 2050.

For floods, a variable that could change over time in Equation (4.1) is the inundation depth h_i. However, since the Klimaateffectatlas provides only the inundation depth h_i for the current scenario in the Netherlands, the inundation depth h_i is constant over time. Therefore we consider time only within the flood probabilities, which is further explained in the next section. This yields four different outcomes for the direct damage resulting from floods $D^{\text{dir,F}}$ for each probability, where the superscript F is added to make a distinction with the direct damage for droughts.

For droughts, variables changing over time in Equation (4.2) are the risk categories r_i^p and r_i^s. Since the current status of foundations is most of the time unknown (Appendix B.2), we assume that the current damage in foundation is not captured within the taxation value. However, if a building reaches a damage class r_i^k for $k \in \{p, s\}$, the owner will observe it. Consequentially, we calculate the direct damage resulting from droughts $D^{\text{dir,D}}$ as the repair costs $c(r_i^k)$ for the highest value of r_i^k in the period of 2023 until 2050.

4.2 Indirect damage

The direct damage D^{dir} impacts the business's LtV and turnover and we evaluate this impact by calculating the change in PD. Since de Volksbank has data available about the Earnings Before Interest, Tax, Depreciation and Amortisation (EBITDA) for one seventh of the businesses, this value is used to determine the increase in PD. However, it might be the case there is no turnover data available and therefore we also describe how it can be approximated with the Cobb-Douglas function (Section 2.3.2). In addition, we compare the results from the methods based on EBITDA and Cobb-Douglas.

4.2.1 PD change based on EBITDA

To estimate the correlation between the PD, LtV and EBITDA, we distinguish between the situation before and after the natural disaster. In this context, we denote with the superscript 'old' the situation before the disaster, and 'new' after it. Next, the taxation value of the business building i before the disaster is denoted by V_i^{old}, while the value after the disaster is $V_i^{\text{new}} := V_i^{\text{old}} - D_i^{\text{dir}}$ where D_i^{dir} is calculated in the previous section. Then, the postdisaster LtV $\text{LtV}_i^{\text{new}}$ is determined as

$$\text{LtV}_i^{\text{new}} = \text{LtV}_i^{\text{old}} \frac{V_i^{\text{old}}}{V_i^{\text{new}}} \tag{4.3}$$

for business i. Notice that LtV is always between zero and one, and the fraction $V_i^{\text{old}} / V_i^{\text{new}}$ reflects how much the business building is decreased in value and hence the LtV is changed.

For the EBITDA, the postdisaster value $\text{EBITDA}_i^{\text{new}}$ is the predisaster value $\text{EBITDA}_i^{\text{old}}$ minus the direct damage D_i^{dir}. As a result, we estimate for the predisaster situation the linear relationship between the dependent variable pd_i^{old} and independent variables $\text{LtV}_i^{\text{old}}$ and $\text{EBITDA}_i^{\text{old}}$ as

$$\text{pd}_{ij}^{\text{old}} = \gamma_0 + \gamma_1 \text{LtV}_i^{\text{old}} + \gamma_2 \text{EBITDA}_i^{\text{old}} + \sum_{k=1}^{m-1} \lambda_j \mathbb{1}_{\{k=j\}} + \epsilon_i \tag{4.4}$$

where we control for the industry sector j of business i with the parameters λ_j, $j = 1, \ldots, m-1$ for m the amount of industry sectors. After the regression, we calculate the post-disaster PD pd^{new} with the estimated parameters as

$$\text{pd}_{ij}^{\text{new}} = \hat{\gamma}_0 + \hat{\gamma}_1 \text{LtV}_i^{\text{new}} + \hat{\gamma}_2 \text{EBITDA}_i^{\text{new}} + \sum_{k=1}^{m-1} \hat{\lambda}_j \mathbb{1}_{\{k=j\}} \tag{4.5}$$

after which we are able to compare pd^{old} and pd^{new}. It is expected that $\hat{\gamma}_1$ will be positive, as businesses that have borrowed a larger proportion of their building collateral typically have a higher PD due to needing more funds compared to those with a lower LtV. Conversely, $\hat{\gamma}_2$ is expected to be negative, since a higher turnover generally leads to a lower PD.

4.2.2 Turnover estimate with Cobb-Douglas

In case data about turnover of companies is unavailable, the turnover can be estimated using the Cobb-Douglas function. Notice that the Cobb-Douglas function returns the value added which is approximately equal to the difference in turnover and production costs and a further interpretation of the function is contained in Section 2.3.2. The Cobb-Douglas function returns the value added Y of a business based on the business's capital K and labor L with the following formula

$$Y = bK^{\alpha} L^{\beta} \tag{4.6}$$

where b is a scaling factor and α, β are output elasticities. To use the Cobb-Douglas functions, first the parameters b_j, α_j and β_j are calibrated for each business sector j. For this, we use data from Statistics Netherlands, where the value added Y_j, capital expenditures K_j, and wages L_j for each business classification j are provided for each year t in the period 2011 until 2020 (Centraal Bureau voor de Statistiek, 2024b). Note the business classification used is SBI2008, corresponding to the classifications within the data of de Volksbank. To come up with a linear regression to estimate b_j, α_j and β_j, a natural logarithm of the variables Y_j, K_j and L_j is taken (Tirfi and

Oyekale, 2023), resulting in a linear regression model of the form

$$\log Y_{j,t} = \log b_j + \alpha_j \log K_{j,t} + \beta_j \log L_{j,t} + \epsilon_{j,t} \tag{4.7}$$

for $t = 2011, \ldots, 2020$. After the regression, we obtain estimated parameters $\hat{b}_j, \hat{\alpha}_j, \hat{\beta}_j$ for each of the fifteen business sectors j. As a result, for a company i within sector j, the value added can be estimated as

$$\hat{Y}_{ij} = \hat{b}_j K_i^{\hat{\alpha}_j} L_i^{\hat{\beta}_j}. \tag{4.8}$$

Since total capital expenditures are unknown for the businesses within de Volksbank's portfolio, we approximate K_i by taking into account the balance sheet total and the value of the business building. In this context, capital includes a variety of assets used in the production process. For the enterprises within de Volksbank's portfolio, often the major part of capital is the value of the collateral. Besides the business's building, capital also covers among others machinery, equipment, and land. To estimate K_i, we calculate the average ratio of the building value of the balance sheet total for the years for which the numbers are known and assume this ratio remains constant for the upcoming years. Moreover, wages are also unknown, hence we assume the average ratio over they years 2011 until 2020 between capital $K_{j,t}$ and labor $L_{j,t}$ remains constant too after 2020 and come up with an approximate for L_i.

