Integrating Climate Risks into Structural Default Risk Models: Reviewing PGGM's Corporate Bond Portfolio

by

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Abstract

This research focuses on the incorporation of climate risks in structural default risk models. Academics, regulators, and financial institutions are incentivised to better quantify the impact of climate risks on firm default risk, as climate risks can lead to various financial risks such as asset devaluation and increased operational costs. Due to the novelty of the topic, many advancements can still be made in quantifying climate risks. Existing research focuses on empirically showing the relation between climate risks and default risk, without emphasising the underlying mechanisms through which climate risks influence default risk. To address this gap in literature, this research focuses on incorporating climate risks in structural default risk models. These models have strong roots in economic theory and treat default endogenously.

The contribution of this research is twofold. Firstly, structural default risk models have been used to incorporate climate risks, although to a limited extent. Within these models, several channels exist through which default can occur. This research presents a novel methodology that adapts the asset value channel of the well-known Merton jump diffusion model, making it suitable for integrating climate risks. The model is empirically validated through a case study using PGGM's corporate bond portfolio. The evaluation shows that the model's behaviour aligns with economic theory: more negative and frequent shocks lead to an increase in the probability of default (PD). This, combined with the model's strong economic foundations and its ability to focus on a specific channel, suggest that structural default risk models could be suitable for quantifying climate risks. As such, this methodology can serve as a foundation for future research and practitioners that want to have better climate-integrated insights in default risk.

Secondly, the case study indicates that, on average, climate risks have a relatively small impact on default risk when assessed through the asset value channel. However, under the fast-transitioning Net Zero 2050 climate scenario, shocks exceeding 1 percentage point in PD are observed, with a peak of over 22 percentage points. This potentially causes real-world effects like credit rating downgrades. Nevertheless, it is not expected that over 50% of the companies show no change in PD when accounting for climate risks, even in fast-transitioning scenarios. This is explained by the data limitations, as the emission data may not fully capture the future extent of climate risks. Moreover, climate risks can affect firms through various channels, beyond just the asset value.

This research demonstrates that climate risks can be quantified using structural default risk models. The results show that climate risks can have significant impact on the PD of several companies. Overall, this research contributes to more complete financial risk management at asset managers. As a result, it could help asset managers in improving their asset allocation.

Keywords: Default Risk, Climate Risks, Structural Default Models, Probability of Default, Asset Value Channel, Jump Diffusion Model, Merton's Model, Corporate Bonds, Financial Risk Management

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This thesis marks the completion of my master's in Industrial Engineering & Management, with a specialisation in Financial Engineering & Management. Obtaining the degree of Master of Science also marks the end of my academic journey at the University of Twente. My time in Enschede has been incredible, allowing me to grow extensively on personal, academic, and professional fronts. Over the years, I have met many amazing people, whom I can now call my best friends. Thank you to everyone who has made my time in Enschede unforgettable.

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Writing this thesis has been an incredible journey, allowing me to explore complex and novel topics such as default risk modelling and climate risks. The interplay between finance, mathematics, and the world around us fuels my passion and has led me to pursue a career in the financial sector. Once again, I would like to thank everyone who has supported me throughout the process and I hope you enjoy reading the thesis.

Sincerely,

Dennis Maneschijn
Utrecht, 26th of March 2025

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Chapter 1

Introduction

Financial risk management (FRM) involves identifying, quantifying, mitigating, and monitoring risks to minimise financial damage within a firm. Traditionally, financial risks are categorised into credit, market, liquidity, model, and operational risk (Christoffersen, 2003). To prevent financial institutions - like banks, insurers, and asset managers - from taking on unacceptable levels of risk, regulators require financial institutions to report on their financial risks and hold adequate capital buffers accordingly (Hull, 2018). In recent years, there has been increasing awareness among academics, regulators, and financial institutions regarding the impact of climate change on financial risks (Carè, 2023). Therefore, financial institutions actively work on identifying, quantifying, mitigating, and monitoring such climate risks. Furthermore, attention is put on the underlying channels through which climate risks influence financial risks. However, due to the novelty of the topic and limited data availability, many improvements can still be made.

In cooperation with Deloitte and PGGM Investments, the effects of climate risks on financial risks are studied. Deloitte, a professional services firm, collaborates on this research through the Climate Risk capability of its Financial Risk Management team. They advise clients on climate risk management procedures and quantitatively modelling such risks. PGGM Investments (hereafter PGGM) is the asset manager of a Dutch pension fund. Their Risk Control department models the financial risks of PGGM's investment portfolio and quantifies emerging risks. The focus of this research will be on quantifying such emerging risks. More specifically, the impact of climate risks on firm default risk is studied for the corporate bond portfolio of PGGM. These insights aim to improve FRM procedures within PGGM by enabling a more accurate assessment of firm default risk in their corporate bond portfolio.

1.1 Problem Context

The enactment of the Paris Agreement made it legally binding for the 196 participating countries to follow a set of climate-related regulations (United Nations Framework Convention on Climate Change (UNFCCC), 2015). The agreement aims to keep the increase in global average temperature to well below 2 °C. To achieve this, greenhouse gas (GHG) emissions must decline as soon as possible and a carbon-neutral economy must be achieved by 2050. This indicates the far-reaching transition that resulted from the Paris Agreement. With the introduction of the European Green Deal, the European Union (EU) aims to be the first continent to meet the Paris Agreement targets (European Commission, 2019b). The financial sector plays a crucial two-sided role in achieving this goal. First, financial institutions have an impact on climate change and the transition to a carbon-neutral economy and society through their investments. Second, they must recognise and address the impact of climate change on their investments to properly quantify financial risks and better transition to a carbon-neutral economy (European Commission, 2019a).[1] As stated, this research will focus on the latter by examining the financial risks brought forward by climate change. The objective is to quantify the impact of climate change on default risk through structural default risk models.

Climate-related regulation is still developing rapidly. With the introduction of the Corporate Sustainability Reporting Directive (CSRD), not only listed companies but also small and medium-sized enterprises (SMEs) are required to report on various climate-related data (European Commission, 2022). The aim is to enhance data availability, leading to a better understanding of climate risks. Furthermore, De Nederlandsche Bank (DNB) states that asset managers should, at a minimum, analyse the extent to which climate risks affect financial risks within their portfolios (De Nederlandsche Bank, 2023). However, in a recent publication, DNB noted that insufficient emphasis is being placed on investigating climate risks, with 37% of Dutch pension funds not even having started the process (De Nederlandsche Bank, 2024). It also mentioned that more stringent assessments will be implemented by mid-2025. For PGGM this is relevant as they manage the assets of a Dutch pension fund.

Climate risks are typically divided into two main categories: physical risks and transition risks. Physical risks refer to the physical impacts of climate change and environmental degradation. These can be acute (e.g. floods, storms, and droughts) or chronic (e.g. sea level rise and biodiversity loss). Transition risks are related to the transition to a carbon-neutral economy, such as changes in policies, technology or consumer sentiment (De Nederlandsche Bank, 2023). Physical risks can damage assets, disrupt supply chains, and increase costs for insurance. Transition risks can cause business models to become less relevant, induce costs for diversifying revenue streams, and lead to higher emission-related taxes (Blasberg & Kiesel, 2024). Therefore, climate risks can have a large impact on various traditional financial risks (Carè, 2023). The channels through which climate risks influence financial risks in the real world are sometimes referred to as transmission channels (De Nederlandsche Bank, 2023). For example if climate risks impact default risk through damaged assets, "damaged assets" is the transmission channel.

In addition to the regulatory and financial incentives for enhancing the assessment and mitigation of climate risks, the significant effect of climate risks on the reputation of companies forms a motivation. As society becomes more conscious about climate change, it expects those responsible to take accountability. Guastella et al. (2022) found that these reputational risks affect the company through financial markets. Others state customer satisfaction and brand value increase when companies operate more sustainably (Atif & Ali, 2021; Khan et al., 2016). These in turn impact profitability and consistency of cash flow, affecting various financial risks.

1.2 Core Problem

Given the broad implications of climate risks, financial institutions are encouraged to quantify them appropriately, allowing for proper risk mitigation. PGGM acknowledges that significant uncertainties remain when assessing climate risks in their portfolios. These uncertainties are shared by other financial institutions as there is no standardized method yet to quantify climate risks (Bell & van Vuuren, 2022; De Nederlandsche Bank, 2023; Gallet et al., 2024; van Dijk, 2020). Hence, literature on how to quantify the effects of climate risks on financial risks has surged in recent years (Carè, 2023; De Giuli et al., 2023). These literature reviews indicate that the impact of climate risk has been examined across various traditional financial risks (e.g. credit risk, market

[1]The two-sided role of financial institutions is often referred to as double materiality. The two sides that can be distinguished within double materiality are: 'Environmental & Social' materiality, describing the impact of investments on climate change, and 'Financial' materiality, detailing how climate change affects investments. A climate risk is said to become material when it inflicts financial damages (European Commission, 2019a).

risk, and operational risks). As mentioned, the goal of this research is to quantify the effect of climate risks on default risk, a subset of credit risk.

Empirical evidence exists on the effects of climate risks on default risk. This evidence is based on the outcomes of so-called reduced-form default risk models. Here default is treated as exogenous, meaning it is seen as a random event and variables are used to predict the outcome of this random event. Hence, reduced-form models focus on the relation between climate risks and default risk, rather than understanding the underlying channels through which climate risks affect firm default risk. According to Capasso et al. (2020), there is a positive association between corporate default risk and a company's carbon footprint. This effect has intensified after the introduction of the Paris Agreement. Similarly, Gutiérrez-López et al. (2022) also identified this relationship. Furthermore, they note that technical innovation within a company can mitigate default risk. This finding supports the expectation that a company's ability to adapt to the technological demands of a future carbon-neutral economy will contribute to a more robust and less risky business model. Atif and Ali (2021) finds that companies performing well on sustainability matters have a significantly lower risk of default. An important contribution of their work is identifying the factors of sustainability that relate the most to default risk. These are profitability, performance variability, and cost of debt. Several other studies also analyse the effects of climate risk on creditworthiness through cost of debt (Henisz & McGlinch, 2019; Jung et al., 2018; Kölbel et al., 2022). They all find that climate risks increase the cost of debt. If a company faces higher costs when issuing debt, it inherently indicates that the company is perceived as riskier. Another view on climate-related default risk is through the notion of stranded assets. Stranded assets are defined as "...assets that have suffered from unanticipated or premature write-downs, devaluations, or conversion to liabilities..." (Chaudhary, 2024). By transitioning towards a carbon-neutral economy, assets like fossil fuel plants or aeroplanes can become obsolete. This can incur rising costs or declining revenue, leading to increased default risk.

Considering physical risks, Nobletz (2024) presents evidence that natural disasters increase the probability of US corporate defaults. This holds for both acute and chronic physical risks. Storms and floods can lead to damaged assets and supply chain disruption, causing financial damages and reduced incomes, leading to increased default risk. On the other hand, rising sea levels and biodiversity loss can lead to damages and increased costs of resources, increasing default risk.

In a broader view, several studies suggest that effective climate risk management can significantly reduce the chances of a company experiencing rare but severe negative events (Henisz & McGlinch, 2019; Vasileva et al., 2024). For example, a company with production facilities located near a river is more vulnerable to flood risks, and companies causing significant environmental harm are more likely to face damage claims or get involved in scandals. These outcomes potentially cause substantial costs and disruption of business operations, increasing the risk of default.

1.2.1 Literature Gap

The aforementioned studies have in common that the focus lies on empirically assessing the effects of climate risk on default risk, using reduced-form models. Although this is relevant, the studies call for a more theoretical understanding of how climate risks impact financial risks. This is needed as it gives a more economically profound method of quantifying such risks, rather than only empirically assessing the effects (Blasberg & Kiesel, 2024). Furthermore, as climate change intensifies, each increment in the global average temperature is expected to bring more severe consequences. Consequently, historical climate data may not accurately reflect future climate scenarios or the regulatory measures necessary to mitigate these effects (Bank for International Settlements, 2023; IPCC, 2023; van Dijk, 2020). Hence, demonstrating that climate change influences default risk in the present might not provide a complete picture of the future. Adopting an approach more firmly grounded in economic theory for quantifying climate risks partially addresses this limitation. This is because such an approach provides a stronger theoretical basis for understanding how climate risks influence default risk, ensuring that their incorporation is in line with economic principles. This makes the insights less reliant on data and more widely applicable. Overall, this results in a deeper and more economically aligned method of quantifying the impact of climate risks on firm default risk. Several studies investigate the effect of climate risks on default risk through an economic lens (Blasberg & Kiesel, 2024; Gallet et al., 2024). These studies use structural default risk models to quantify the impact of climate risks on default risk. Opposed to reduced-form models, structural models treat default as endogenous. In these models, default arises as a result of the interaction between the assets and liabilities of a company. These interactions are explicitly modelled (Jumbe & Gor, 2022a; Oyamienlen, 2024). An elaborate overview is presented in Chapter 2, but some key examples are presented below. First, Blasberg et al. (2022) and Gallet et al. (2024) adjust the growth process the assets of a firm follow. Adjustments to this channel can be proportional to the physical or transition risks a firm is exposed to. Their approaches seem promising but could be further extended and applied in different real-world settings, such as pension funds and asset managers (Gallet et al., 2024). Others introduce climate-related shocks to the value process of the assets of the firm (Agliardi & Agliardi, 2021; Bell & van Vuuren, 2022; Kölbel et al., 2022). The magnitude and frequency of the shocks can be deterministic or stochastic. Stochastic shocks are particularly helpful in addressing the uncertainty in the development of climate risks, as both the magnitude of future climate change and related regulations are unknown. Challenges remain in calibrating a climate event to an appropriate financial shock (Bell & van Vuuren, 2022). To overcome these challenges, a link can be made with predetermined climate scenarios. For example the growth rate of the asset value process can be adjusted based on carbon emissions and carbon costs under a certain scenario (Bouchet & Le Guenedal, 2020). Scenarios and their effects can be modelled as stochastic processes as well, accounting for climate uncertainty (Le Guenedal & Tankov, 2022). Finally, optimal production levels for a certain carbon scenario can be obtained and used to determine the associated firm value and from that adjusted default probabilities (Bourgey et al., 2024).

Overall, these studies state that the development of a theoretical understanding is still in early forms. They suggest that further emphasis should be put on quantifying the impact of climate risks on firm default risk through structural models, as these models provide insights into the underlying channels through which climate risks influence firm default risk.

The problem cluster, presented in Figure 1.1, describes how the business motivation outlined in Section 1.1 leads to the core problem that this research aims to address. In principle, financial institutions are potentially (1) not in line with future regulation, (2) underestimating climate risks and associated financial losses, and (3) not meeting social expectations from stakeholders. These potential shortcomings arise from the uncertainties surrounding how climate risks influence investments. This boils down to financial institutions' lack of awareness regarding both the impact of their investments on climate change and the effects of climate change on financial risks. This research focuses on the latter, specifically addressing the uncertainties in how climate change affects firm default risk. These uncertainties are present due to the limited understanding of how structural default risk models can be adapted to incorporate climate risks. This is the core problem addressed in this research.