After the value added $\hat{Y}_{ij}$ is estimated for each business i, we can replace EBITDA in regressions (4.4) and (4.5) with the value added. To analyse the pre- and postdisaster situation, we assume labor is unaffected by the flood or drought. However, the capital K_i is decreased in value, because the business building is damaged. Therefore the new value added $\hat{Y}_i^{\text{new}}$ is calculated using the new building value V_i^{new}, where it is assumed the ratio with the balance sheet is unchanged.

As described in Section 4.1, the direct damage D^{dir} is calculated for four different flood scenarios and four different drought scenarios. Additionally, the previous paragraph describes how the PD before and after a natural disaster is evaluated. Hence, for each of the eight climate scenarios, pd_i^{old} and pd_i^{new} are determined for each business i within the portfolio. As a result, the credit risk impact and losses of the portfolio is assessed for each of the eight scenarios, with the methodology detailed in the following section.

4.3 Portfolio losses

The thesis aims to describe how the damage from floods and droughts to micro and small enterprises leads to a loss in a mortgage portfolio. For a commercial real estate mortgage portfolio, the damage to firms is only relevant when it leads to a default. As long as a financial institution receives the mortgage payments, there is no impact on the portfolio. However, in the case of a firm's default, the financial institution takes ownership of the collateral. Since this collateral decreases in value, the institution incurs a loss on the mortgage if the foreclosure value falls short of the outstanding loan amount to the mortgage. This entire idea of reasoning is captured within the calculation of the Expected Loss (EL) of a mortgage, which is addressed in this section.

The Expected Loss EL_i of mortgage i is computed with the formula,

$$\mathrm{EL}_i = \mathrm{pd}_i \mathrm{LGD}_i \mathrm{EAD}_i \tag{4.9}$$

where the Exposure at Default EAD_i is the outstanding loan amount from the bank to the business (Caloia, Jansen, and Ginkel, 2023).

Additionally, the Loss Given Default (LGD) LGD_i is the proportion of the outstanding loan amount the bank loses in the event of a business default. As described in the introduction of the section, this percentage is determined using the foreclosure value. De Volksbank estimates the foreclosure value at eighty percent of the market value, which we write as δV for $\delta = 0.8$. Hence the LGD equals

$$\mathrm{LGD}_i = \frac{\max\{0, \mathrm{EAD}_i - \delta V_i\}}{\mathrm{EAD}_i} \tag{4.10}$$

where V_i is the market value of the collateral building.

Consider the pre- and postdisaster values of the EL, $\mathrm{EL}^{\mathrm{old}}$ and $\mathrm{EL}^{\mathrm{new}}$. Notice the EAD does not change after the disaster, but the LGD might change as the collateral value can be damaged. In the case $\mathrm{EAD}_i \geq \delta V_i^{\mathrm{old}}$ (and hence $\mathrm{EAD}_i \geq \delta V_i^{\mathrm{new}}$, because $V_i^{\mathrm{new}} = V_i^{\mathrm{old}} - D_i^{\mathrm{dir}}$), we have that the change in EL can be rewritten as

$$\begin{aligned}
\Delta \mathrm{EL}_i := \mathrm{EL}_i^{\mathrm{new}} - \mathrm{EL}_i^{\mathrm{old}} &= \mathrm{pd}_i^{\mathrm{new}} \left(\mathrm{EAD}_i - \delta V_i^{\mathrm{new}}\right) - \mathrm{pd}_i^{\mathrm{old}} \left(\mathrm{EAD}_i - \delta V_i^{\mathrm{old}}\right) \\
&= \Delta \mathrm{pd}_i \mathrm{EAD}_i - \delta \left(\mathrm{pd}_i^{\mathrm{new}} V_i^{\mathrm{new}} - \mathrm{pd}_i^{\mathrm{old}} V_i^{\mathrm{old}}\right) \\
&= \Delta \mathrm{pd}_i \left(\mathrm{EAD}_i - \delta V_i^{\mathrm{old}}\right) + \delta \mathrm{pd}_i^{\mathrm{new}} D_i^{\mathrm{dir}}
\end{aligned} \tag{4.11}$$

where $\Delta \mathrm{pd}_i := \mathrm{pd}_i^{\mathrm{new}} - \mathrm{pd}_i^{\mathrm{old}}$. Notice this change in EL is positive, because $\mathrm{EAD}_i \geq \delta V_i^{\mathrm{new}}$ and both $\mathrm{pd}_i^{\mathrm{new}}$ and D_i^{dir} are non-negative. It can also be shown for the case $\mathrm{EAD}_i < \delta V_i^{\mathrm{new}}$ that $\Delta \mathrm{EL}_i$ is non-negative, therefore the natural disaster always impacts the bank negatively.

Chapter 5

Results

This chapter contains the results from the model as described in Chapter 4 and the outline of the sections remains the same. In the first section, the outcomes of the direct damage calculation are provided. The next section includes the changes in the PD and a comparison of the Cobb-Douglas function estimates with the actual numbers of de Volksbank. The losses for de Volksbank are presented in the final section.

5.1 Direct damage

From Table 3.3 and Table 3.4 we derive that only a certain part of the portfolio is prone to floods or droughts. For the susceptible part the results of the direct damage calculation are shown in this section together with a comparison to existing literature.

Combining the building information with the data from the Klimaateffectatlas, the direct damage for the collateral buildings due to different flood and drought scenarios is shown in Table 5.1 and Table 5.2. Since there are only sixteen buildings damaged by the flood with the highest probability, the direct damage is merely 74.1 thousand euros. However, for the flood with the lowest probability, the direct damage is 348 million euros, which averages to more than $100,000$ euros in damage per collateral building. If we calculate expected damages per year, it is striking the flood with probability of occurring once in 100 years, is the highest with an expected damage value of $697,000$ euros per year. This is one hand, because relatively many collateral buildings are prone to this scenario (Table 3.3) and on the other hand, the probability is relatively high.

Probability (years)	Damage Floods $D^{\text{dir,F}}$ (mln)	Percentage of Portfolio
1/10	0.0741	$2.48 \cdot 10^{-3}$
1/100	69.7	2.33
1/1,000	236	7.90
1/100,000	348	11.7

TABLE 5.1: Direct damage calculated with Equation (4.1) resulting from floods for different scenarios for a portfolio value of $2,986$ million euros

These results can be compared with the damages known from the Limburg floods in 2021. Since the probability of this event is unknown, a direct comparison is impossible. However, the average damage to houses is $25,000$ euros, which is larger than the average damage for the flood with the lowest probability (around $5,000$ euros), but lower than the flood with probability of occurring once in hundred years (around 80,000 euros) (Slager, 2023). The same holds true for the estimates of the Dutch Central Bank which range between 0.30 and 0.50 % of a total portfolio value (Caloia, Jansen, and Ginkel, 2023).

For droughts the comparison is more difficult due to limited data availability. First, notice that for droughts, the results do not significantly differ across the different climate scenarios. From Table 5.2 we see that the damages due to pile rot and settlement are 17.1 and 82.8 million, and 19.3 and 112 million for the different climate scenarios, respectively. It is worth noting that the sum of the damages is higher than the total damage for each scenario, because each building can be damaged up to a maximum of its market value.

The drought damages come down to averages of approximately 6,000 euros for pile rot and 17,000 euros for settlement. The KCAF estimates that foundation damages can reach values of 50,000 to 100,000 euros. Notice however that the pile rot and settlement risk for only a minor part of the portfolio exceed two (Table 3.4). From this we derive that this minor part constitutes to the major part of the damage, since the damages increase exponentially within the damage classes (Appendix A.3). As a result, our results are not significantly different from those of the KCAF (Kennis Centrum Aanpak Funderingsproblematiek, 2022a).

Scenario (2050)	Damage Pile rot	Damage Settlement	$D^{\mathrm{dir,D}}$ (mln) Total	Percentage of Portfolio
Pile rot low & Settlement low	17.1	82.8	99.4	3.33
Pile rot low & Settlement high	17.1	112	129	4.32
Pile rot high & Settlement low	19.3	82.8	102	3.42
Pile rot high & Settlement high	19.3	112	131	4.39

TABLE 5.2: Direct damage with Equation (4.2) resulting from droughts for different scenarios for a portfolio value of 2,986 million euros

In summary, the direct damage differs among the different flood scenario, where the damages from the Limburg floods and the estimates of the Dutch Central Bank correspond to a flood scenario with probability of occurring between once in 10 and once in 100 years. For droughts, the damages do not significantly differ among the climate scenarios. The average damage per building is low compared to estimates from the KCAF, which is because the major part of the portfolio has a low vulnerability to both pile rot and settlement.

5.2 Indirect damage

The damage values shown in Table 5.1 and Table 5.2 represent damages to buildings that serve as collateral for the commercial real estate mortgage portfolio of de Volksbank. As explained in Section 4.2, this leads to losses for de Volksbank when they need to sell the collateral building in the event of a default. The first subsection highlights the changes in the PD for the businesses within the mortgage portfolio based on EBITDA amounts. A comparison of the EBITDA data with Cobb-Douglas estimates is included in the second subsection.

5.2.1 PD change

The change in PD of a business is calculated based on the parameters in the regression as given in Equation (4.4). The estimated parameters are given in Table 5.3. As shown in the table, EBITDA data is available for 804 businesses. From Table 5.3 we derive there is data available for each business category and therefore we assume the results from Table 5.4 do also hold for the other business within each industry.

Additionally, the table indicates that the PD for industries F, G, I, K, Q, R and S is significantly different from the reference industry A. For example, the PD is on average 0.94% lower for industry F compared to industry A, ceteris paribus the other variables. This might be because industry A is 'Agriculture, Forestry and Fishing', which has an uncertain future in the Netherlands due to climate change and new regulations. Industry A also exhibits the highest average PD, given that each industry coefficient is negative.

Furthermore, coefficient $\hat{\gamma}_0$ is positive (and larger than the industry dummy coefficients $\hat{\lambda}_j$, $j = 1, \ldots, m-1$) meaning that there is a probability each business will not be able to repay the loan. In addition, the coefficient $\hat{\gamma}_1$ of LtV is positive and equal to 0.0099 meaning that if for example if half of the building value is damaged, the LtV doubles and thereby the PD increases by $2 * 0.0099$, so 1.98%. This might be lower than we would expect, because a damage of half of the building is relatively high, while an increase of the PD with 1.98% is relatively low.

In contrast to $\hat{\gamma}_1$, the coefficient $\hat{\gamma}_2$ of EBITDA is negative, as expected (Subsection 4.2.1). The coefficient of EBITDA is insignificantly different from zero meaning that the PD as estimated by de Volksbank does not linearly depend on cash flows of the business as represented by EBITDA.