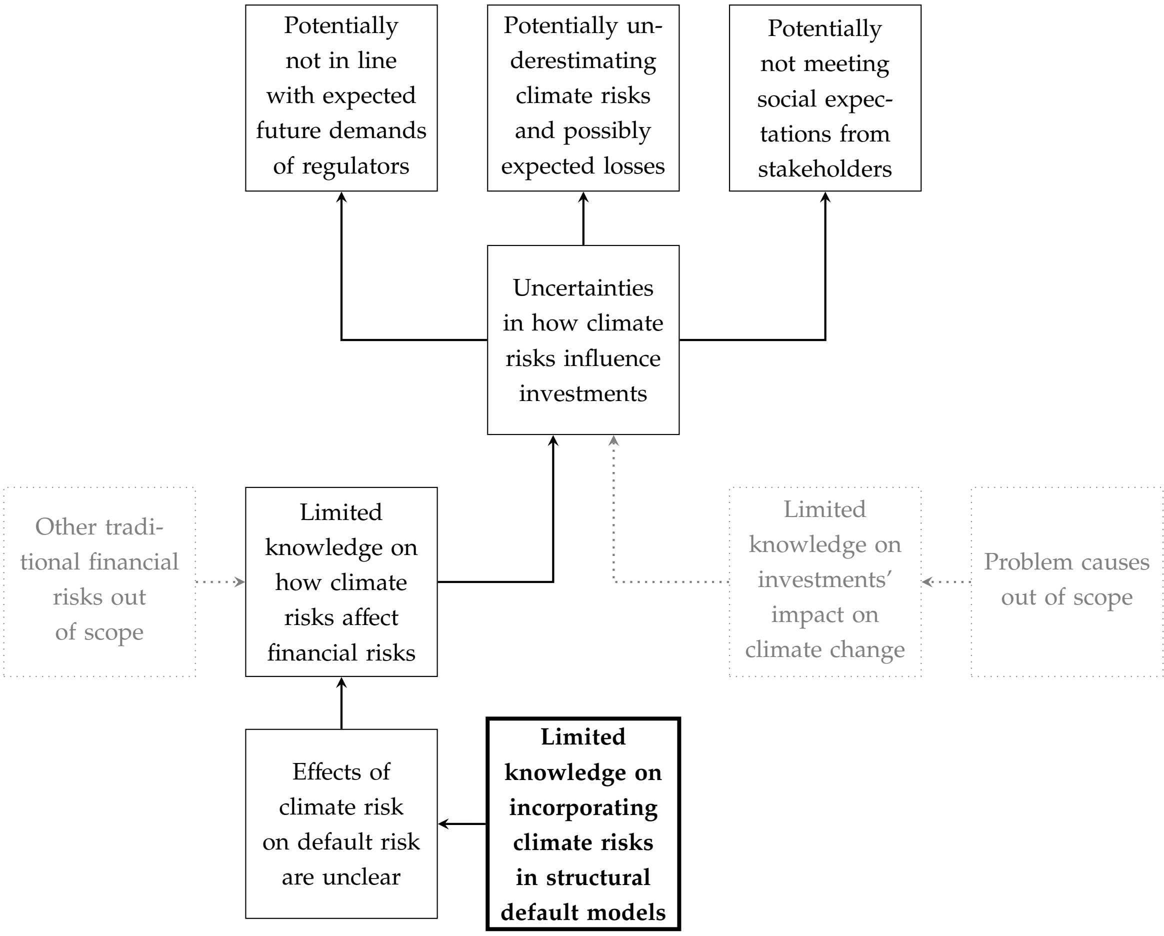

Figure 1.1: Problem cluster for incorporating climate risks into firm default risk modelling

1.3 Research Problem

Financial institutions are incentivised to quantify the impact of climate risks on firm default risk and better understand how climate risks influence default risk, allowing for more appropriate risk mitigation. Current efforts mainly focus on empirically showing the relation between climate risks and default risk, using reduced-form models (Atif & Ali, 2021; Blasberg & Kiesel, 2024; Capasso et al., 2020; Gutiérrez-López et al., 2022). To the best of our knowledge, it would be relevant to focus more on understanding the mechanisms behind the effect of climate risks on firm default risk. Structural models could be (part of) a solution to this, as they have strong roots in economic theory. Moreover, due to their endogenous treatment of default, more emphasis is put on the underlying channels through which climate risks affect firm default risk (Blasberg & Kiesel, 2024; Jumbe & Gor, 2022a; Oyamienlen, 2024). Essentially, there is a gap in academic literature focusing on incorporating climate risks in structural firm default risk models (Gallet et al., 2024). This research will try to help bridge this gap by providing a comprehensive overview of existing efforts to incorporate climate risks into structural models. Moreover, a structural default risk model will be extended to incorporate climate risks and empirically reviewed on PGGM's corporate bond portfolio. The goal of this research is to quantify the impact of climate risks on firm default risk and provide a deeper understanding of the channels through which this impact occurs. The findings address a gap in the academic literature and assist financial institutions in their financial risk management by offering insights into the underlying mechanisms of climate risk's effect on firm default risk. This enhanced understanding of climate risks enables institutions to mitigate these risks more effectively.

Consequently, this has led to the following main research question (RQ):

> *How can climate risks be integrated into structural default risk models through the underlying channels that cause default, to quantify their impact on firm default risk?*

In this research, it is hypothesised that the use of structural default models can properly quantify the effects of climate risk on default risk and help gain a more theoretical understanding of the channels through which climate risks influence default risk. To answer the main research question and address the hypothesis, several smaller research questions are defined. They are listed below, together with a small motivation regarding the question.

- **RQ1:** *What climate risks can be distinguished and how do they affect firm default risk?*
  The effect of climate change on default risk is studied, and different types of climate risks are highlighted to provide a meaningful context. The goal is to highlight the channels through which climate risks influence default risk.
- **RQ2:** *What are structural default risk models and how do they address the channels underlying the occurrence of default?*
  The theory behind structural default risk models is explained and attention is put on the different channels that exist in these models that influence the likelihood of default occurring.
- **RQ3:** *Through which channels can climate risks be incorporated in structural firm default risk models?*
  State-of-the-art literature is reviewed to get an understanding of the channels through which climate risks can be incorporated in structural firm default risk. For each different channel, several approaches are discussed.
- **RQ4:** *What climate risk indicators exist to quantify climate risks?*
  An overview is presented of frequently used data points for climate risks that can be used to quantify the effects of climate risks on firm default risk. Moreover, the applicability of the indicators for the different channels is discussed.
- **RQ5:** *How can an extended structural default risk model be implemented in a case study?*
  An extended structural default risk model is empirically reviewed through a case study. The impact of climate risks on firm default risk is quantified within PGGM's bond portfolio. Robustness checks will be performed to reason on the quality of the model outputs.

1.4 Methodology & Data Availability

The methodology for answering the research questions consists of both qualitative and quantitative research:

1. *Qualitative Research*
   The qualitative part of this research involves a literature review that starts with obtaining relevant background knowledge on climate risks and their impact on firm default risk. The literature review will then form a theoretical background on structural default models and the channels through which default can occur in these models. Afterwards, an overview is given of existing approaches to incorporate climate risks in structural default models through several channels. The literature ends with studying frequently used climate risk indicators that are suitable for measuring climate risks. The first four research questions are answered by the means of a qualitative research.

2. *Quantitative Research*
   The quantitative part of this research focuses on estimating the impact of climate risk on firm default risk, by using real-world data. This is done through a case study on PGGM's corporate bond portfolio. The outcomes address the fifth research question and, along with the qualitative findings, contribute to a comprehensive answer to the main research question. Climate-related data is sourced from Aladdin Climate, a third-party model developed by BlackRock. This model contains physical and transition climate risk indicators from various data providers. Financial data is retrieved from Yahoo Finance through an open-source Python library that connects to the Yahoo Finance API. Additionally, portfolio information is available within Aladdin Climate.

1.5 Research Outline

The remainder of this research is structured as follows. First, Chapter 2 presents related literature on climate change, structural firm default risk models, incorporating climate risks in such models, and climate risk indicators. Second, Chapter 3 discusses the methodology that will be used to extend a structural firm default risk model. The data used in the case study is prepared and analysed in Chapter 4. Next, Chapter 5 presents the results on how climate risks affect default risk, based on the case study outcomes. Moreover, the chapter validates the model implementation through its application in a real-world case study. Finally, concluding remarks and a discussion of the results and model implementation are provided in Chapter 6.

Chapter 2

Literature Review

In this Chapter, relevant literature is discussed to form a theoretical basis for this research. First, Section 2.1 discusses climate change and its effects on default risk, providing an answer to RQ1. Next, Section 2.2 answers RQ2, by describing the theoretical background of structural default risk models and the channels through which default can occur. Afterwards, Section 2.3 explores approaches that can be taken to extend structural default risk models with climate risks. With that RQ3 is addressed. Finally, an answer is provided to RQ4 in Section 2.4. Here, an overview is given of frequently used climate risk indicators.

2.1 Climate Risks

This section provides a small background on climate change and highlights two distinct types of climate risks, including their impact on firm default risk and the channels through which this occurs.

2.1.1 Climate Change

According to the United Nations, climate change refers to long-term shifts in temperatures and weather patterns. Historically, these shifts occurred naturally and spanned long time frames. However, during the past 50 years, it has become evident that humankind has an accelerating and possibly irreversible effect on climate change (IPCC, 2023). This was first acknowledged by Meadows et al. (1972). Their work simulates several scenarios in terms of population growth, industrialization, malnutrition, exploitation of raw materials and destruction of the living environment. Almost all of their simulations resulted in unstoppable environmental destruction and global depletion of raw materials after the year 2050. Although their concerns have been widely acknowledged, research shows that, even 50 years later, existing economic systems are still far away from green growth in terms of sufficient reductions of resource use or emissions (Döring & Aigner-Walder, 2022). In their latest report, the Intergovernmental Panel on Climate Change (IPCC) has stated that human activities have unequivocally caused global warming through emissions of greenhouse gases (IPCC, 2023). Human activities have directly led to widespread and rapid changes in the ocean and atmosphere, including more extreme weather and climate events. Moreover, they state that risks and adverse impacts escalate with every increment of global warming, indicating that current estimates even underestimate the effects of climate change. Current estimates state that the global GDP takes a 12% hit for every 1°C increase in global temperature (Bilal & Känzig, 2024). Typically, climate risks are divided into two categories: Physical and transition risks. They were introduced in Chapter 1 and will be explained in further detail below.

2.1.2 Physical Risks

Physical climate risks, as defined by the Financial Stability Oversight Council (2023), contain both acute and chronic climate-related events. Examples of acute events are hurricanes, wildfires, floods, and heatwaves. Chronic events are more long-term phenomena, including rising average temperatures, shifting participation patterns, sea level rise, and ocean acidification.

These risks pose significant potential financial damages that extend across various sectors. The consequences of physical climate risks can also create a domino effect of financial risks, eventually leading to defaults and impacting the financial system as a whole. For instance, floods and storms may disrupt supply chains, introducing operational risks for businesses to perform day-to-day activities. This in turn can cause firms to default due to reduced income and increased costs. Hence, physical risks influence default risk through less profitability. Wildfires and droughts further threaten crops and natural resources, reducing the availability of raw materials and impacting industries dependent on these inputs. These events also lead to significant losses for individuals, with property damage impacting homes and assets, often causing larger-than-usual withdrawals from personal savings. Through this channel, climate risks can incur liquidity risks for banks and insurers, causing them to fail to meet debt obligations and go into default. Additionally, extreme weather events can alter consumer behaviour, with spending habits shifting due to repair costs or loss of disposable income, which in turn can impact corporate revenues and increase the likelihood of inventory surpluses. Moreover, climate risks can influence default risk through a reduced asset-value channel. As severe weather events become more frequent, companies in vulnerable regions or sectors may experience sharp fluctuations in asset valuations, which can undermine financial stability and increase default risk. According to the Network for Greening the Financial System (NGFS) (2024), the frequency and severity of extreme weather events are increasing drastically. The report states that annual global damages from weather-related hazards have more than doubled in the past two decades, reaching $275 billion in 2022 alone.

2.1.3 Transition Risks

Transition climate risks are defined by the Financial Stability Oversight Council (2023) as stresses to certain institutions or sectors that may arise from transitioning towards a lower GHG economy. This can include changes in law and policy, changes in consumer and business sentiment, and technological advances. These risks can have significant financial implications.

For example, regulatory changes such as stricter emission standards or carbon taxes increase operational costs for companies reliant on fossil fuels. A potential channel through which these transition risks can influence default risk is when assets become stranded. This means they become obsolete and have no place in a sustainable business model or they use significant value (Chaudhary, 2024). Also, ambitious regulation and technological advances can lead to rapid transitions of business models. This can force companies to make large investments to stay competitive, which can result in enormous transition costs. This limited profitability is another channel through which the default risk of a company is affected by transition risks. As for physical risks, banks can face liquidity risk due to companies needing to use their savings to make certain investments. This can influence the default risk of banks. Furthermore, transitioning towards a greener economy can lead to investors adjusting their investment decisions and re-allocate capital towards companies that are perceived to be better aligned with a lower GHG economy (Faccini et al., 2023; Giese et al., 2019). This can lead to funds drying up for companies that investors see as less green, leading to increased default risk. Moreover, legal risks are becoming more relevant due to the transition to a lower GHG economy. Climate litigation took off in the last two decades, with more than 200 cases in 2021 (Sato et al., 2023). Climate litigation risks can channel through to default risk as these cases can bring forward significant costs. Expectations are that the financial and operational implications of climate litigation will become more severe if plaintiffs begin to secure favourable rulings in high-profile cases.

2.2 Structural Default Risk Models

This section provides a theoretical background on structural default risk models. Default risk is the likelihood of an obligor failing to make payments on any type of debt at the time of maturity. Default risk models use data to model the likelihood of a default event occurring (Hull, 2018; Zhang, 2017). This likelihood is called the probability of default (PD). Structural models treat default as endogenous. This means that default is a result of the model through the modelling of the assets and liabilities of the company. Hence it provides information on the mechanisms behind the default. Despite the existence of numerous structural default risk models, they all originate from a single base model, introduced by Merton (1974). This model has strong roots in economic theory, as it has a foundation in option theory, following the work of Black and Scholes (1973). This section will first explain the option pricing model of Black and Scholes as it forms the basis of Merton's model. Then, the Merton model is explained, including how it can be used for measuring the PD of a firm. Finally, the different channels through which default can occur within the Merton model are discussed.

2.2.1 The Black-Scholes Model

Following the notations given in Hull (2014), the change in a variable at an infinitesimal time step can be modelled as follows:

$$dx = a \cdot dt + b \cdot \epsilon \sqrt{dt} \tag{2.1}$$

Here a - the drift rate - and b are constants and ϵ is a so-called Wiener process. This means at every time step the value of ϵ is sampled from a standard normal distribution, $N(0, 1)$, from now denoted as $\Phi(\cdot)$. The process in (2.1) is called a generalised Wiener process. Figure 2.1 shows how the individual components behave. To make this process suited for stock price modelling,

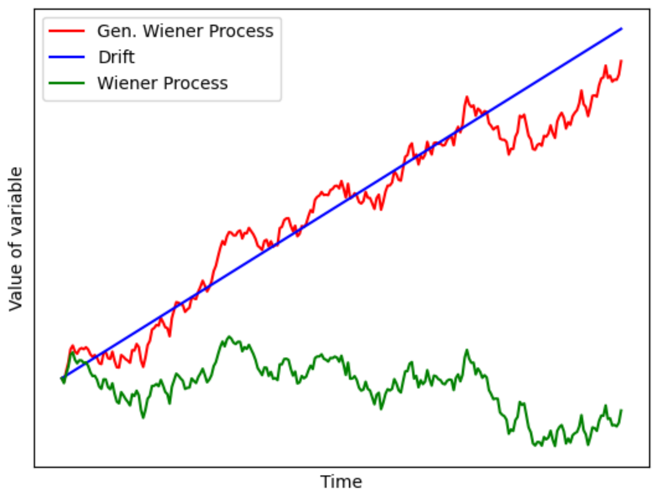

Figure 2.1: Components of the Generalised Wiener process ($a = 0.3$, $b = 0.1$)

it is necessary to avoid assuming constant drift and variability. This is because a $y\%$ return corresponds to a different absolute value when the stock price is at \$10 or \$50. The same holds for the volatility. To achieve this, an Itô process can be used:

$$dx = a(x,t) \cdot dt + b(x,t) \cdot \epsilon \sqrt{dt} \tag{2.2}$$

In this equation, a and b are functions of the variable, x, and current time step, t. A specific instance of the Itô process is the Geometric Brownian Motion (GBM). This process forms the basis for modelling the stock price S:

$$\begin{aligned} dS &= \mu S \cdot dt + \sigma S \cdot \epsilon \sqrt{dt} \\ &= \mu S \cdot dt + \sigma S \cdot dz \end{aligned} \tag{2.3}$$

Here, μ is the expected rate of return of the stock price and σ is the volatility of the stock price. Note that dz is written down for notational simplification. Now, consider a variable C that is a function of S and t, where S follows a GBM. According to Itô's lemma, the change in C can be modelled by

$$dC = \left(\frac{\partial C}{\partial S}\mu S + \frac{\partial C}{\partial t} + \frac{1}{2}\frac{\partial^2 C}{\partial S^2}\sigma^2 S^2\right)dt + \frac{\partial C}{\partial S}\sigma S \cdot dz \tag{2.4}$$

Here, C could be the price of a call option or any other derivative. An important assumption made in (2.4) is that both S and C depend on the same source of uncertainty dz. Consider the creation of a portfolio Π consisting of buying one C and shorting $\frac{\partial C}{\partial S}$ shares:

$$\Pi = C - \frac{\partial C}{\partial S}S \tag{2.5}$$

The change in this portfolio at an infinitesimal time step, $d\Pi$, is represented by

$$d\Pi = dC - \frac{\partial C}{\partial S}dS \tag{2.6}$$

By substituting (2.3) and (2.4) in (2.6), $d\Pi$ can be modelled as

$$\begin{aligned} d\Pi &= \left(\frac{\partial C}{\partial S}\mu S + \frac{\partial C}{\partial t} + \frac{1}{2}\frac{\partial^2 C}{\partial S^2}\sigma^2 S^2\right)dt + \frac{\partial C}{\partial S}\sigma S \cdot dz \quad - \quad \frac{\partial C}{\partial S}(\mu S \cdot dt + \sigma S \cdot dz) \\ &= \left(\frac{\partial C}{\partial t} + \frac{1}{2}\frac{\partial^2 C}{\partial S^2}\sigma^2 S^2\right)dt \end{aligned} \tag{2.7}$$

All uncertainty, dz, in the change of the portfolio has now disappeared. Hence this portfolio cannot earn more than the risk-free rate, r. Thus the drift rate in $d\Pi$ should be equal to the risk-free rate:

$$d\Pi = r\Pi \cdot dt \tag{2.8}$$

Substituting (2.5) and (2.7) in (2.8) gives

$$\begin{aligned} \left(\frac{\partial C}{\partial t} + \frac{1}{2}\frac{\partial^2 C}{\partial S^2}\sigma^2 S^2\right)dt &= r\left(C - \frac{\partial C}{\partial S}S\right)dt \\ \frac{\partial C}{\partial t} + rS\frac{\partial C}{\partial S} + \frac{1}{2}\sigma^2 S^2 \frac{\partial^2 C}{\partial S^2} &= rC \end{aligned} \tag{2.9}$$

Equation 2.9 is the Black-Scholes differential equation that forms the basis for all structural default risk models. This result explains the assumption of a risk-neutral world by Black and Scholes. It states that stock prices have a drift rate equal to the risk-free rate. Therefore, (2.3) becomes

$$dS = rS \cdot dt + \sigma S \cdot dz \tag{2.10}$$

From this point on, this research adheres to the risk-neutral world. This means that all probability measures and the obtained probability of defaults are under the risk-neutral assumption.