Parameter	Variable	Coefficient	Amount
$\hat{\gamma}_0$	constant	0.0212**	-
$\hat{\gamma}_1$	LtV	0.0099**	-
$\hat{\gamma}_2$	EBITDA	$-6.596 \cdot 10^{-9}$	804
$\hat{\lambda}_1$	Industry C	-0.0082	38
$\hat{\lambda}_2$	Industry F	-0.0094*	203
$\hat{\lambda}_3$	Industry G	-0.0131**	198
$\hat{\lambda}_4$	Industry H	-0.0109	11
$\hat{\lambda}_5$	Industry I	-0.0147**	54
$\hat{\lambda}_6$	Industry J	-0.0081	18
$\hat{\lambda}_7$	Industry K	-0.0102*	171
$\hat{\lambda}_8$	Industry N	-0.0118**	36
$\hat{\lambda}_9$	Industry Q	-0.0112*	24
$\hat{\lambda}_{10}$	Industry R	-0.0169**	12
$\hat{\lambda}_{11}$	Industry S	-0.0137**	32

TABLE 5.3: Results from Regression (4.4) where * and ** denote significance at the 10% and 5% levels respectively and industry A is the reference category.

Using the coefficients from Table 5.3, we estimate a new PD for each business with Equation (4.5). Subsequently, we compare the pre- and post-disaster probabilities of default by calculating the difference. It is important to note that de Volksbank uses seven bucket values ranging from 0 to 1 to categorize PD values. Therefore, we also analyze the change in PD while considering the bucket values, and the results are presented in Table 5.4. It is noteworthy that there is only a minor difference between the flood scenario with a high probability and the scenario with a very small probability. Moreover, there is no difference at all for the various pile rot and settlement scenarios, which is attributed to the fact that the direct damages from Table 5.2 exhibit only slight variations. In addition the pd bucket shifts are in general quite low, which can be explained due to the small coefficient $\hat{\gamma}_1$ and insignificant parameter $\hat{\gamma}_2$ leading to relatively minor changes.

Industry j	Flood 1/10	Flood 1/100	Flood 1/1,000	Flood 1/100,000	Drought scenarios
A	2	2	2	2	2
C	1	2	2	2	2
F	1	1	1	1	1
G	1	1	1	1	1
H	1	1	1	1	1
I	1	1	1	1	1
J	1	1	1	1	1
K	1	1	1	2	1
N	1	1	1	1	2
Q	2	2	2	2	2
R	1	1	2	2	1
S	2	2	2	2	2

TABLE 5.4: PD bucket shifts resulting from estimate 4.5. The pd bucket shifts are the same for the four pile rot and settlement scenarios.

5.2.2 Comparison Cobb-Douglas

In cases where turnover data is unavailable, EBITDA values can be substituted with Cobb-Douglas function estimates (Equation (4.8)). These estimates require industry parameters b_j, α_j, and β_j to be calibrated, using data from Centraal Bureau voor Statistiek (*Statistics Netherlands*) (Centraal Bureau voor de Statistiek, 2024b). As shown in Table 5.5, the parameters $\hat{b}_j$ and $\hat{\alpha}_j$ are insignificant for most industries j, indicating that capital expenditures do not significantly impact the value added for most industries. However, labor does affect the value added, as reflected in the significant parameters $\hat{\beta}_j$. Notice this might effect the results, because for the value added estimates labor is approximated by the industry labor over capital average multiplied with capital.
The insignificance of many parameters already suggests that the Cobb-Douglas estimates might not be very accurate. When estimating the value added $\hat{Y}ij$ for each company i, as explained in Subsection 4.2.2, it becomes apparent that the correlation with known EBITDA values is only 28.1%. Additionally the coefficient of $\hat{Y}ij$ in regression 4.4 is 4.984×10^{-10}, which is positive, contrary to the negative coefficient $\hat{\gamma}_2$.

One reason the Cobb-Douglas estimates do not match the EBITDA values well can be illustrated with the following example. Consider a business with relatively high turnover and thus a low PD. Moreover, the business has an inexpensive collateral building and belongs to an industry where $\hat{\alpha}_j$ (capital) is valued highly relative to $\hat{\beta}j$ (labor). In this scenario, the value of $\hat{Y}_{ij}$ will be relatively low, correlating with a low PD. However, the actual EBITDA value might be high, leading to a discrepancy between the Cobb-Douglas estimate and the actual situation.

Industry j	$\hat{b}_j$	$\hat{\alpha}_j$	$\hat{\beta}_j$
A	1.315	0.242	0.786**
C	0.006*	0.32	1.238**
F	0.02	-0.071	1.462**
G	0.032	-0.098	1.448**
H	0.011	0.415	1.115**
I	0.051**	0.213**	1.162**
J	9.015	-0.057	0.884**
K	0.537	0.188	0.992
N	0.267*	-0.244**	1.377**
Q	0.088	0.041**	1.195**
R	78.327**	0.433**	0.185
S	1.61	-0.018	0.961**

TABLE 5.5: Cobb-Douglas calibration with data from Centraal Bureau voor de Statistiek (2024b) where * and ** denote significance at the 10% and 5% levels respectively

5.3 Portfolio losses

Based on the changes in PD, the losses for de Volksbank can be calculated. Since the expected loss depends on the LGD, first the mean and 95th percentile of the LGD of the mortgage portfolio are given in Table 5.6. Note that the LGD is zero if the Exposure at Default (EAD) is less than eighty percent of the damaged collateral building (Section 4.3). This applies to the majority of loans for the two floods with the highest probability of occurring. Even for the flood with the lowest probability, the average LGD is 0.0332, meaning that a maximum of 3.32% of the outstanding loan amount can be lost for de Volksbank. For droughts, this percentage is approximately 2%. Since the total outstanding amount for the mortgage portfolio is about 1.28 billion euros, on average approximately 25.6 million euros can be lost due to pile rot and settlement scenarios.