2.2.2 Merton's Model

Following Jumbe and Gor (2022a) and Bell and van Vuuren (2022), consider a company at time t, with assets A, fully financed by equity E, and zero-coupon debt D. The debt has a face value of K and matures at time $T > t$. This gives

$$A_t = E_t + D_t \tag{2.11}$$

From now, subscript t is omitted to simplify the notation. If at maturity, $A > D$ the debt holders will receive back D and the equity still has value $A - D$. However, if the company defaults, that is, $A < D$, the debt holders will receive A and equity value equals zero. Hence, at maturity, the equity can be modelled as a European call option on the assets and face value of the debt:

$$E = max(A - D, 0) \tag{2.12}$$

Assuming assets follow a GBM, like the stock price in (2.10), it can be shown using (2.9) that the market value of equity is defined as

$$E = A \cdot \Phi(d_1) - e^{-rT} D \cdot \Phi(d_2) \tag{2.13}$$

where,

$$d_1 = \frac{\ln(\frac{A}{D}) + (r + \frac{1}{2}\sigma_A^2)T}{\sigma_A \sqrt{T}}, \qquad d_2 = \frac{\ln(\frac{A}{D}) + (r - \frac{1}{2}\sigma_A^2)T}{\sigma_A \sqrt{T}} = d_1 - \sigma_A \sqrt{T} \tag{2.14}$$

Here $\Phi(d_2)$ is the probability that the call option will be exercised in a risk-neutral world. Hence, $1 - \Phi(d_2) = \Phi(-d_2)$ is the probability that the option will not be exercised. This means the asset value is lower than the face value of the debt and a default has occurred. Hence, the PD can be represented as

$$PD = \Phi\left(-\frac{\ln(\frac{A}{D}) + (r - \frac{1}{2}\sigma_A^2)T}{\sigma_A \sqrt{T}}\right) \tag{2.15}$$

Often, the distance to default (DD) is used instead of the PD. The DD is the number of standard deviations the firm is away from defaulting:

$$DD = \frac{\ln(\frac{A}{D}) + (r - \frac{1}{2}\sigma_A^2)T}{\sigma_A \sqrt{T}} \tag{2.16}$$

The above is schematically presented in Figure 2.2. It shows how the PD follows from the probability of the assets being below the default threshold at maturity.

2.2.3 Default Channels

Within the Merton model, there are several channels through which default is influenced. These channels can make the modelling of default more explicit and provide a better theoretical understanding of how default occurs. In explaining the channels that impact default, Figure 2.2 is referenced, as it provides an intuitive visual representation of how the channels interact with the PD. Moreover, the theory behind the explanations of the channels is derived from Hull (2014, 2018) and Thompson and Jessop (2018).

Asset values serve as one of the primary channels influencing default risk in Merton's model. As a key driver, they directly represent the likelihood that asset values will fall below the default point at maturity. Therefore, when asset values increase, the likelihood of them lying below this default threshold diminishes, leading to a reduction in the PD. Conversely, a decrease in asset

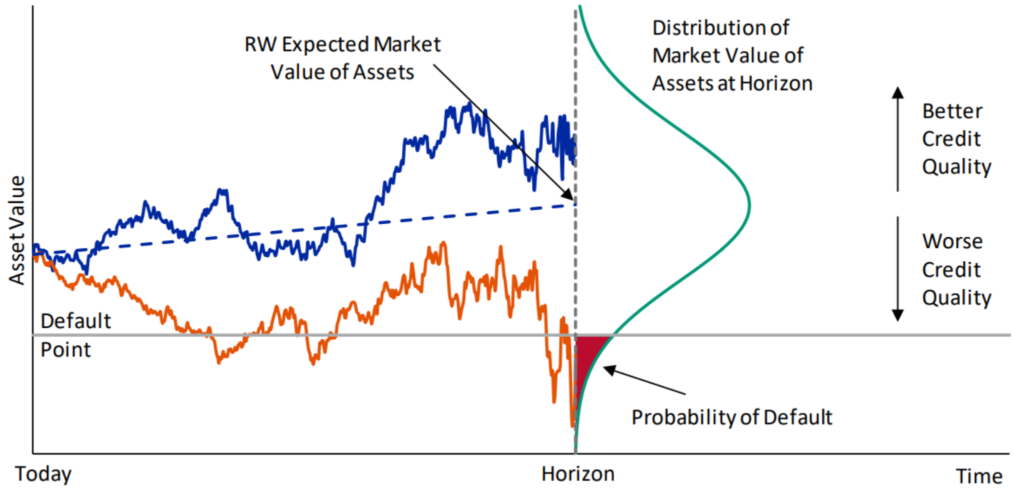

Figure 2.2: Visual representation of the PD in Merton's model (Thompson & Jessop, 2018)

values results in an increased PD, as can be seen in Figure 2.2. A real-world example could be a real estate company experiencing a significant drop in asset values during a housing market crash. It is expected that this leads to an increased likelihood of defaulting.

Related to the asset value channel is the drift rate channel. The drift rate channel plays a significant role in the standard Black-Scholes model, yet its mechanics cannot be directly applied to Merton's model. In the Black-Scholes model, under the risk-neutral assumption, stocks are expected to grow at the risk-free rate. Hence, a lower risk-free rate reduces stock growth, increasing the likelihood of the stock price falling below the strike price at maturity and, in turn, raising the probability of the call option not being exercised. Directly translating these mechanics to Merton's model and replacing stocks with a firm's assets is not feasible due to the more complex relationships involved in Merton's model. Nevertheless, it is possible to reason intuitively on the effects of a reduced asset growth rate. Several scenarios could be imagined where the growth rate of assets diminishes or even become negative. For instance, a firm's business model could become less relevant or its competitors could take over the market. This results in a negative outlook for the firm, resulting in reduced asset growth values and likely higher financial distress. Hence, scenarios can be imagined where reduced asset growth levels lead to a larger PD, but the relation is less direct compared to the asset value channel.

Related to the drift rate channel is the asset volatility channel. This channel directly influences the range of possible asset values at maturity. The larger the volatility, the larger this range of possible values and the larger the PD. It can be seen as smoothening out the green distribution in Figure 2.2. For reduced volatility levels, the range of possible values will become smaller, leading to a reduced PD. Again, parallels can be drawn with the real world. As stated in Crosbie and Bohn (2002), asset volatility is directly linked to the nature and maturity of the business. Higher asset volatilities correspond to less mature companies and less mature industries. This explains the link that in general higher asset volatility corresponds to larger default risk.

Another important channel in Merton's model is the debt level. If a company has higher debt levels, the default barrier will increase. This in turn increases the likelihood of the asset values being below the default barrier at maturity, thus increasing the PD. A translation to the real world is rather straightforward for this channel. The higher the debt burden of a firm, the higher the likelihood of a firm not being able to meet its debt obligations.

Finally, the time to maturity significantly influences the PD. This time horizon channel determines when a default check occurs. Essentially, the longer the maturity, the greater the opportunity for random fluctuations in asset value to cause the value to be below the default barrier. Because of this, a longer time to maturity generally results in a higher PD. In Figure 2.2 this corresponds to the dotted horizon moving further to the right. This concept is evident in the real world, where loans spanning 10 years carry more uncertainty compared to those lasting just 1 year, as much uncertainty is carried in the additional 9 years. While shorter time horizons typically have a lower PD, they also offer less opportunity to recover from negative developments in asset value, which could lead to a slight increase in PD. An overview of all channels and their effect on the PD is summarised in Table 2.1.

Table 2.1: Channels in Merton's Model

Channel	**Effect on PD when increased**	**Effect on PD when decreased**
Asset value	Assets are expected to lie further above the default threshold, resulting in decreased PD.	Assets are more likely to lie below the default threshold, increasing the PD.
Drift rate	Assets are expected to grow faster and therefore more likely to lie further above the default threshold. This decreases the PD.	Assets are expected to grow slower, or even decline, resulting in a larger likelihood of the assets lying below the default threshold. This increases PD.
Asset volatility	The range of possible asset values increases, including the probability of ending up below the default threshold.	The range of asset value possibilities is decreased, resulting in a lower PD.
Debt level	The threshold at which default is considered is increased, causing the likelihood to end up below this threshold to increase.	The threshold at which default is considered is decreased, reducing the likelihood of default occurring.
Time horizon	The longer the period for which the PD is calculated, the more potential uncertainty is introduced, causing the PD to increase.	The shorter the considered period, the smaller the potential for uncertainties, leading to a lower PD.

2.3 Incorporating Climate Risks in Structural Default Models

With the theoretical background of structural models established and the default channels in Merton's model outlined, focus is put on the various approaches for incorporating climate risks into structural default models. This will be done by grouping the approaches based on the default channels that they influence. The goal is to identify emerging trends and gaps in incorporating climate risks into structural default risk models. The outcome of the review is presented in Table 2.2 at the end of this section.

To the best of our knowledge, all relevant papers that discuss the extension of structural default risk models with climate-related risks have been identified. The search queries and resulting papers can be found in Appendix A. From these queries, a total of 95 papers were found. Afterwards, these papers were screened in terms of language and duplicates. Only English papers were kept, resulting in the removal of one paper. A total of 22 duplicates were found.

The remaining 72 papers were screened on their title and abstract, this resulted in the removal of 38 papers. Especially the older papers discussed topics that are not related to the scope of this section of the literature review. A full-text screening of the 34 papers was then conducted. This resulted in removing an additional 26 papers. Two of these could not be accessed through the available academic licences. The other 24 methods mainly employed methods or structural model extensions not relevant to this research. Often, no climate risks were considered or Merton's DD was treated exogenously and predicted using climate-related variables in a regression model. This means a total of 87 papers were excluded, leaving 8 papers that can be thoroughly studied.

Out of the 8 selected studies, one is a literature review (Blasberg & Kiesel, 2024). This paper summarises different approaches that can be taken when adjusting structural default models. This resulted in 4 additional papers. Moreover, DNB published a working paper in August 2024 that adapts a structural default risk model to account for climate risks (Gallet et al., 2024). This paper was not found in the observed databases but is included in the review. Hence, the literature review encompasses a total of 13 papers. The upcoming subsections highlight these studies and group them based on the channel through which they try to model the impact of climate risks on firm default risk.

2.3.1 Asset Value Channel

As mentioned in Section 2.1, climate risks can directly influence the value of assets through shocks and write-offs like stranded assets. Several studies leverage this idea by directly incorporating climate risks through the asset channel in Merton's model.

Gallet et al. (2024) introduce a continuous discounting factor to the assets, based on the climate risk exposure of the industry of the company. Their definition of the DD is similar to Merton's, but now with a direct effect on the assets, based on a dependency score *dep* related to firm *i*:

$$DD_i^{dep} = \frac{\ln(\frac{A \cdot e^{-dep_i}}{D}) + (r - \frac{1}{2}\sigma_A^2)T}{\sigma_A \sqrt{T}} = \frac{\ln(\frac{A}{D}) + (r - \frac{1}{2}\sigma_A^2)T}{\sigma_A \sqrt{T}} - \frac{dep_i}{\sigma_A \sqrt{T}} \tag{2.17}$$

Here, $0 \leq dep_i < 1$, where 0 corresponds to no dependency. In this case climate risks do not affect default through the asset channel. A dependency score of 1 represents the scenario where asset values are approximately 37% of their original value, corresponding to a severe climate-related shock. In their work, dep_i is defined as

$$dep_i = \alpha_{ES} \cdot Vuln_{ES,i} \tag{2.18}$$

α_{ES} represents a theoretical shock on a firm's balance sheet due to an ecosystem service on which the firm depends. $Vuln_{ES,i}$ represents the vulnerability of the firm to that shock, based on its main activities. Gallet et al. (2024) apply the model to a case study for European banks and find that incorporating climate risks directly through the asset channel has a significant impact on the PDs of the debtors. They call for further application of their framework, specifically mentioning that it would be valuable to test the applicability to pension funds and asset managers.

A different way to incorporate climate risks through the asset channel is to introduce shocks to the value process of the firm. As stated in Section 2.1, climate risks can cause unexpected shocks to the asset values of companies. This affects the PD, as mentioned in Section 2.2.3. In Kölbel et al. (2022) a Poisson jump process is added to the GBM followed by the assets. Suppose this Poisson process has a jump frequency λ and a mean jump size of ν. Then the following expression for the PD is given by

$$PD = \sum_{i=0}^{\infty} e^{-\lambda T} \cdot \frac{(\lambda T)^i}{i!} \cdot \Phi(-d_{2,i}(A, T)) \tag{2.19}$$

where

$$d_{2,i}(A,T) = \frac{\ln(\frac{A}{D}) + (r - \frac{1}{2}\sigma_A^2 - \lambda\nu)T + i\mu_J}{\sigma_A^2 T + i\sigma_J^2} \tag{2.20}$$

Note that in this context, μ_J and σ_J^2 represent the mean and variance of the assumed log-normal distribution of jump sizes. The analysis indicates that when climate risks are incorporated as shocks in the asset channel, several conclusions can be made. Firstly, the more positive the jump size (μ), the smaller the resulting PD. This outcome is anticipated because climate risks are often modelled through negative shocks. Consequently, a more extreme climate-related event (i.e., a more negative μ) leads to a larger PD. Additionally, the relationship

$$\frac{\partial PD}{\partial \lambda}\Big|_{\mu<0} > 0 \tag{2.21}$$

indicates that an increase in the number of jumps corresponds to a larger PD. This suggests that introducing more shocks to the asset value channel negatively impacts the PD, a notion supported earlier in this literature review. A similar method is employed by Agliardi and Agliardi (2021), although their focus is more on bond pricing, which falls outside the scope of this research.

In the extension of Kölbel et al. (2022), the question remains how appropriate shock sizes and frequencies can be determined. As highlighted in Section 2.1, various climate scenarios exist, and there are significant uncertainties associated with the evolution of climate change. Consequently, it seems intuitive to study the effects of climate risks within the context of specific scenarios. To do so, several studies incorporate climate risks through the asset value channel, based on climate scenarios. These scenarios can be based on projected future climate damages or the expected climate regulations. For example, Bouchet and Le Guenedal (2020) assume k different regulatory policies, where C^k represents the additional costs that will be inflicted in policy-scenario k. They define $k = 0$ as the baseline scenario with no additional costs, meaning $C^0 = 0$. Then, the shock on the asset value channel, in terms of the initial asset value, A_0, is

$$\xi^k = \frac{C^k}{A_0} \tag{2.22}$$

which can be incorporated into the value channel as

$$A^k = (1 - \xi^k)A_0 \tag{2.23}$$

leading to the scenario-adjusted DD

$$DD^k = \frac{\ln\left(\frac{(1-\xi^k)A_0}{D}\right) + (r - \frac{1}{2}\sigma_A^2)T}{\sigma_A\sqrt{T}} \tag{2.24}$$

They use this approach to study the effects of transition risks. Carbon emissions are used to model these effects. Suppose a company operates in the set of regions $\mathcal{J}$. Now, the reported carbon emissions of a company in region j are noted as CE_t^j. Moreover, each scenario k has an associated carbon price $CP_t^{k,j}$. Then, CC_t^k can be defined as

$$CC^k = \sum_{j\in\mathcal{J}} CE^j \cdot CP^{k,j} \tag{2.25}$$

It is interesting to note that this approach can be adjusted to take into account physical risks. In order to do so, firm-specific costs resulting from physical events should be identified for the regions in which the company operates. The severity and frequency of the events can then be determined by the scenario k. This is an open direction for future research. A similar method is used in Schult et al. (2024). Here an asset shock ω is defined:

$$\omega = \frac{NPV_{tax}}{A_0} \tag{2.26}$$

In this context, the net present value (NPV) of the tax is, among other factors, dependent on the company's carbon emission reduction factor. This adjustment affects the asset value, which is then incorporated into the model:

$$A = (1 - \omega)A_0 \tag{2.27}$$

Building further on Bouchet and Le Guenedal (2020), another study assumes stochasticity of the scenarios, by modelling the costs originating from a climate scenario with a jump process (Le Guenedal & Tankov, 2022). Explaining this model is beyond the scope of the research, but it does show the different approaches that can be taken when incorporating climate risks in the asset value channel. Moreover, several approaches model the adjusted value through increased costs/taxes. This means there are some touchpoints with the debt channel. More on this in Section 2.3.4.

2.3.2 Drift Rate Channel

Rather than directly adjusting the asset channel, several papers incorporate climate risks in structural default risk models through the drift rate channel (Blasberg et al., 2022; Reinders et al., 2023). As mentioned in Section 2.2.3, adjusting the drift rate in Merton's model is not as straightforward as in the Black-Scholes option pricing formula. However, examples are provided as to why intuitively climate risks could affect the drift rate. Climate risks could namely have some effect on the growth of the asset value of the firm. This was already highlighted in Section 2.1. However, when interpreting the mathematical relations below, the assumptions must be acknowledged.

In Blasberg et al. (2022), the growth value of the asset process is adjusted by introducing carbon rate, δ. The adjusted value process

$$dA = (r - \delta)A \cdot dt + \sigma A \cdot dz \tag{2.28}$$

diminishes the growth rate using δ. It can be a constant, in which it is modelled the same as constant dividend payments in Merton's model. However, the carbon rate can also be time-varying. In this case, δ is modelled with a stochastic process:

$$d\delta = \mu_\delta \cdot dt + \sigma_\delta \cdot dz_\delta \tag{2.29}$$

Here dz_δ indicates the uncertainty is governed by a different Wiener process than the one in (2.28). The idea behind a stochastic rate is that climate risks are expected to increase due to increased climate intensity. This effect can be introduced in the stochastic process of the carbon rate. The adjusted DD now becomes

$$DD = \frac{\ln(\frac{A}{D}) + \left(r - \frac{(\mu_\delta T + \sigma_A^2)}{2}\right)T}{\sigma_T \sqrt{T}} \tag{2.30}$$

Where σ_T stands for the total volatility, more on this in Section 2.3.3. An interesting finding from Blasberg et al. (2022) is that the partial derivative of the DD with respect to the growth rate of the carbon rate, $\frac{\partial DD}{\partial \mu_\delta}$, is negative. This means that the larger the increase in the carbon rate, the smaller the DD. Hence, the larger the impact of climate risks, the sooner a firm is expected to default. Their findings indicate that when climate risks are incorporated through the drift rate channel, an increase in these risks is expected to lead to a higher probability of firm default. A similar approach is taken by Reinders et al. (2023). They introduce a shock

$$\xi_k = f(\tau_{t,k}, \Omega_{k,t}) \tag{2.31}$$

for each segment k. Then $\tau_{t,k}$ represents the CO_2 tax for a given segment, $\Omega_{k,t}$ a set of vulnerabilities for the segment, and f is a stylised discounted cash flow model. Then this shock is added to drift value channel as in (2.28).

2.3.3 Asset Volatility Channel

Another channel through which climate risks are incorporated in structural default risk models is the asset volatility channel. This channel governs the inherent uncertainty present in the value process of the assets. Therefore, incorporating climate risks through this channel suggests that climate risks should influence the uncertainty associated with the asset value. Again, support for this suggestion was already provided in Section 2.1.

As mentioned in Section 2.3.2, Blasberg et al. (2022) introduces a stochastic carbon rate to the asset value process to incorporate climate risks through the drift rate channel. As can be seen in (2.30), this results in a new term, σ_T. This term represents the total volatility present in asset value process as a result of introducing the stochastic carbon rate.

A similar, yet more practically oriented, study is presented by Bell and van Vuuren (2022). In this study, price paths are simulated using a standard GBM; however, at various points in time, the asset value process is subjected to shocks of a certain magnitude. Similar to Kölbel et al. (2022) they incorporate climate risks through the asset value channel. In the end, the PDs for the shocked and unshocked paths are compared to assess the impact of climate risks. They distinguish between two types of shocks, representing physical and transition risks. Physical shocks not only reduce asset value but also increase the volatility of price paths after the shock to account for the uncertainty introduced by climate risks. This implies that physical climate risks are modelled to influence default risk not only through the asset value channel but also through the volatility channel. The study's findings indicate that firms with lower credit ratings are particularly vulnerable to climate risks. This vulnerability applies to both physical and transition risks. Future research could expand on their approach to test the robustness of these results. Additionally, a significant limitation of their work is the calibration of a specific climate event to an asset value shock and volatility adjustment. This is currently determined quite arbitrarily.

2.3.4 Debt Level Channel

To the best of our knowledge, there are no studies that incorporate the impact of climate risks on firm default risk, directly through the debt channel. However, several studies have an approach that has some association with the debt channel. These are discussed below. As mentioned, the debt channel influences the PD as a higher debt burden increases the likelihood of the assets ending up below the default level at maturity.

First, the approach presented in Bouchet and Le Guenedal (2020) is revisited. This approach introduces a shock, ξ^k on the assets, dependent on carbon costs. The study presents two approaches to transform carbon costs to a fractional shock. The first approach, divides the carbon costs under climate scenario k by the current value of the assets A_0. This is shown in (2.22). Alternatively, an approach is suggested in which the carbon costs are divided by the firm's earnings before interest, taxes, depreciation, and amortization (EBITDA):

$$\xi^k = \frac{CC^k}{EBITDA_0} \tag{2.32}$$

By adding this shock to the value process of the assets, a carbon price margin (CPM) can be calculated. The CPM is the maximum average emission price at which the company's PD does not exceed a certain threshold F:

$$CPM = \max\{CP : PD \leq F\} \tag{2.33}$$

Although the approach leverages parts of the asset channel, the CPM does involve the calibration of asset values using the climate-adjusted earnings and costs for the firm. Hence the touchpoints with the debt channel.

Recent work from Bourgey et al. (2024) focuses on modelling the optimal response of a firm in terms of production to announced climate policies. The goal is to align the CO_2 emissions of the company with a target trajectory. They present detailed proof for the optimization problem related to the optimal production levels of a firm. These production levels are used to compute the firm value process and obtain the PD:

$$PD = P(\hat{A} \leq L(t)) \tag{2.34}$$

In this framework, $\hat{A}$ represents the value of assets under an optimal production strategy aligned with a specific climate regulation. The function $L(t)$ is a deterministic representation of total liabilities at time t, which includes debt payments as well as labour and other operational costs. This highlights how both the debt channel and asset value channel are used to incorporate climate risks in the structural default model. Although detailing the definitions and proofs of these terms is beyond the scope of this research, the paper demonstrates how a default threshold, similar to that in Black and Cox (1976), can define default not only in terms of debt payments but also operational and capital expenses. Their model exclusively considers transition risks, but it can be extended to include physical risks. The findings indicate that stronger transition scenarios lead to higher default rates, particularly for emission-intensive firms. Similarly, Cormack et al. (2020) develops a range of economic models to calculate adjusted revenues and costs influenced by energy prices. These adjustments are then applied to modify the drift rate inputs of the Merton model, thereby examining the effects of transition risks on the PD. Again this highlights that the debt is never a standalone channel through which climate risks are incorporated in structural default models. To the best of our knowledge, the debt channel is always supported by the drift rate or asset value channels. An overview of all the aforementioned approaches can be found in Table 2.2.

Table 2.2: Incorporating Climate Risks Through the Channels in Merton's Model

Channel	**Climate Risk**	**Description**	**Method**	**Study**
Asset value	Physical	Exponential decay of asset values, based on exposure to nature degradation.	Theoretical shock on firm's balance sheet, based on vulnerability towards ecosystem.	Gallet et al. (2024)
	Physical	Add random shocks to the asset value process.	Add Poisson process to GBM with jump frequency and jump intensity based on firm-specific characteristics.	Kölbel et al. (2022)
	Transition	Direct shock to asset value based on carbon costs in a climate scenario.	Direct shock based on expected future growth of carbon prices and carbon regulation. Shocks are related to initial asset value.	Bouchet and Le Guenedal (2020)
	Transition	Extension of Bouchet and Le Guenedal (2020)	Stochasticity is included in the scenario definition to create more realistic model behaviour	Le Guenedal and Tankov (2022)

Table 2.2: Incorporating Climate Risks Through the Channels in Merton's Model (continued)

Channel	**Climate Risk**	**Description**	**Method**	**Study**
Asset value	Transition	Direct shock to asset value based on carbon taxes.	Calculate the NPV of carbon taxes, which is also influenced by the company's carbon reduction factor.	Schult et al. (2024)
Drift rate	Transition	Adjust growth value of the asset process, based on carbon rate.	Carbon rate is added similarly to dividends in Merton's model. It can be stochastic or scenario-dependent.	Blasberg et al. (2022)
	Transition	Create a shock based on carbon taxes for a segment and a set of vulnerabilities for a given segment	Stylised discounted cash flow model is used to add shock to drift channel	Reinders et al. (2023)
Asset volatility	Transition	The stochastic carbon rate of Blasberg et al. (2022) introduces an additional uncertainty component	A total volatility, σ_T is used in PD calculation. It reflects the combined asset and carbon rate volatilities	Blasberg et al. (2022)
	Physical & Transition	Add physical & transition shocks to the value process at pre-defined times.	Physical shocks increase the volatility of the asset price path, due to the uncertainty that comes with it.	Bell and van Vuuren (2022)
Debt level	Transition	The approach from Bouchet and Le Guenedal (2020) can be used to determine climate-adjusted earnings and costs.	Calculate carbon price margin (CPM) at which PD stays above a predetermined threshold. CPM is calculated using climate-adjusted EBITDA	Bouchet and Le Guenedal (2020)
	Transition	Model the optimal response of a firm in terms of production to announced climate policies.	Optimal production strategy in terms of climate-adjusted liabilities is modelled. Asset values are determined by the optimal production strategy.	Bourgey et al. (2024)
	Transition	Calculate adjusted revenues and costs influenced by energy prices	Use adjusted costs to adapt the drift rate to find adjusted PD	Cormack et al. (2020)

2.3.5 Model Risk

When extending structural default risk models, it is crucial to consider the potential for model risks, which are a subset of operational risks. Model risks can arise from two primary sources: the model itself may be flawed, or the model might be used incorrectly (Hull, 2018). Flaws in the model can occur due to incorrect assumptions, too much complexity, or improper calibration. For example, a model that does not accurately account for the impact of extreme weather events on a company's assets could underestimate the PD. On the other hand, even a well-designed model can lead to incorrect decision-making if its results are misinterpreted or applied in the wrong way. For example, using a model calibrated for one industry to assess risks in a completely different industry without necessary adjustments could lead to inappropriate risk mitigation.

Extending models to incorporate climate risks into structural default risk frameworks inherently increases their complexity. Thereby, the potential for model risk also rises. First, the increased complexity can cause the model to contain noise or be implemented incorrectly. Moreover, as models grow more complex, the challenge of accurately interpreting their results increases, leading to a higher risk of inappropriate use. Integrating climate risks into structural default risk models is a relatively novel and complex task, further complicated by the limited availability of reliable data. This motivates the importance of thoroughly evaluating model risks throughout the research process. It is important to recognise that increased complexity does not inherently lead to improved accuracy or reliability. Instead, a balanced approach is needed that considers both the robustness of the model and the clarity of its application.

2.4 Climate Risk Indicators

The final part of the literature review concentrates on climate risk indicators, which are numerical measures used to quantify climate risks. First, data used to measure physical risks is considered. Next, the focus is shifted towards transition risks. Following that, some light is shed on the widely used environmental, social, and governance (ESG) ratings. Within this section, the limitations and challenges that come forward when measuring climate risks are highlighted. Moreover, the different indicators that can be applied within various default risk channels are presented.

2.4.1 Physical Risk Indicators

A wide range of indicators is available to quantify the different types of physical climate risks, as extensively outlined by European Central Bank (2024). As previously mentioned, physical risks are typically divided into acute and chronic risks, with different measures applicable to each type. Since physical risks are inherently linked to specific geographical locations, factors to quantify such risks are also highly dependent on the physical location of assets or activities. Therefore, a bottom-up approach is commonly employed to assess these risks effectively.

Developing a physical risk indicator usually involves a structured, four-step process, which is illustrated in Figure 2.3. This method ensures that the details of location-specific vulnerabilities are adequately captured and integrated into the analysis. Numerous research institutes rely on climate models to obtain physical hazard data. For example, the IPCC provides models to estimate the number of consecutive dry days across 12.5 km^2 areas worldwide, while the Delft University of Technology models coastal and river floods with a resolution of 100 meters. Although the methodologies behind these measures differ, they all utilise historical data and are calibrated to align with predefined climate scenarios known as Representative Concentration Pathway (RCP) scenarios. These scenarios, adopted by the IPCC, project future GHG concentrations (Pörtner et al., 2019). From these projections, temperature increases are derived, which are then used to

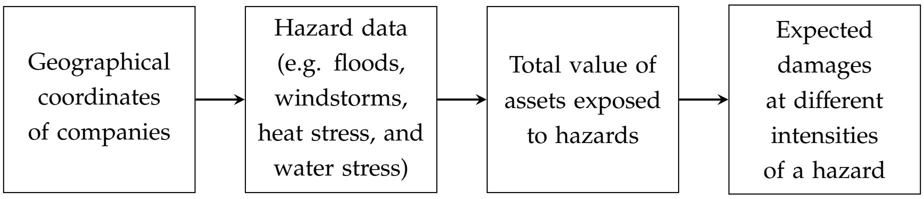

Figure 2.3: Bottom-up approach for developing physical risk indicators (European Central Bank, 2024)

model the likelihood and severity of physical hazards. These physical hazards can then form the basis for incorporating shocks in the asset value channel, to study their effect on default risk. Furthermore, they can be used to calculate adjusted asset volatilities to model default risks through the volatility channel.

When studying physical risks, understanding the specific RCP scenario on which the metric is based is essential. Additionally, analysing the effect of physical risks on financial risks can benefit from comparing the severity of outcomes across various RCP scenarios. While these standardised scenarios provide a framework for comparing different physical risk indicators, significant uncertainties and methodological differences remain. A comprehensive review of physical climate risk assessments (PCRA) highlights that there is no single, universally suitable approach that addresses all contexts (Attoh et al., 2022). Limitations in data availability and data quality are critical factors that must be carefully considered when conducting such analyses.