Scenario	LGD (mean)	LGD (95th percentile)
Flood $1/10$	0.000293	0
Flood $1/100$	0.00291	0
Flood $1/1,000$	0.0169	0.0689
Flood $1/100,000$	0.0332	0.269
Pile rot low & Settlement low	0.0157	0.0463
Pile rot low & Settlement high	0.0209	0.0675
Pile rot high & Settlement low	0.0162	0.0498
Pile rot high & Settlement high	0.0215	0.0689

TABLE 5.6: Change in LGD for each flood and drought scenario where the fifth percentile is zero for all scenarios

Combining the LGD, the EAD and the PD results in an expected loss for de Volksbank for each of the eight scenarios, as reflected in Table 5.7. If we calculate the expected loss per year for the flood scenarios, we arrive at values of 3.57, 17.5, 6.07 and 0.0196 thousand euros of expected loss per year for each scenario respectively. We see the Flood $1/100$ scenario has the largest expected loss per year, which is in line with the results from the direct damage. Notice it holds for all the flood and drought scenarios, the expected loss is a value that belongs to the year after the climate scenario has occurred.

For droughts, the interpretation differs because damages are calculated for various scenarios projected for 2050. Depending on climate change, the risk of pile rot and settlement may increase or decrease in the future. Assuming the situation matches one of the four pile rot and settlement scenarios, the expected loss for that situation corresponds to the relevant value in Table 5.7. A limitation of the calculated expected loss due to pile rot and settlement is that the expected loss is value per year after the damage has occurred. However, foundations of houses are repaired at different times and after a repair the risk is significantly reduced due to the renewed foundation. This makes it difficult to reduce the damage to a yearly figure, but the values in Table 5.7 provide an indication of what the damage to the bank regarding pile rot and settlement could be. Other limitations and possible further research topics are discussed in the next chapter.

Scenario	EL (mln)	EL/EAD
Flood 1/10	0.0357	0.0000279
Flood 1/100	1.75	0.00137
Flood 1/1,000	6.07	0.00475
Flood 1/100,000	19.6	0.0153
Pile rot low & Settlement low	2.89	0.00227
Pile rot low & Settlement high	4.50	0.00353
Pile rot high & Settlement low	2.93	0.00229
Pile rot high & Settlement high	4.54	0.00356

TABLE 5.7: Expected Loss for eight different scenarios

Chapter 6

Conclusion

The research presented in this thesis has delved into the relationship between physical climate risks, specifically floods and droughts, and their financial impact on a mortgage portfolio consisting of loans to micro and small enterprises. This analysis considered damage to collateral buildings and uniquely assessed the direct impact on the creditworthiness of businesses, referred to as the indirect impact throughout this thesis. By integrating damage models, credit risk analysis and financial risk management, this thesis has addressed the main research question for the commercial real estate mortgage portfolio of de Volksbank:

What implications does the predicted financial impact, resulting from floods and droughts on micro and small enterprises up to 2050, have on the expected loss of a commercial real estate mortgage portfolio?

The findings indicate moderate expected loss ratios ranging from 0.00279% to 1.53% for four different flood scenarios and a range of 0.227% to 0.356% for four different scenarios of pile rot and settlement. These ratios reflect the expected loss over the total exposure at default of de Volksbank's mortgage portfolio. The results highlight the limited expected financial impact on de Volksbank, even for climate scenarios with a low probability of occurring up to 2050.

However, the damage to collateral buildings to businesses could be large with a maximum of 11.7% and 4.39% damage to the total value of the buildings for the most unlikely flood and drought scenarios, respectively. This indicates that on an individual business level, both floods and droughts are likely to significantly harm business buildings, leading to high restoration costs.

Additionally, our research shows that the impact of direct damage on the creditworthiness of businesses (indirect damage) is small. As demonstrated, the decline in turnover does not lead to substantially higher probabilities of default. Consequently, most businesses will still be able to fulfill their mortgage payments, resulting in insignificant impact on the bank.

This is consistent with the outcomes based on Cobb-Douglas estimates. Contrary to initial expectations, there was a positive relationship between the value added estimates and the PD. One important reason is that the estimates did not align well with the turnover values with a correlation of merely 28%. From this we conclude that the Cobb-Douglas estimates are not appropriate for replacing the turnover values in the indirect damage calculation.

In conclusion, while the damages due to floods and droughts at the individual business level are expected to be significant, the expected loss for de Volksbank is moderate due to the limited increase in the PD. These findings underline the importance of considering both direct and indirect financial effects when assessing the vulnerability of commercial mortgage portfolios to climate risks.

Chapter 7

Discussion

The analysis conducted by this thesis, resulting in a limited expected loss for de Volksbank, addresses a hot topic in times of climate change. With regulatory frameworks increasingly emphasizing the assessment of climate risks, this thesis represents a valuable addition to existing literature. Nevertheless, the analysis is subject to certain limitations that require further investigation. These include issues related to data quality, data availability, underlying assumptions and potentially significant factors that have not been fully addressed.

First it becomes clear, among others from Figure 4.1, that the calculation of direct damage plays a crucial role in the analysis. There have been assumptions made regarding this calculation that affect its reliability. On one hand, the results are more accurate than previous research, due to the flood data used having an accuracy of 25 square meters. In contrast to an accuracy of 100 square meters or postcode level, this precision allows for estimating whether the property location is inside or outside a dike, which has significant implications for expected damages.

On the other hand, there are limitations regarding data on pile rot and droughts. The main limitation is that the data is provided at neighborhood level, meaning the risk for buildings within a region is assumed to be equal. Consequently, it is likely that properties are assessed with a risk for pile rot or settlement when this is not the case. Additionally, the risk needs to be converted into a damage class for which there is no consensus in the literature.