Below are examples of studies that use physical risk indicators to quantify the financial risks brought forward by physical climate risks. Gallet et al. (2024) use NACE codes to categorise the firms based on their main process. Based on that, the dependency of a firm on a certain ecosystem is determined through the ENCORE and EXIOBASE databases. Then, the ND-GAIN index is used to quantify the degree of nature degradation within a country. From there, the vulnerability of a firm towards a certain ecosystem degradation can be determined. This vulnerability is then used to obtain an adjusted price path of the assets of the firm to obtain an adjusted PD. Focusing more on acute physical risks, Nobletz (2024) uses historical US extreme weather events that exceeded $1 billion in losses from the NOAA NCEI climate disaster database. This database includes numerous statistics related to extreme weather events, including the estimated damage from the event, adjusted for CPI. This data is transformed into a monthly time series and used to study the effect on the US credit market. Their results indicate a significant increase in the corporate credit spread due to a natural disaster shock.

2.4.2 Transition Risk Indicators

As mentioned in Section 2.1, the primary driver of climate change is the increased GHG emissions from companies and the resulting temperature changes. Transition risks emerge from the shift towards a lower-emission economy, meaning that companies with substantial GHG emissions are most affected. These companies must either adapt their business models to reduce emissions or incur significant costs per ton of GHG emitted. Consequently, a company's GHG or carbon emissions are often used as a foundation for developing transition risk indicators (European Central Bank, 2024).

When assessing emissions, it is important to distinguish between the different Scopes of emission. According to the GHG Protocol, there are three Scopes to consider regarding a company's emissions (World Resources Institute, 2011). Scope 1 includes a firm's direct emissions. Scope 2 accounts for indirect emissions from the use of electricity and heat necessary for conducting business. Lastly, Scope 3 includes all other indirect emissions associated with a firm and its products, excluding those covered under Scope 2. This includes emissions from suppliers and customers who use the products. An illustration of these Scopes is provided in Figure 2.4.

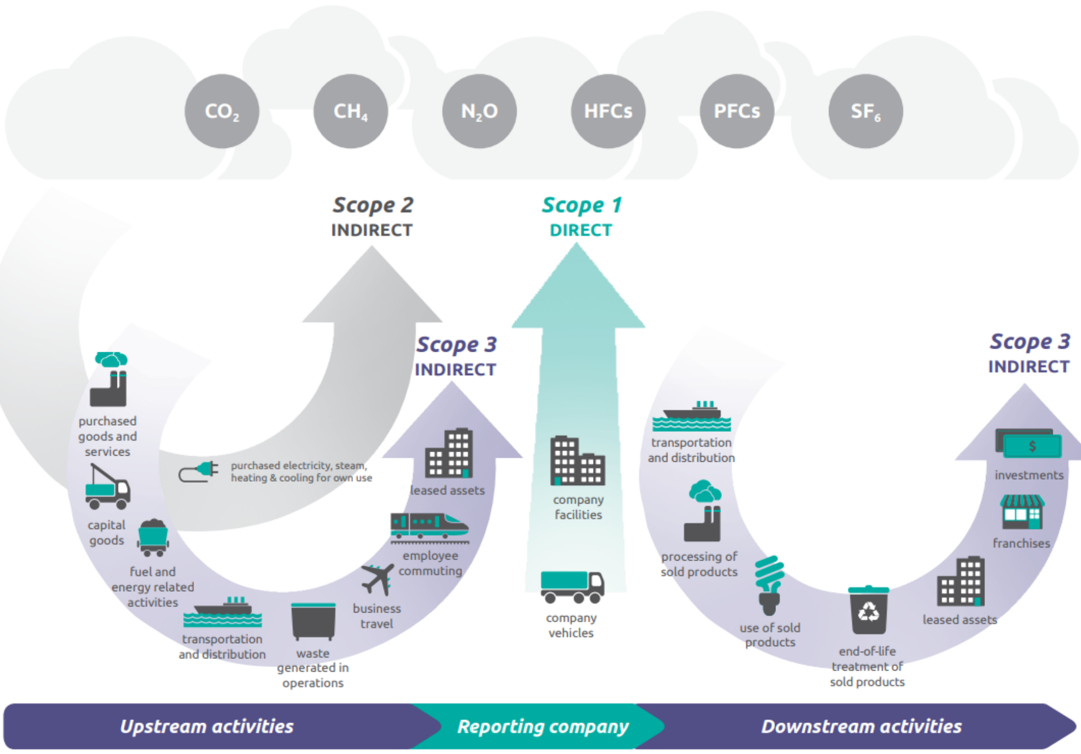

Figure 2.4: Scope 1, 2, and 3 emissions (World Resources Institute, 2011)

Measuring the emissions of a company can be challenging and there is currently a lack of publicly available GHG data with proper granularity (European Central Bank, 2024). Often, GHG emissions are not considered directly, instead GHG emissions are used to calculate various transition risk indicators. Examples are the financed emissions (FE) and weighted average carbon intensity (WACI) (Berkhout et al., 2024). The FE of an investor is the total GHG emissions of a company weighted by the share of the investment over the total company value. Suppose an investor i, has a holding $H_{i,c}$ in company c. Moreover, the value and GHG emissions of company c are denoted by V_c and E_c respectively. Then, the financed emissions can be defined as

$$FE_{i,c} = \frac{H_{i,c}}{V_c} \cdot E_c \tag{2.35}$$

The FE can then for example be used to measure the regulatory costs an investor faces from financing emissions. Comparing the FE can be hard when looking at different sectors or financial institutions with very different portfolio sizes. Therefore, the WACI can be used. First, the carbon intensity (CI) of a company is calculated. This is the GHG emissions per million dollars in revenues, R_c. Afterwards, these are weighted by their holding size in the portfolio of the financial institution. The CI and WACI are defined as

$$CI_c = \frac{E_c}{R_c} \tag{2.36}$$

and

$$WACI_{i,c} = \sum_c \frac{H_{i,c}}{\sum_c H_{i,c}} \cdot CI_c \tag{2.37}$$

Multiple data suppliers provide these metrics and one can again decide whether Scope 1, 2, 3, or combination of emissions is used to measure the FE and WACI.

In addition to physical climate risk scenarios, transition scenarios also exist, outlining expected costs for emissions. Le Guenedal and Tankov (2022) uses Scope 1 emissions data from the S&P Trucost data provider, combined with company financials, to calculate a firm's CI. They then estimate the total emission costs of a company based on its business activities in a specific region and the carbon costs outlined in an IPCC scenario. Other studies, such as Capasso et al. (2020), simply use raw Scope 1 emission data to explore its relationship with default risk.

Together with the pre-defined scenarios, transition risk indicators can be used within several channels to allow for the incorporation of climate risks in structural default models. Generally, transition risks are not modelled as shocks in the asset value channel directly, but more focus is put on quantifying them through the asset growth or asset volatility channels. In this way, the effect of climate risks are modelled over a more long-term period, which is expected for transition risks.

As previously mentioned, transition risks can affect financial risk in several other ways, such as through a lack of technological innovation or reputation risks. Often, proxies are used to quantify such transition risks. Vasileva et al. (2024) employs the RepRisk database to compile a list of corporate scandals from 2011 to 2022. This database includes records of various risk events reported in the media, each with an associated severity score. In Gutiérrez-López et al. (2022), the impact of transition risks on DD is assessed using measures such as company innovation, proxied by Research & Development expenditures and the number of patents submitted by the company. As can be seen, researchers employ creative methods to quantify transition risks.

2.4.3 Environmental, Social, and Governance (ESG) Ratings

A widely recognised measure for assessing a company's sustainability performance is the ESG rating. These ratings provide numerical evaluations of a company's performance in areas such as environmental sustainability, human resource practices, business ethics, and corporate governance. They are typically offered as aggregate measures by commercial rating agencies like Standard & Poor's and Moody's. In addition to the overall score, individual scores for the E, S, and G pillars are often available.

Numerous studies have studied the relationship between ESG performance and creditworthiness (Atif & Ali, 2021; Jung et al., 2018). Additionally, Henisz and McGlinch (2019) argue that companies with strong ESG performance, particularly regarding climate risks, tend to be involved in fewer low-probability adverse events. Furthermore, De Giuli et al. (2023) conducted a comprehensive review of over 550 papers published between 1983 and 2022, exploring the intersection of ESG and risk from a financial perspective. Their findings indicate that the relationship between ESG performance and financial risks is gaining increasing importance in the literature. Many of the top-cited papers in their review directly examine the connection between ESG ratings and financial risks or performance.

Despite their popularity, ESG ratings are far from being criticised. The well-known work of Berg et al. (2022) compares ESG ratings from six prominent ESG rating agencies. They show that correlation between the ESG ratings from these agencies range from 0.38 to 0.71. This disagreement can make it hard to evaluate ESG performance of companies. Moreover, companies receive mixed signals from rating agencies, making it hard to truly become more sustainable. Their results show that the divergence between the ESG ratings is mainly driven by measurement divergence. This means that agencies measure their ratings differently and that they fundamentally disagree on the underlying data. Several categories are particularly sensitive to this measurement divergence, of which climate risk management and environmental management are two. Finally, they find support for the so-called rater effect. This means that a company scoring good on one category is likely to get a good score from that rater on other categories as well.

The aforementioned limitations and inherent lack of transparency in the methodology behind the constitution of an ESG-rating, have led to the exclusion of these ratings as input data for the experiments in this research.

2.5 Conclusion

The aim of this literature review was to provide a solid theoretical background on (1) climate change and the financial risks this brings forward; (2) structural default risk models and the underlying channels that influence the probability of default; (3) the default channels through which climate risks can be incorporated in structural default risk models; and (4) the data and variables often used to measure climate risks. Hence this literature review addresses the first four RQs of this research.

It is shown that climate risks can be divided in physical and transition risks. Both can have a large potential impact on financial risks, especially firm default risk. This impact is made through various channels. Moreover, the increasing severity of climate change makes proper climate risk management even more required.

A comprehensive theoretical background is provided of the Merton model. This is the first structural default risk model and serves as a basis for the numerous extensions that were introduced in later years. This theoretical background is used to identify five channels through which default risk is influenced within the Merton model. These are the asset value, drift rate, volatility, debt, and time horizon channels. Merton's model, including its main assumption of risk-neutral PDs are used for the remainder of this research.

Four out of the five default channels were found to be used to incorporate climate risks in structural default risk models. Within each channel, several different approaches can be taken, depending on the type of climate risk that is addressed.

Finally, common climate risk indicators for both physical and transition risks are discussed. A wide range of physical risk indicators exist, depending on what physical risks need to be quantified. Transition risks usually take GHG emissions as a basis for their analysis. Both physical and transition risk indicators depend a lot on various climate scenarios that make projects of changes in temperature and carbon costs. ESG ratings are also discussed, but due to their limitations they are disregarded for the rest of this research.

Chapter 3

Methodology

Building on the previous works discussed in Section 2.3, this chapter focuses on adapting the asset value channel within Merton's framework to reflect climate-related vulnerabilities. The goal is to provide an answer to RQ5: "How can an extended structural default risk model be implemented in a case study?". This chapter starts by motivating the choice for the asset value channel. Afterwards, the implementation of the regular Merton model is presented in the context of the case study. A step-by-step outline of defining and implementing the climate-adjusted asset value channel, is then provided. Finally, the criteria for evaluating the model implementation are highlighted. These criteria help in determining whether the model implementation is valid and robust.

The outcomes of this chapter form the foundation for the remainder of the research. This chapter establishes the theoretical framework required to develop the model extension, prepare the data, and evaluate the model. The following chapters present the relevant summary statistics of the data and the actual results of the model implementation within the case study.

3.1 Adapting the Asset Value Channel

In Section 2.2.3, five distinct channels through which the PD is influenced within Merton's model are distinguished. As shown in Table 2.2, four of these channels have been adapted in existing literature to incorporate climate risks. This research will primarily focus on one of these four channels: the asset value channel.

The asset value channel is the most prominent and direct channel in Merton's model. The PD represents the likelihood of a company's asset value falling below a certain threshold. This relation is highlighted in Figure 2.2. It shows how any adjustment to the asset value directly influences the value of the asset value process at the time horizon. This in turn has a direct effect on the PD. One advantage of the asset value channel is its flexibility in incorporating climate risks. Two approaches can be distinguished. The first involves introducing a direct shock to the asset value on the current day, meaning A_0 is shocked. The second approach leaves A_0 untouched but modifies the asset value process between A_0 and the time horizon at which default is assessed. Figure 3.1 provides a visual representation of these two methods. Within each approach, numerous assumptions, modelling decisions, and variables can be customised to reflect climate risks as realistically as possible. For example, introducing a direct shock to A_0 corresponds to shifting the asset value distribution at the time horizon, which in turn adjusts the PD. The shock can, for example, reflect a sudden exposure to extreme weather events or a competitor entering the market with a greener alternative. As shown in Section 2.3.1, the size of the shock is often made firm dependent. Alternatively, adapting the asset value process can lead to various changes in the asset value distribution at the time horizon. Like the shock on A_0 the distribution can be shifted, but it is also possible that the actual distribution is changed. In the figure, for example, shocks are introduced to the asset value process, which results in a skewed distribution. Note that this is illustrative, as it is often highly complex to derive an analytical definition of the asset value distribution resulting from changes to the asset value process. Section 3.3 elaborates on the approach presented in this research and its effect on the PD.

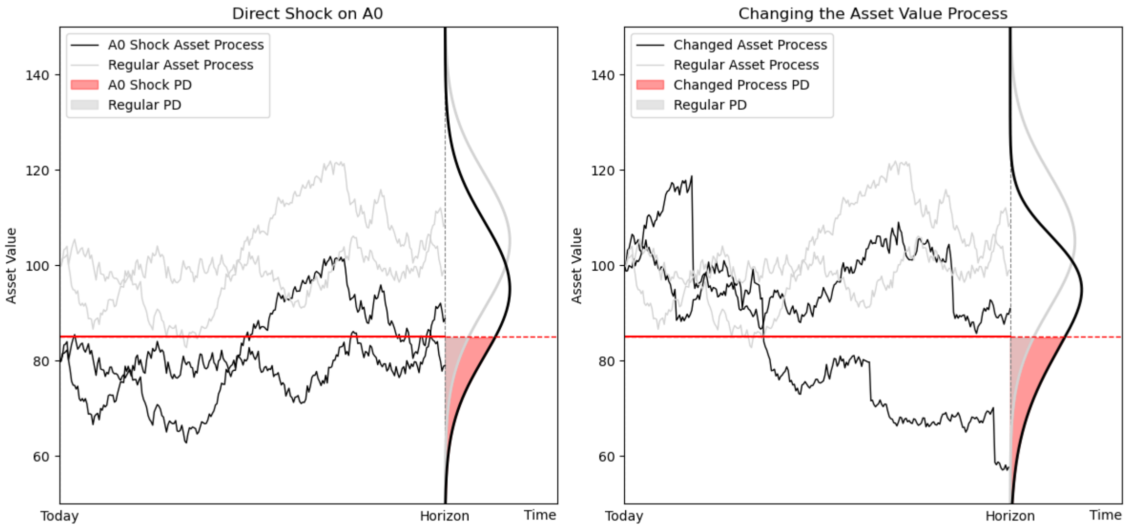

Figure 3.1: Different methods to adapt the asset value channel (shaded areas correspond to PD)

This research focuses on transition risks. As shown in Table 2.2, existing literature has integrated these risks into the asset value channel by adding a (stochastic) direct linear shock to A_0. This means the actual asset value process is not altered. Directly shocking A_0 treats climate risks exogenously and and does not consider them as inherent risks present in the model. As a result, this research incorporates transition risks by modifying the actual asset value process. This approach treats climate risks endogenously, meaning transition risks are an inherent part of the model. Moreover, the novelty of incorporating transition risks using this approach, highlights the academic relevance of the research. In addition to academic relevance, the focus is influenced by the available data. Scope 1, 2, and 3 emissions for all companies in the portfolio enable the creation of a range of transition risk measures. Section 3.3.2 defines the transition risk measure used in the adapted asset value channel.

Transition risks can have numerous effects on the asset value of a firm. Some of these effects were already discussed in Section 2.1, but the most important ones are repeated here because the effects can now be put in the context of Figure 3.1. First, transition risks affect companies by causing their carbon intensive assets to become less valuable or obsolete, also known as stranded assets. Additionally, increased costs due to carbon taxes reduce profitability. Transition risks also introduce reputation risks, where customers become less inclined to engage with the company, potentially resulting in reduced sales. Similarly, competitors that transition more quickly may enter the market with greener alternatives, drawing customers away. These factors either directly affect the asset value of the company or influence its profitability and revenue. Since Merton's model does not include variables corresponding to profitability and revenue, the objective is to quantify these factors through the asset value channel. This approach is motivated by the dependence of asset values on the profits and revenue generated by the assets. Consequently, companies more exposed to transition risks, like companies with higher carbon emissions, are expected to have lower asset values. As a result, these companies are expected to have a higher PD when transition risks are considered, compared to a regular PD.

3.2 Implementation of Merton's Model

This section details the initial phase of the model implementation used in this research, focusing on the application of the standard Merton model with real-world data from PGGM's corporate bond portfolio. The objective is to determine the 1-year PD for each firm within this portfolio. The PD is calculated using the following formula:

$$PD = \Phi\left(-\frac{\ln(\frac{A}{D}) + (r - \frac{1}{2}\sigma_A^2)T}{\sigma_A\sqrt{T}}\right)$$

Although this formula is provided in (2.15), it is restated here for convenience. The method behind each component of this formula will be explained to accurately calculate the PD for the firms in the portfolio using real-world data. This includes detailing how to derive proper values for each variable while addressing the complexities of working with real-world data. Due to the inherent imperfections in real-world data, certain assumptions and simplifications must be made. A comprehensive summary of all terms and their methods of calculation is presented in Table 3.2.

3.2.1 Firm-Independent Variables

The analysis begins with the two most straightforward terms of this formula: T and $\Phi(\cdot)$. These terms are straightforward because their values are independent of the individual firm that is considered. First, T represents the time period for which the PD is calculated. In this research, a 1-year time frame is considered unless otherwise specified, so $T = 1$. Second, $\Phi(\cdot)$ denotes the standard normal cumulative distribution function (CDF), which is the integral over the standard normal probability density function (PDF).

$$\Phi(x) = P(X \leq x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{x} e^{-\frac{1}{2}u^2} du \tag{3.1}$$

Here X is a standard normal distributed random variable. Figure 3.2 shows the standard normal PDF and the areas corresponding to an area of $\Phi(0) = 0.5$ and $\Phi(1.96) = 0.975$.

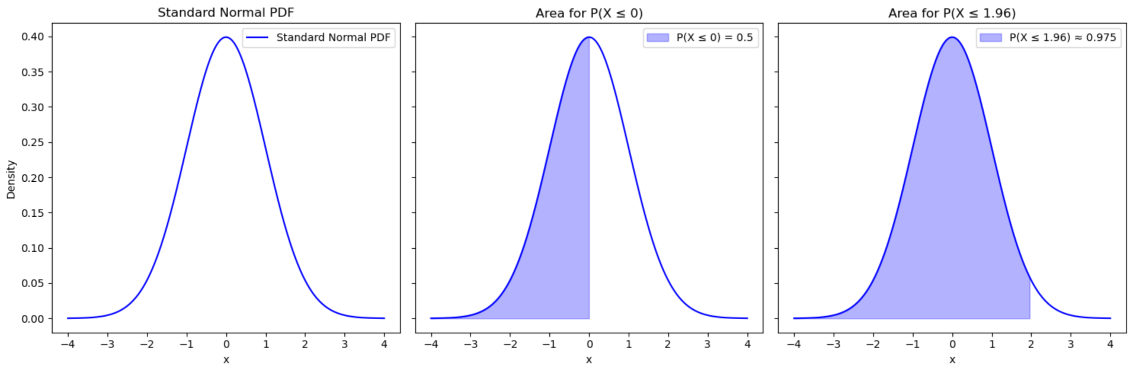

Figure 3.2: Normal PDF with shaded areas corresponding to $\Phi(0)$ and $\Phi(1.96)$

3.2.2 Firm-Dependent Variables

This section explores the firm-dependent variables, which are slightly more complex to determine when dealing with real-world firms. This complexity arises because certain assumptions cannot be made, some data points are unobservable and market-dependent, and data must be gathered from various sources to ensure the model's realism. This last point is discussed further in Section 4.1.

The first firm-dependent term discussed is r, the risk-free rate. Applying a uniform risk-free rate across all companies would be an oversimplification because companies operate in different regions and rely on various currencies. The yield on government securities is often used as a proxy for the risk-free rate. This is because government securities are seen as investments that are closest to being risk-free. In this research, the yield on 1-year government bonds serves as the proxy for the risk-free rates. This choice aligns with the 1-year period for which the PD is calculated. Furthermore, the country from which the 1-year government bond is selected, depends on the currency in which the company reports its financials. A company's financial documents, such as balance sheets and income statements, provide significant insights into its operations. Therefore, the currency of these financial statements is most closely related to the company's operations. Hence, the risk-free rate is chosen based on the country associated with this currency. For instance, a company that reports its financials in Turkish Lira will have a risk-free rate corresponding to the yield on 1-year Turkish government bonds. It is important to note that this approach could result in a risk-free rate that is not actually risk-free. This is especially the case for government bonds from countries with varying levels of economic stability. Nonetheless, the method is justified as it aligns the risk-free rate with a company's specific context. Selecting a risk-free rate from a more economically stable country could potentially lead to an underestimation of the actual risk associated with the firm's financial environment.

Next, the debt level of the company is studied. This is a crucial factor in calculating the PD of a firm, as it establishes the threshold at which default is considered. According to Crosbie and Bohn (2002), a method to determine an appropriate default threshold is a mixture of the short and long term debt obligations of the company:

$$D = \text{Short term debt} + k \cdot \text{Long term debt} \tag{3.2}$$

Here, k is a constant typically set at 0.5. The motivation behind this choice of default threshold is that a firm should always be able to meet its short-term debt obligations. Nevertheless, it would be unreasonable to expect a firm to fulfil all long-term debt obligations, especially when considering a 1-year time period. Therefore, only 50% of the long-term debt is often considered, which is the approach adopted in this research. It is possible to adopt a more risk-averse approach by increasing the value of k, resulting in an earlier default and a stricter evaluation of a company. Conversely, lower values of k would have the opposite effect. Note that the value of k has a significant effect on determining the PD, potentially biasing the results towards the chosen value of k. Consequently, the research adheres to a value of k that is perceived as an industry standard. The potential bias caused by k is discussed further in Chapter 6.

Since the 1-year PD is calculated, it is necessary to estimate the default threshold for one year. To achieve this, the average historical year-over-year change in D for each company is calculated and used to project the default threshold one year into the future. The resulting value is then used for D in the PD calculations.

The two remaining firm-specific terms, A and σ_A, require a more sophisticated approach to be determined. This is because the balance sheets cannot be simply referenced to obtain the asset value and asset volatility. First, daily asset values are required, however, company financials are published only once a year. Simply interpolating between annual asset values fails to accurately reflect how the market values the assets. Moreover, it would lead to incorrect asset volatility estimations. Second, the equity value derived from Merton's model should equal the equity value observed in the market. This alignment is not achieved when directly using the book value of the assets. Instead the daily market implied value of assets (MIVA) of the firm must be calculated. Once the MIVA is calculated, its standard deviation can be obtained and used to define σ_A.

Although the MIVA is unobservable, it can be derived using the market value of equity and the book value of debt. Since only publicly traded firms are considered, both the market value of equity and the book value of debt are known. This allows for the establishment of an algorithm to iteratively find the MIVA and its volatility. This approach aligns with the methodologies outlined in (Bharath & Shumway, 2008; Crosbie & Bohn, 2002; Vassalou & Xing, 2004). The final algorithm developed to obtain the MIVA and the corresponding σ_A is presented in Appendix B.

First, a complete financial year of historical equity values of the company is considered, specifically the most recent closed financial year. This period is chosen because it allows for the utilization of other financial values from the company's balance sheets, making the analysis more consistent. Selecting a complete financial year ensures that the values at the beginning and end of the year are known, as annual reports are published at these dates, providing certainty regarding several required items in the financial statements. The observed equity value of a company on day t is denoted as E_t^{obs}. For the companies in the portfolio, this value is calculated as follows:

$$E_t^{obs} = \text{Share price on day } t \cdot \#\,\text{Outstanding shares on day } t \tag{3.3}$$

Second, the default threshold for each day t within the chosen financial year is determined by interpolating between the observed default thresholds at the beginning and end of the financial year. Since the analysis uses the most recent completed financial year, the exact default thresholds at the beginning and end of this year, denoted as D_0 and D_τ respectively, can be observed when the balance sheets are published. More details on this process are provided in Section 4.1. As daily default thresholds cannot be directly observed, interpolation between D_0 and D_τ is necessary. Therefore, on day t, the value of the default threshold, D_t, is defined as

$$D_t = D_0 + t \cdot \frac{D_\tau - D_0}{\tau - 1} \quad \text{for } t \in \{1, 2, \dots, \tau - 1\} \tag{3.4}$$

Note that τ corresponds to the number of days in the year. On average $\tau = 252$, as only trading days are considered.

The above quantities are used to iteratively estimate the MIVA of the firm. This is done using the result from Merton stated in (2.13) and (2.14). For convenience, the formulas are repeated below with subscripts t added to indicate that Merton's equity value is being calculated on day t:

$$E_t^{Merton} = A_t \cdot \Phi(d_{1,t}) - e^{-rT} D_t \cdot \Phi(d_{2,t})$$

where,

$$d_{1,t} = \frac{\ln(\frac{A_t}{D_t}) + (r + \frac{1}{2}\sigma_A^2)T}{\sigma_A \sqrt{T}}, \qquad d_{2,t} = \frac{\ln(\frac{A_t}{D_t}) + (r - \frac{1}{2}\sigma_A^2)T}{\sigma_A \sqrt{T}} = d_{1,t} - \sigma_A \sqrt{T}$$

All variables in these equations are known, except for A and σ_A. As an initial approximation, $\sigma_A = \sigma_E$ is assumed, where σ_E is the equity return volatility. Equity returns are calculated by taking the fractional difference between two consecutive equity values:

$$R_t^E = \frac{E_t^{obs} - E_{t-1}^{obs}}{E_{t-1}^{obs}} \tag{3.5}$$

which can be used to calculate the equity returns volatility:

$$\sigma_E = \sqrt{\frac{1}{\tau}\sum_{i=0}^{\tau}(R_t^E - \mu_E)^2} \cdot \sqrt{\tau} \tag{3.6}$$

Here μ_R is the average of the observed equity returns during the year that is considered. Furthermore, τ represents the number of trading days in the year. Multiplying by the square root of τ translates the daily volatility to yearly volatility. The goal is to find the daily MIVAs, A_t, for which $E_t^{Merton} = E_t^{obs}$. This can be rewritten as a mathematical minimization problem:

$$MIVA_t = \arg\min_{A_t} |E_t^{Merton} - E_t^{obs}| \quad \forall t \in \{0, 1, \dots, \tau\} \tag{3.7}$$

This problem is addressed using a solver in python. Once all A_t are found, σ_A is updated using (3.6). In this update, R_t^A and μ_A are used instead of R_t^E and μ_E. The updated value of σ_A, will result in a different value for E^{Merton} if all other variables are kept the same. Consequently, it is necessary to solve (3.7) again and obtain new values for A_t, given the updated value of σ_A. This new set of daily MIVAs leads to an adjusted value for σ_A. These steps are repeated until σ_A converges within a specified tolerance level. In this research, convergence is achieved when the change between two consecutive values of σ_A is less than or equal to $1 \cdot 10^{-5}$.

It is important to note that, using the above algorithm, an estimate for the drift rate of the assets can also be obtained. This is because a year of daily asset values is estimated, allowing the calculation of the associated drift rate of this time series. This drift rate could potentially replace the risk-free rate to obtain real-world PDs. That said, as stated in Section 2.2, this research sticks to the risk-neutral assumption and because of that the drift rate estimate for the assets is not of interest. Furthermore, Jessen and Lando (2015) found that this drift rate often exhibits a large standard deviation, which is why it is rarely used in empirical studies.

After performing an initial empirical validation of the model, there were quite some firms for which the minimization problem of (3.7) gave unstable results. The solution found by the algorithm gave a set of MIVAs for which the daily return between two consecutive asset values exceeded 1500%. To overcome this, a regularization term was added to the objective function. This means equation (3.7) got adjusted to

$$MIVA_t = \underset{A_t|A_{t-1}}{\arg\min} |E_t^{Merton} - E_t^{obs}| + 0.01 \cdot |A_t - A_{t-1}| \quad \forall t \in \{0, 1, \ldots, \tau\} \tag{3.8}$$

The additional term functions as a penalty. The greater the difference between two consecutive asset values, the larger the penalty, moving the solution further away from minimization. Regularization is a well-known technique in regression, typically used to keep coefficients small and reduce overfitting. This approach has been slightly adapted, as favouring small coefficients could result in asset values approaching zero, which is unrealistic. It is important to note that the larger the scaling parameter in front of the regularization term, the stronger the regularization becomes and the larger the penalty for differences in consecutive asset values. There is generally no single best value for the scaling parameter and it is very dependent on the characteristics of the problem. In this research, it is set at 0.01. After making some adjustments, this value was found to provide the best results. This is because (1) it gave identical results for firms that were already properly converging when using the minimization definition in equation (3.7) and (2) it enabled proper convergence for the few firms that did not initially converge using the minimization problem of equation (3.7).

After determining all values of A_t for which the minimization problem in equation (3.8) is solved and σ_A has converged, all the necessary terms to calculate the 1-year PD are available. To proceed, the final day of the financial year discussed earlier is treated as the present for calculating the 1-year PD. Therefore, the MIVA on this final day, A_τ, and the corresponding σ_A are used. Additionally, the risk-free rate associated with the company's country is taken, along with the default threshold extrapolated one year ahead, denoted as $D_{\tau+1}$. Finally, T is set to 1, and the PD can be calculated as follows:

$$PD_\tau = \Phi\left(-\frac{\ln(\frac{A_\tau}{D_{\tau+1}}) + (r - \frac{1}{2}\sigma_A^2)}{\sigma_A}\right) \tag{3.9}$$

To illustrate the PD calculation, a numerical example is given below, using the values stated in Table 3.1:

$$PD = \Phi\left(-\frac{\ln(\frac{12{,}322{,}276{,}630}{7{,}562{,}849{,}426}) + (0.045 - \frac{1}{2} \cdot 0.2363^2)}{0.2363}\right) \approx \Phi(-2.1376) \approx 0.01627 = 1.627\%$$

Table 3.1: Variables Obtained Through the Iterative Algorithm

Variable	Value
r	4.5%
$D_{\tau+1}$	€7,562,849,426
A_τ	€12,322,276,630
σ_A	23.63%

The table below summarises the different terms, used to calculate the PD and how each term is obtained in this research.

Table 3.2: Methods to Obtain Required Variables of Merton's Model

Variable	Description	Method
$\Phi(\cdot)$	Standard normal CDF	Not firm-specific.
T	Time period	Only 1-year PDs are considered, meaning $T = 1$.
r	Risk-free rate	1-year government bond yield corresponding to the country of the currency in which the financials are reported.
$D_{\tau+1}$	Default threshold	1-year extrapolated default threshold, using historical default threshold drift.
A_τ	Market value of assets at the date from which the 1-year PD is calculated.	Found through iteratively applying the minimization problem stated in (3.8).
σ_A	Yearly volatility of returns on market value of assets	Calculated by applying (3.6) on the final iteration of the MIVA.

3.3 Incorporation of Climate Risk

Having explained the procedure for obtaining the necessary input parameters to calculate the 1-year Merton PD, this section will discuss the adjustment introduced to account for climate risks within this procedure.

It is important to note that the climate adjustment is applied after determining the MIVA. This means no climate adjustment is made within the MIVA algorithm, presented in Appendix B. The rationale behind this approach is is based on the assumption that market participants are not yet explicitly modelling climate risks. Therefore, the climate adjustment relies on the MIVA derived from the standard Merton model. Again, this MIVA serves the starting point from which the climate-adjusted PD is calculated.