Regarding indirect damages, there are initial remarks to be made about calibrating the PD. Because the PD is an estimate from de Volksbank, it may not accurately reflect reality. Moreover, it is possible that the LtV, EBITDA and business category may not accurately describe the impact on the PD, as indicated by the insignificant parameter for EBITDA. Note here that for six out of seven businesses in de Volksbank's business mortgage portfolio EBITDA is unknown and the available EBITDA values come from businesses with relatively high turnover. The impact for small businesses may therefore differ from the results shown in Chapter 5.

Furthermore, it is noticeable that the Cobb-Douglas estimates moderately match the EBITDA figures. Causes for this may lie in the number of assumptions made to arrive at these estimates. Firstly, capital expenditure has been used as a proxy for the capital. Secondly, it is assumed that the ratio between capital and labor within a business category remains constant over the years. It is also assumed that the collateral is a constant fraction of the total balance sheet. We do not claim that the Cobb-Douglas function is incorrect due to the number of assumptions, but that further research could investigate whether the Cobb-Douglas function, with more data, could serve as a more reliable replacement for the turnover figures.

In summary, it appears that further research could improve the results by applying increased accuracy in pile rot and settlement risk assessments. Instead of a risk value per neighborhood level, an individual risk value based on year of construction, foundation type and soil type could be considered. There is also further research possible regarding the estimation of the relevant damage amounts for these risk values.

Additionally, the reliability of the study could be enhanced by considering more variables that could influence the PD. Examples of variables that could be added include inventory values, profit margins and the extent to which businesses depend on customers who may themselves be affected by natural disasters. In addition, the PD change could be transformed into a statistical distribution, giving the opportunity to examine unlikely changes in creditworthiness. Although the expected loss for Volksbank now appears to be limited, this way the unexpected loss can be examined to determine if the impact then significantly differs.

In conclusion, there is room for improvement, but this thesis is an important addition to the literature by providing valuable insights into the assessment of direct damages to buildings, the corresponding impact to the PD and the implications on the business mortgage portfolio of de Volksbank.

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Appendix A

Damage documentation

This appendix contains information used to determine the direct damage. The way this information is used is described in Section 4.1.

A.1 Damage functions

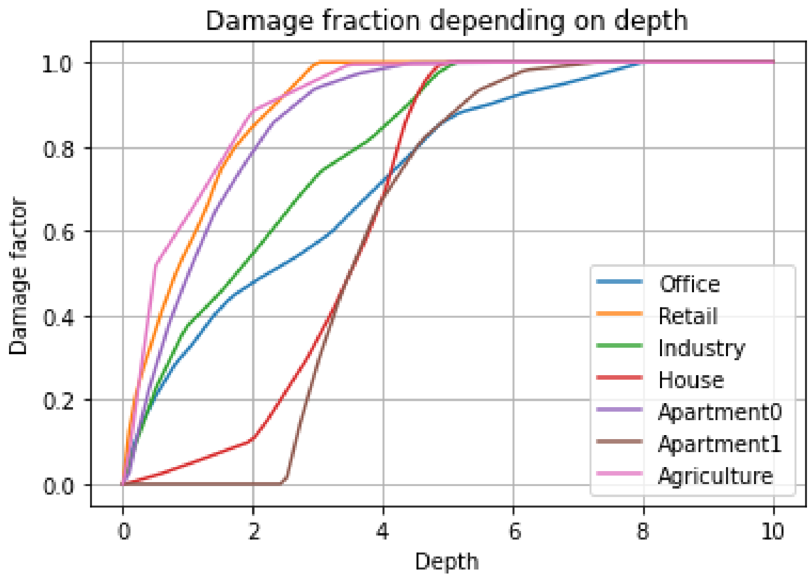

FIGURE A.1: Damage functions for different building categories.

Figure A.1 displays the damage function used to determine the fraction of damaged collateral at specific inundation depths. Appendix A.2 provides additional details on each building category. Notably, variations between buildings are most pronounced for inundation depths up to four meters, with all buildings experiencing maximum damage at depths exceeding eight meters. These functions are derived from formulas given by Berg et al. (2000).

A.2 Business building categories

Table A.2 shows the building category of each combination of de Volksbank's types and Kadaster types. The definition of the building category numbers used in this table can be found in Table A.2 together with the repair costs. These repair costs are provided by Slager and Wagenaar (2017) and indexed from 2017 to 2023 using the construction costs Centraal Bureau voor de Statistiek (CBS) index (Centraal Bureau voor de Statistiek, 2024c). We reviewed each of the 109 combinations of the Kadaster and de Volksbank building types by viewing buildings on Google Maps. Based on the observations the following assumptions are made.

Since neither de Volksbank nor Kadaster provides details about the apartment floors, we distinguish only between ground and first floors, assuming that apartments on higher floors are included in the first-floor category, consistent with existing literature Caloia, Jansen, and Ginkel (2023). Apartments with a living function are typically located above shops and are considered to be on the first floor. However, apartments with a gathering function are often situated on the ground floor, serving as canteens. Retail apartments are most closely associated with the retail category. Business spaces are often housed within buildings that also serve residential purposes, such as those accommodating family doctors. Apartments with an industrial function are commonly found in warehouse settings within business areas and are categorized accordingly. Business spaces with gathering functions are similar to ground-floor apartments. However, those with industrial functions are typically used as storage buildings. Farms with an industrial function often include storage buildings, whereas those with a living function are more similar to houses. Garage boxes are considered similar to ground-floor apartments. Land used as collateral is not subject to devaluation after a flood or drought and is therefore left uncategorized. An office with a gathering function is often housed within a building that includes meeting facilities. Other gathering functions are almost always found in canteens.