3.3.1 Merton's Jump Diffusion Model

As shown previously, climate risks are often introduced as shocks to the asset value. Either a direct climate-related shock is introduced, or adjustments to the actual asset value process are introduced to allow for shocks. From an economical perspective adjusting the actual asset value process makes sense. Climate risks are known for having an uncertain nature. This means there is no certainty in the frequency and severity of climate-related risks. Consequently, this also holds for the climate policies that are needed to mitigate the climate risks. The sudden introduction of a carbon tax for example could lead to a direct impact on the value of the assets. Moreover, the uncertain nature could lead to an immediate revaluation of the assets by investors, as motivated in the scenario analysis of European Central Bank (2023). In addition, the size and frequency in which carbon taxes are introduced are not known beforehand and could be spread out over time. Finally, competitors transitioning faster could lead to certain assets becoming obsolete. For instance, a knowledge gap could exist that accelerates the rate at which the assets of late-transitioning firms become stranded (Bos & Gupta, 2019). To address the inherent uncertainty regarding the impact of climate risks on asset values, using an approach that adds stochastic shocks to the asset value process, could be a suitable strategy.

A well-known model that allows for shocks in the asset value process is the jump diffusion model introduced in Merton (1976). This model originally served as an extension to the GBM followed by the stock price in the Black-Scholes option pricing model. In Merton (1976) an analytical formula for the price of an option when the stock price follows an adjusted GBM is provided. It is the first analytical formula for the price of an option when the underlying stock price follows a discontinuous price path. This means there are certain points in time in which the stock price path experiences a shock. The original goal of this extension is to achieve better alignment between model outcomes and empirical observations. Several studies suggested that investors tend to overreact on good or bad news, leading to shocks in the value process. This section introduces Merton's jump diffusion model and derives the definition of the PD under the model dynamics. In explaining the jump diffusion Jumbe and Gor (2022b), Matsuda (2004), and Merton (1976) served as a basis.

As stated in (2.10), the stock price in the regular Black-Scholes model follows the GBM

$$dS = rS \cdot dt + \sigma S \cdot dz$$

which corresponds to

$$\frac{dS}{S} = r \cdot dt + \sigma \cdot dz \tag{3.10}$$

The goal is to add jumps to the process in a way so that in small time interval dt, the stock price jumps from S to yS. In case a jump occurs, the change $\frac{dS}{S}$ is modelled as

$$\frac{dS}{S} = \frac{yS - S}{S} = y - 1 \tag{3.11}$$

Jump sizes y are sampled from random variable Y, which is assumed to be log-normally distributed with parameters m and s. Therefore

$$Y = e^X \quad \text{, where} \quad X \sim N(m, s^2)$$

Note that it is possible to assume different distributions for the jump sizes. However, Merton demonstrated that, when assuming a log-normal distribution along with several other conditions, it becomes possible to analytically define the price of a call option on a stock following a jump diffusion process. To do so, the number of jumps during the observed period is modelled as a Poisson process N with intensity λ. Here intensity is the expected number of jumps per unit of time. This Poisson process can be added to the GBM as follows:

$$\frac{dS}{S} = (r - \lambda k) \cdot dt + \sigma \cdot dz + d\sum_{n=1}^{N}(Y_n - 1) \tag{3.12}$$

It is important to note that all uncertainty components dz, Y, and N are assumed to be independent. Besides adding the compound Poisson process to the GBM, the drift term in (3.12) is also adjusted, by adding $-\lambda k$. The reason for this is that the jump process also has an expected value that can be calculated as follows:

$$\begin{aligned}
\mathbb{E}\left[d\sum_{n=1}^{N}(Y_n-1)\right] &= \mathbb{E}[(Y_1-1)+(Y_2-1)+\cdots+(Y_N-1)] \\
&= \mathbb{E}[N]\cdot\mathbb{E}[Y-1] \\
&= \mathbb{E}[N]\cdot(\mathbb{E}[Y]-1) \\
&= \lambda dt\cdot\left(\exp\left(m+\frac{1}{2}s^2\right)-1\right) \\
&= \lambda\cdot\left(\exp\left(m+\frac{1}{2}s^2\right)-1\right)\cdot dt \\
&= \lambda k\cdot dt
\end{aligned} \tag{3.13}$$

where

$$k=\mathbb{E}[Y-1]=\exp\left(m+\frac{1}{2}s^2\right)-1 \tag{3.14}$$

By subtracting the expected value of the jump process $\lambda k\cdot dt$ from the drift rate, the expected change in stock price still equals $r\cdot dt$, meaning it stays risk-neutral. This is shown below:

$$\begin{aligned}
\mathbb{E}\left[\frac{dS}{S}\right] &= \mathbb{E}\left[(r-\lambda k)\cdot dt+\sigma\cdot dz+d\sum_{n=1}^{N}(Y_n-1)\right] \\
&= \mathbb{E}[(r-\lambda k)\cdot dt]+\mathbb{E}[\sigma\cdot dz]+\mathbb{E}\left[d\sum_{n=1}^{N}(Y_n-1)\right] \\
&= r\cdot dt-\lambda k\cdot dt+\sigma\cdot 0+\lambda k\cdot dt \\
&= r\cdot dt
\end{aligned}$$

Now that the stock price dynamics under the jump diffusion model are defined, it is possible to derive the jump diffusion counterpart of the standard Black-Scholes PDE. As in the original Black-Scholes model a no-arbitrage assumption is made, which lies at the basis of the risk-neutral world. Moreover, shocks are assumed to be idiosyncratic, meaning they are completely uncorrelated with market behaviour. The capital asset pricing model (CAPM) refers to such events as zero-beta events, indicating that they can be diversified away. As a result, investors require no additional returns for an investment that experiences shocks in the underlying value process. This justifies the use of the risk-neutral assumption in the jump diffusion model. Therefore, the risk-neutral assumption in the jump diffusion model follows from both the no-arbitrage and zero-beta assumptions. Like in (2.5), a portfolio consisting of buying one option C and shorting $\frac{\partial C}{\partial S}$ shares is created to derive the jump diffusion PDE. In Matsuda (2004) the following relation is stated:

$$\frac{\partial C}{\partial t}+rS\frac{\partial C}{\partial S}+\frac{1}{2}\sigma^2S^2\frac{\partial^2 C}{\partial S^2}+\lambda\mathbb{E}[C_{yS}-C_S]-\lambda S\frac{\partial C}{\partial S}\mathbb{E}[Y-1]=rC \tag{3.15}$$

Here $\mathbb{E}[C_{yS}-C_S]$ is the expected difference in option value when a shock occurs. It is important to see that when jumps cannot occur (i.e. $\lambda=0$), the jump diffusion PDE reduces to the standard Black-Scholes PDE from (2.9).

As mentioned earlier, one of the assumptions required for obtaining the analytical price of a European call option on a stock that follows a jump diffusion process, is the log-normal distribution of jump sizes Y. This assumption, together with the previously mentioned no-arbitrage and zero-beta assumptions, will be discussed further in Chapter 6. Although a detailed derivation of the analytical formula for the price of a European call option is beyond the scope of this research, its existence enables the transformation of the problem into a setting where asset values follow a jump diffusion process and equity is represented as a call option on the assets and the company's debt. From this perspective, the PD can be defined similar to the regular Merton model. The PD for assets following a jump diffusion process is denoted as PD^*. Following Blasberg and Kiesel (2024) and Matsuda (2004), PD^* is defined as

$$PD^* = \sum_{i=0}^{\infty} \underbrace{e^{-\bar{\lambda}T} \cdot \frac{(\bar{\lambda}T)^i}{i!}}_{\text{P}(i \text{ jumps})} \cdot \underbrace{\Phi(-d_2^i)}_{\text{PD if } i \text{ jumps}} \tag{3.16}$$

where

$$\bar{\lambda} = \lambda(1+k) = \lambda(1 + e^{m+\frac{1}{2}s^2} - 1) = \lambda e^{m+\frac{1}{2}s^2} \tag{3.17}$$

and

$$d_2^i = \frac{\ln(\frac{A}{D}) + (r_i - \frac{1}{2}\sigma_i^2)T}{\sigma_i\sqrt{T}} \tag{3.18}$$

with

$$r_i = r - \lambda k + \frac{i\ln(1+k)}{T} \tag{3.19}$$

$$\sigma_i = \sqrt{\sigma_A^2 + \frac{is^2}{T}} \tag{3.20}$$

Intuitively, PD^* can be seen as the sum of the PD for all $i \in \{0, 1, \ldots, \infty\}$, weighted by the probability of i jumps occurring. In the implementation, summing till infinity is infeasible. Consequently, the summation is stopped when PD^* is not increased by $1 \cdot 10^{-5}$, as increases beyond this point are regarded negligible. This will happen eventually, because the likelihood of observing i jumps becomes infinitesimal for large i and $\Phi(-d_2^i)$ has an upper bound at 1 as it reflects a probability. The expression of d_2^i can be simplified further to show $\lambda = 0$ causes PD^* to reduce back to the standard Merton PD from (2.15). This relation is stated in other research, but to the best of our knowledge, it has never been made explicit. Therefore, this research provides a clear explanation below. First, r_i and σ_i are substituted in d_2^i and the expression is simplified:

$$\begin{aligned} d_2^i &= \frac{\ln(\frac{A}{D}) + (r - \lambda k + \frac{i\ln(1+k)}{T} - \frac{1}{2}(\sigma_A^2 + \frac{is^2}{T}))T}{\sqrt{\sigma_A^2 + \frac{is^2}{T}} \cdot \sqrt{T}} \\ &= \frac{\ln(\frac{A}{D}) + (r - \lambda k - \frac{1}{2}\sigma_A^2)T + i\ln(1+k) - \frac{1}{2}is^2}{\sqrt{\sigma_A^2 + \frac{is^2}{T}} \cdot \sqrt{T}} \\ &= \frac{\ln(\frac{A}{D}) + (r - \lambda k - \frac{1}{2}\sigma_A^2)T + i\ln(1+k) - \frac{1}{2}is^2}{\sqrt{\sigma_A^2 T + is^2}} \end{aligned}$$

Using (3.14) this can be reduced further to

$$
\begin{aligned}
d_2^i &= \frac{\ln(\frac{A}{D}) + (r - \lambda k - \frac{1}{2}\sigma_A^2)T + i\ln(1 + \exp\left(m + \frac{1}{2}s^2\right) - 1) - \frac{1}{2}is^2}{\sqrt{\sigma_A^2 T + is^2}} \\
&= \frac{\ln(\frac{A}{D}) + (r - \lambda k - \frac{1}{2}\sigma_A^2)T + i\ln(\exp\left(m + \frac{1}{2}s^2\right)) - \frac{1}{2}is^2}{\sqrt{\sigma_A^2 T + is^2}} \\
&= \frac{\ln(\frac{A}{D}) + (r - \lambda k - \frac{1}{2}\sigma_A^2)T + i(m + \frac{1}{2}s^2) - \frac{1}{2}is^2}{\sqrt{\sigma_A^2 T + is^2}} \\
d_2^i &= \frac{\ln(\frac{A}{D}) + (r - \lambda k - \frac{1}{2}\sigma_A^2)T + im}{\sqrt{\sigma_A^2 T + is^2}} \qquad (3.21)
\end{aligned}
$$

Now when zero jumps are expected, meaning $\lambda = 0$, d_2^i reduces back to the regular d_2 of Merton's model (2.14) and PD^* turns into the regular Merton PD:

$$
\begin{aligned}
PD^* &= \sum_{i=0}^{\infty} e^{-\bar{\lambda}T} \cdot \frac{(\bar{\lambda}T)^i}{i!} \cdot \Phi(-d_2^i) \\
&= \sum_{i=0}^{\infty} e^0 \cdot \frac{(0)^i}{i!} \cdot \Phi(-d_2^i) \\
&= 1 \cdot 1 \cdot \Phi(-d_2^0) + \sum_{i=1}^{\infty} e^0 \cdot \frac{(0)^i}{i!} \cdot \Phi(-d_2^i) \\
&= \Phi\left(-\frac{\ln(\frac{A}{D}) + (r - \lambda k - \frac{1}{2}\sigma_A^2)T + im}{\sqrt{\sigma_A^2 T + is^2}}\right) + \sum_{i=1}^{\infty} 1 \cdot 0 \cdot \Phi(-d_2^i) \\
&= \Phi\left(-\frac{\ln(\frac{A}{D}) + (r - 0 \cdot k - \frac{1}{2}\sigma_A^2)T + 0 \cdot m}{\sqrt{\sigma_A^2 T + 0 \cdot s^2}}\right) + 0 \\
&= \Phi\left(-\frac{\ln(\frac{A}{D}) + (r - \frac{1}{2}\sigma_A^2)T}{\sigma_A \sqrt{T}}\right)
\end{aligned}
$$

Which is equal to the expression of the PD in Merton's regular model, stated in (2.15).

3.3.2 Translating Climate Risks into Asset Shocks

With the Merton jump diffusion model defined, its unique properties can be used to quantify climate risks through the asset value channel. As outlined in the previous section, the model introduces three additional variables: (1) the shock intensity λ, which represents the expected number of shocks per time period; (2) m, the mean of the shock size distribution; and (3) s, the standard deviation of the shock size distribution. This section explains how these parameters are determined to incorporate climate risks into the asset value channel as realistically as possible. Several climate parameters have values dependent on a certain climate scenario z. This is highlighted further in Section 4.1.

Shock Intensity

First, the shock intensity λ_z is considered. This research aims to simulate each jump as originating from a type of additional transition risk that negatively impacts the asset value. For transition risks, this could include new laws imposing additional carbon emission taxes, directives banning certain carbon-intensive products, competitors entering the market with a greener alternative, or customers not wanting to engage with the company anymore due to its polluting image. As mentioned in Section 3.1 these all have a direct or indirect effect on the asset value which this research aims to capture in the proposed model. It is challenging and dependent on numerous factors to determine how many transition shocks would occur during a time period. Therefore, the number of shocks is climate-scenario dependent. Meaning a scenario that favours a more rapid transition would experience more transition-related shocks.

World Bank Group (2025), administers a carbon pricing dashboard. This dashboard keeps, among others, track of the number carbon tax and emission trading system instruments. Figure 3.3 shows the development of the number of worldwide GHG-pricing instruments. On average, between 1990 and 2024, 2.15 new instruments are introduced per year.

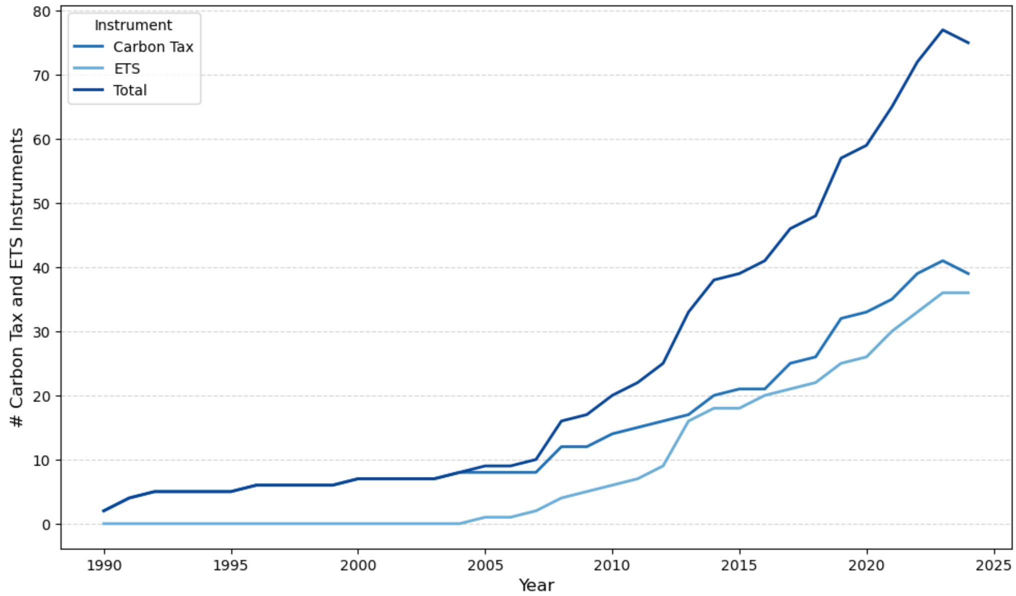

Figure 3.3: Number of worldwide GHG-pricing instruments (World Bank Group, 2025)

As can be seen the number of newly introduced instruments increases more rapidly. This means that setting λ_z at 2 for scenarios in line with current policies is not realistic. Looking at more recent years, between 2020 and 2024, 3.60 new instruments are introduced per year. Therefore, scenarios reflecting current policies, will have $\lambda_z = 4$. Figure 3.4 provides an overview of the NGFS climate scenarios and shows that scenarios in line with current policies are labelled as 'Hot house world', meaning these are the slowest transitioning scenarios. Therefore λ_z is set higher for scenarios that transition faster.