Building category j	Number	Repair cost C_j (€/m^2)
Office	1	1,576
Retail	2	1,852
Industry	3	1,838
House	4	1,228
Apartment ground floor	5	1,228
Apartment first floor	6	1,228
Agriculture	7	1,228

TABLE A.2: Building category definitions

Building type (de Volksbank)	Building type (Kadaster)	Building category
apartment	gathering function	5
apartment	industrial function	3
apartment	Kadaster failure	6
apartment	living function	6
apartment	office function	5
apartment	retail function	2
business space	retail function	2
business space with house	accommodation function	4
business space with house	educational function	4
business space with house	gathering function	4
business space with house	healthcare function	4
business space with house	industrial function	3
business space with house	Kadaster failure	4
business space with house	living function	4
business space with house	office function	1
business space with house	other function	4
business space with house	retail function	2
business space with office space	accommodation function	4
business space with office space	gathering function	4
business space with office space	industrial function	3
business space with office space	Kadaster failure	1
business space with office space	living function	4
business space with office space	office function	1
business space with office space	other function	3
business space with office space	retail function	2
business space with office space	sport function	1
catering property	gathering function	2
catering property	Kadaster failure	2
farm	industrial function	3
farm	Kadaster failure	7
farm	living function	4
farm	other function	3
farm as business	living function	7
garage box	industrial function	5
garage box	Kadaster failure	5
garage box	living function	5
garage box	other function	5
garage box	retail function	5
house	gathering function	4
house	healthcare function	4
house	industrial function	3
house	Kadaster failure	4
house	living function	4
house	office function	1
house	retail function	2
house	sport function	4
land	gathering function	0
land	industrial function	0
land	Kadaster failure	0
land	living function	0
land	other function	0

Building type (de Volksbank)	Building type (Kadaster)	Building category
leasure accommodation	accomodation function	4
leasure accommodation	Kadaster failure	4
leasure accommodation	living function	4
office space	accomodation function	4
office space	educational function	4
office space	gathering function	5
office space	healthcare function	4
office space	industrial function	3
office space	Kadaster failure	1
office space	living function	4
office space	office function	1
office space	other function	1
office space	retail function	2
office space	sport function	3
office space with house	gathering function	4
office space with house	Kadaster failure	4
office space with house	living function	4
office space with house	office function	1
office space with house	retail function	2
others	accomodation function	4
others	gathering function	5
others	industrial function	3
others	Kadaster failure	1
others	living function	4
others	office function	1
others	other function	1
others	sport function	5
retail property	educational function	2
retail property	gathering function	2
retail property	healthcare function	2
retail property	industrial function	3
retail property	Kadaster failure	2
retail property	living function	4
retail property	office function	1
retail property	other function	2
retail property	retail function	2
retail property	sport function	4
retail property with house	accomodation function	4
retail property with house	gathering function	4
retail property with house	healthcare function	4
retail property with house	industrial function	4
retail property with house	Kadaster failure	4
retail property with house	living function	4
retail property with house	office function	4
retail property with house	retail function	2
retail property with office space	gathering function	2
retail property with office space	industrial function	3
retail property with office space	Kadaster failure	2
retail property with office space	office function	1
retail property with office space	retail function	2

TABLE A.2: Building categories based on de Volksbank and Kadaster

A.3 Damage classes

Damage class r	Repair work	Repair cost $c(r)$ (€/m^3)
0	No repairs	
1	Painting	4.0
2	Painting, outer wall cracks	18
3	Painting, outer wall cracks, plastering	65
4	Painting, outer wall cracks, plastering new floors, window-frames repairs	226
5	Painting, outer wall cracks, plastering new floors, window-frames repairs foundation repairs	823

TABLE A.3: Repair costs per damage class (Salerno, 2017; Kok, 2021; Siegers, 2023)

Table A.3 gives an overview of the restoration work needed for each damage class. The description of the damage classes corresponds to the definition in Kok (2021) and Siegers (2023) and the matching repair costs are estimated by Salerno (2017) and indexed from 2017 to 2023 using the construction costs CBS index (Centraal Bureau voor de Statistiek, 2024c).

Appendix B

Background information

B.1 Modelling framework

This section describes the method performed by Koks et al., 2015, where the outline is shown in Figure B.1. Since the direct loss assessment and economic shock are already explained in Section 2.3, this section first gives an interpretation of the prerecovery period and afterwards, the recovery period and total consequences are described.

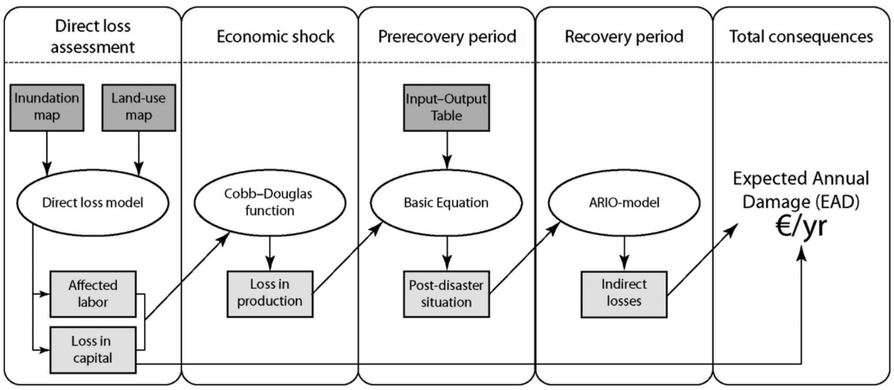

FIGURE B.1: Modelling framework (Koks et al., 2015).

B.1.1 Prerecovery period

As explained in Subsection 2.3.2, the Cobb-Douglas function allows for distinguishing between output before and after a flood or drought. Koks et al. (2015) divides the postdisaster period into a prerecovery and recovery part. The prerecovery period is defined as the period after a natural disaster during which it is impossible to recover. For floods this refers to the time when the water is not drained away, defined as the flood duration. The duration for water to recede varies depending on the type of flood, sometimes extending over several months (Wagenaar, 2012). In contrast to floods, the drought duration is already incorporated within the direct damage, because it is used to determine the associated damage class, and is therefore neglected in the prerecovery losses.

In order to determine the prerecovery losses, the difference between the pre- and postdisaster output is calculated and multiplied by the flood duration. The postdisaster output is then the starting point for describing the economy in the postdisaster situation, where this starting point is defined as the Basic Equation by Koks et al. (2015) (Steenge and Bočkarjova, 2007).

B.1.2 Recovery period

Damages due to business interruption within the recovery period can be assessed using damage functions as described in Subsection 2.3.1. However, Lequeux and Ciavola (2012) proposes that input output models should be used, because of underestimation of the indirect damage calculated with these functions. Additionally, the indirect damage increases linear with the direct damage, while input output models allow for a progressive increase, which is more realistic (Vilier, Kok, and Nicolai, 2014).

The Adaptive Regional Input-Output (*ARIO*) model is an input output model developed by Hallegatte (2008). This model converts direct damage to indirect damage by calculating the loss in value added during the recovery period, starting from the reconstruction costs and production shocks caused by a flood or drought. The outline of the model is shown in Figure B.2.

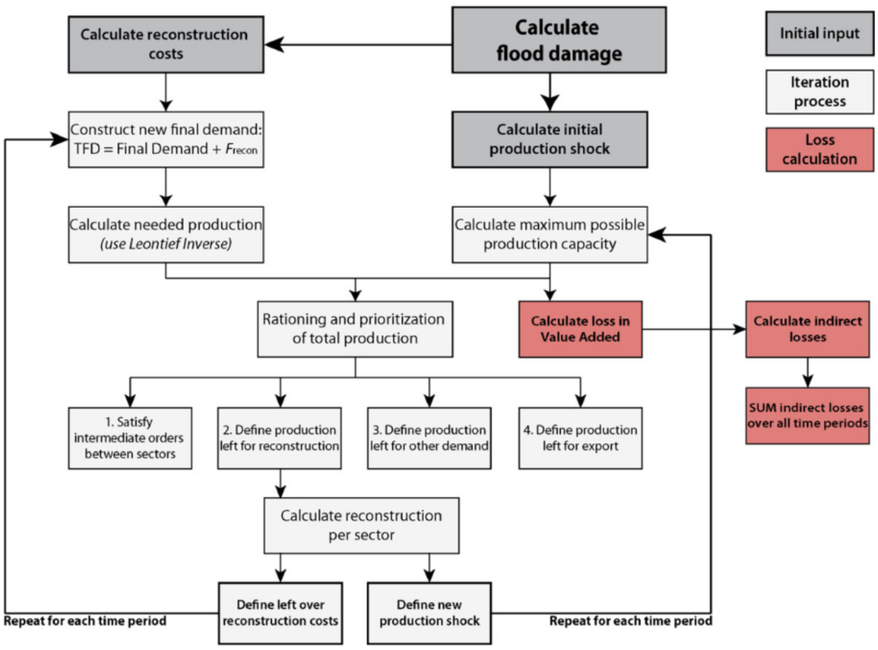

FIGURE B.2: Framework ARIO model (Koks et al., 2015).

On one hand, the direct damage to firms leads to reconstruction costs and, consequently, an increase in demand of F_{recon}, leading to the new final demand TFD. Next, the demand increase requires more production, especially in the manufacturing and construction industries. On the other hand, although there might be overproduction, the maximum possible production has shrunk, which is estimated with the output shock. Therefore, there arises a new production output in the economy. Since it is assumed that the ratio between the output and value added is constant, there results in new value added as well.

After the new production output is determined, it is divided among the different sectors using the ratios of Input Output tables where national economic figures are displayed. The construction industry is one of them, and hence the relevant reconstruction works can be specified. Using this, the remaining reconstruction is calculated, leading to a new demand. Additionally, the restoration works increase the maximum possible production, thereby completing the cycle for a certain time step. The time steps are repeated until the demand and production capacity become equal to the predisaster situation. The total amount of time steps is defined as the recovery period, and the corresponding indirect loss is the total difference between the value added before and after the disaster calculated.

Notice that this approach requires some assumptions and input variables. In addition to the Input Output table, parameters specifying the overproduction, the substitution within different sectors, and the reconstructed speed are necessary (Okuyama, 2004). Baseline parameters used in the literature are provided by Hallegatte (2008) and Hallegatte (2014), but others are presented by for instance Vilier, Kok, and Nicolai (2014).

B.1.3 Total consequences

Finally, Koks et al. (2015) calculates the expected annual damage (EAD) for both direct and indirect damage separately. Up to now, the analysis is performed on one disaster, while it could be possible that multiple disasters of different severities occur in the same year. The EAD allows for estimating the average impact a flood or drought can have on an economy as a whole, but it can also be disaggregated to a specific industry.

The EAD is defined as the area under the damage probability curve, where this curve assigns a damage for each probability corresponding to a specific scenario (Grossi, 2005). This area can be estimated by

$$EAD = \sum_{s=1}^{S-1} (p_{s+1} - p_s) \frac{(D_s + D_{s+1})}{2} \tag{B.1}$$

where p_s is the probability of scenario $s = 1, \cdots, S$ occurring once a year and D_s is the direct damage of the corresponding scenario. Note that it is not possible to sum up the direct and indirect damage, because the direct damage is already annualized. However, the indirect damage covers the entire recovery period, so either the probabilities or the damage value should be adjusted in order to calculate the corresponding EAD (Koks et al., 2015).

B.2 Interview valuation office

The appraisal office enlisted by the Volksbank for business appraisals indicates that a distinction is made between commercial properties and residences. For commercial properties, it is generally assumed that they are quite new, thus no foundation problems are expected. For residences, the cutoff is set at 1980. Houses built before 1980 are inspected from outside. If the house appears straight, it is assumed the foundation is sound, however if it is askew, an expert is brought in. For houses built after 1980, it is assumed the foundation is solid. Lastly, one appraiser noted that issues tend to arise particularly with houses constructed before 1940.