This research focuses on three climate scenarios to provide a comprehensive view of potential future climate risks. The first scenario, Current Policies, serves as a baseline to assess transition risks associated with maintaining existing policies. The second scenario, Net Zero 2050, represents the fastest changing scenario with a smooth transition path. Moreover, it aligns with the Paris Agreement and is therefore likely to be adopted by the 196 participating countries. Lastly, the Below 2 °C scenario is included as a midpoint between the Current Policies and the fast-transitioning Net Zero 2050 scenarios. It also offers a smooth transition path, but the transition is less stringent than the Net Zero 2050 scenario (NGFS, 2024). In the Net Zero 2050 scenario, λ_z is set to 8, indicating twice the number of transition risk-related shocks compared to the Current Policies scenario. The Below 2 °C is assigned a λ_z value of 6, reflecting moderate transition risks.

According to Figure 3.4, two climate scenarios are categorised as experiencing much higher transition risks, due to their accelerated and less smooth transition pathways (NGFS, 2024). These scenarios are excluded from this research because the methodology cannot adequately handle the lack of smoothness in the transition pathways. This is further discussed in Chapter 6.

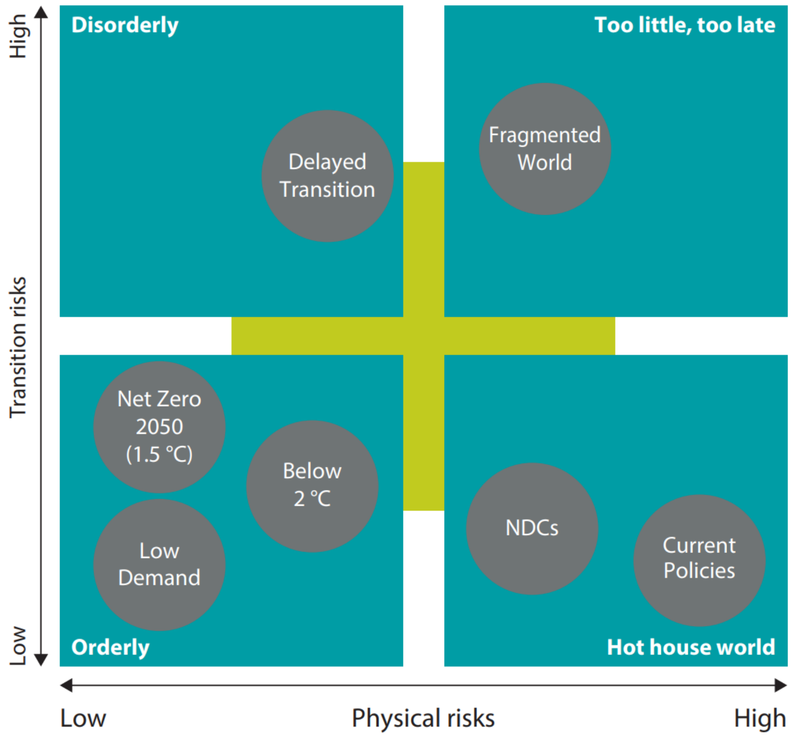

Figure 3.4: Climate scenarios framework (NGFS, 2024)

Mean Jump Size

The average magnitude of a shock, m, depends on several characteristics of the firm. The first characteristic are the company's carbon emissions. In this research, only the Scope 1 and 2 emissions for each firm in the portfolio are considered. Scope 3 emissions are intentionally kept out because these capture the emissions of all up- and downstream activities in the business process of the company. This includes a lot of emissions that belong within Scope 1 and 2 emissions of other companies. As a result, regulators keep these out of GHG-pricing instruments as scope 3 emissions are not under control of the company itself and could lead to a lot of double counting (World Bank Group, 2023).

The second characteristic influencing the value of m, are the additional costs per tonne CO_2 introduced by each new shock. The additional costs are scenario dependent. NGFS (2024) provides carbon price projections for various climate scenarios. To finish the definition m, a translation must be made from the carbon costs to asset values. Studies such as Bouchet and Le Guenedal (2020) divide the carbon costs by EBITDA to determine the size of the shock. Nonetheless, this approach may become unrepresentative when companies make losses, resulting in negative EBITDA. In such cases, the calculated shock would result in a positive jump in the model, which does not accurately reflect the situation.

It is argued that the value of assets should be determined by the profit generated by those assets. By calculating the carbon costs, it is possible to determine how much less profitable the assets have become. Hence, a shock is determined by directly relating the carbon costs to the market implied asset value of the firm.

Given the above description, the mean jump size for company c with carbon price under scenario z, CP_z, is given by

$$m_{c,z} = \frac{(\text{Scope}_{1,c} + \text{Scope}_{2,c}) \cdot CP_z}{A} \tag{3.22}$$

As mentioned in Section 3.1, transition risks can lead to reduced sales, meaning the assets become less profitable and therefore asset values drop. On the other hand however, lower sales, to some extent lead to lower production and therefore fewer emissions. This could have a mitigating effect on the decrease of the asset value. This research assumes that these effects cancel each other out and therefore, transition risks are solely quantified based on emission data instead of making predictions for adjusted sales or production levels.

Standard Deviation of Jump Sizes

The third and final variable is the standard deviation of the jump size, s. This variable governs the uncertainty in the size of the jump. It is realistic to have some uncertainty in the definition of the jump size as it is not possible to predict certainty what a suitable jump size for climate risks should be. As climate risks are quite dependent on the activities of the company, it seems reasonable to set s to the standard deviation in jump sizes for a given industry. This means that for a climate scenario z and company c in industry $\mathcal{I}$, the standard deviation of the jump size is given by

$$s_{\mathcal{I},z} = \sqrt{\frac{1}{|\mathcal{I}|} \sum_{c \in \mathcal{I}} (m_{c,z} - \mu_{\mathcal{I},z})^2} \tag{3.23}$$

Here, $|\mathcal{I}|$ corresponds to the number of companies in industry $\mathcal{I}$ and $\mu_{\mathcal{I},z}$ is the average of mean jump sizes $m_{c,z}$ for the companies in industry $\mathcal{I}$.

With these variables defined, the final step is to calculate the 1-year PD using the MIVA obtained from the existing algorithm. The jump PD is calculated using (3.16). However, instead of using generic values for λ, m, and s the scenario and company-dependent λ_z, $m_{c,z}$, and $s_{\mathcal{I},z}$ are used. The remainder of this research refers to the jump PD for a specific company c under climate scenario z as $PD^*(c,z)$.

3.4 Model Evaluation

With the climate adjustment within the Merton jump diffusion model defined, it is important to determine how to evaluate the model implementation. The model evaluation process is twofold: (1) a climate shock is defined based on the characteristics of a company and a climate scenario, and (2) a method is developed to add this shock to Merton's model through the asset value channel. Both components need to be evaluated in order to reason on the validity of the obtained results.

The primary focus of this research is to demonstrate how climate risks can be integrated through the asset value channel in structural default models. Thus, most emphasis is put on quantitatively reviewing the method in which the climate shocks are added to Merton's model. However, to make sure the shocks themselves are as realistic as possible, a qualitative assessment is conducted. This qualitative assessment has been provided in Section 3.3.2, where a motivation was given for each additional parameter in the jump diffusion model. Furthermore, Sections 2.1 and 3.1 give an economic motivation as to why transition risks can be modelled using shocks. Therefore, the remainder of this section will explain how the incorporation of the climate shock in the asset value channel can be evaluated. To do so, first an alternative view is provided on the channels in Merton's model. Afterwards, this alternative view is projected on the jump diffusion model.

3.4.1 Alternative View on Channels

As described in Section 2.2.3, several channels can be distinguished in Merton's model through which the PD is affected. Mathematically, the effect of interest of a channel can be described as the partial derivative of the PD with respect to the inputs of the channel. For the asset channel this effect of interest would look like:

$$\text{Asset Channel Effect of Interest} = \frac{\partial PD}{\partial A} \tag{3.24}$$

Parallels can be drawn with the Greeks from the regular Black-Scholes model. These quantities capture the change in option price with respect to one of the input variables of a channel. For example Δ in the Black-Scholes model models the effect of interest of the underlying stock price channel as $\frac{\partial C}{\partial S}$. In this research, the quantity of interest is the PD, meaning the channels are not identical to the channels in the Black-Scholes model. However, making a connection to the Greeks helps in forming an intuitive understanding of what the channels represent in Merton's model and the effect of introducing climate risks to a channel.

Having a mathematical representation of the effect of interest of a channel gives the possibility to evaluate how the model as a whole behaves under certain conditions. This effect of interest can then be analysed for given (macro-)economic scenarios to review whether the model behaves in a way as expected.

3.4.2 Asset Channel in Merton's Jump Diffusion Model

In the jump diffusion model three additional parameters are introduced: λ, m, and s. These parameters influence the asset value process either by setting the frequency of shocks or the size of a shock. In essence, this can be seen as an extension of the asset value channel. Thus, in Merton's jump diffusion model, the effect of interest of the asset channel cannot be modelled exclusively by the relation described in (3.24). Instead, the effect of the additional parameters on the behaviour of the asset value channel must be acknowledged:

$$\text{Jump Diffusion Asset Channel Effect of Interest} = f\left(\frac{\partial PD^*}{\partial A}, \frac{\partial PD^*}{\partial \lambda}, \frac{\partial PD^*}{\partial m}, \frac{\partial PD^*}{\partial s}\right) \tag{3.25}$$

Here f is some function that governs the relation between the four partial derivatives. It is beyond the scope of this research to find analytical formulas for the partial derivatives of the PD with respect to the jump diffusion parameters. However, economic theory and results from existing research can be used to reason on the expected contribution of each individual parameter to the asset value channel.

First, λ, governs the number of shocks observed. As shown in 3.12, the jump size is adjusted by -1. Hence, on average, negative jump sizes are expected when $m < 0$. When the average jump size is negative, it is expected that the more shocks present, the lower the asset value will be. In turn, this leads to a larger likelihood of the asset values being below the default threshold at the time horizon. Hence, for larger values of lambda, the PD is expected to be larger, given negative jump sizes. Mathematically, this expectation is defined as

$$\frac{\partial PD^*}{\partial \lambda}\Big|_{m<0} > 0 \tag{3.26}$$

This relation in (3.26) is already stated in (Kölbel et al., 2022). When evaluating the model, it is empirically tested if this relation holds and whether the model behaviour is in line with the economically expected behaviour.

Second, m, represents the mean of the log-normal jump size distribution. As shown in 3.26, m plays an important role in the contribution of λ to the asset value behaviour. If $m < 0$, negative shocks are expected, increasing the PD. Alternatively, $m > 0$, results in positive shocks, meaning there is a larger likelihood that the asset value ends up above the default threshold at the horizon. The contribution of m to the behaviour of the asset value channel is therefore expected to be (Kölbel et al., 2022):

$$\frac{\partial PD^*}{\partial m} < 0 \tag{3.27}$$

Finally, the standard deviation of the jump size distribution, s, contributes to the asset value channel behaviour in a slightly less straightforward manner. To the best of our knowledge, no analytical definition has been provided for $\frac{\partial PD^*}{\partial s}$ in previous studies. Again, deriving such an analytical definition is beyond the scope of this research. In the jump diffusion model, jump sizes follow a log-normal distribution. By examining this distribution, the expected influence of s on the asset value channel behaviour can be assessed.

When m is kept fixed, an increase in s leads to a greater right-skewness, resulting in a larger average jump size. This behaviour is illustrated in Figure 3.5. At first glance, this would imply that for larger values of s, more positive jumps are expected and the PD will therefore become smaller $\left(\frac{\partial PD^*}{\partial s} < 0\right)$. However, when s increases, the uncertainty in the jump sizes and therefore the uncertainty in the model becomes larger. This uncertainty is expected to be reflected in the PD, meaning it will increase. Furthermore, the effect of s could be dependent on λ. If the shock intensity is large, it is more likely that jumps from the tail of the distribution are present, potentially having significant effects on the PD. The behaviour of the model under varying values of s is studied in Chapter 5.

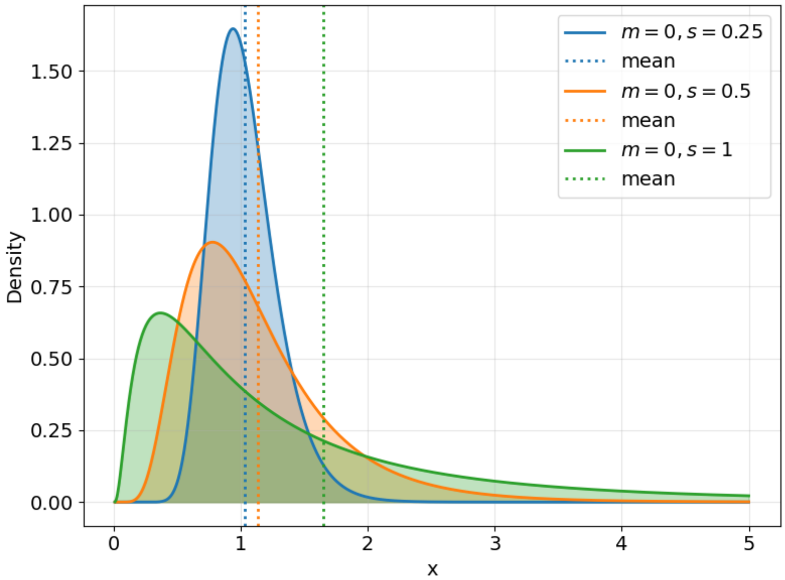

Figure 3.5: Log-normal PDF for several values of s

3.5 Conclusion

In this chapter, an answer to the fifth research question is formulated. This research question focuses on how an extended structural default risk model can be implemented in a case study.

First, the choice for adapting the asset value channel is motivated. This is because it is the channel that influences the PD in the most direct way. Also, it offers great flexibility in the approach that can be taken to include climate risks. Generally, two approaches are distinguished. Either a direct shock is introduced to the asset value or the asset value process itself is adjusted. In this research focus is put on the latter because to the best of our knowledge it has not been done before for transition risks. Moreover, adapting the asset value process itself provides greater flexibility in incorporating climate risks, potentially leading to a more realistic integration of these risks through the asset value channel.

Next, the approach for obtaining the regular Merton PD of the companies in the portfolio is highlighted. This is done by explaining how each individual variable can be calculated using real-world data and several algorithms. Specific focus was put on the complexity that arose from working with real-world data, to provide an adequate answer to the fifth research question.

After describing the methodology for the regular Merton PD, the methodology for obtaining the climate-adjusted PD was introduced. This research incorporates climate risks in the asset value channel using Merton's jump diffusion model. An analytical formula for the PD under the jump diffusion model is derived. Based on economic theory and studies presented in the literature review, climate shocks are defined in terms of parameters in the jump diffusion model. This model can be used to calculate the climate-adjusted PD for the companies in the portfolio. Moreover, techniques to evaluate the model implementation are presented.

In summary, this chapter provides a step-by-step explanation of the method to calculate the PDs in PGGM's corporate bond portfolio. Furthermore, it shows how this method can be extended to calculate the climate-adjusted PD for each company in the portfolio. It therefore answers the fifth research question and provides a basis for the empirical validation presented in the upcoming chapters.

Chapter 4

Data

In this chapter, the process of collecting and preparing data suitable for implementing the methodology described in the previous section is discussed. Following this, the data is analysed to gain a better understanding and provide additional context for the case study. To facilitate this analysis, plots and summary statistics of key model variables will be presented. This chapter further addresses the fifth research question: "How can an extended structural default risk model be implemented in a case study?".

4.1 Data Collection & Preparation

This section discusses the required data and data preparation activities to appropriately perform the empirical validation of the model. From the description of the methodology in the previous chapter, it has become clear what variables are required. Table 4.1 provides a one-to-one mapping of the model variables and data source used.

Table 4.1: Model Variables and Data Sources

Variable	Underlying Data	Source(s)
r	1-year government bond yields corresponding to the currency in which company financials are reported.	Public sources[1]
D	Combination of short and long term debt from the balance sheet of the company.	Yahoo Finance
E^t_{obs}	Daily share prices and outstanding number of shares during the most recent complete financial year.	Yahoo Finance
A_t	Equity data is used to calculate the MIVAs used in the model.	Output of Appendix B
σ_A	Calculated from the obtained MIVAs.	Output of Appendix B
λ	Yearly number of worldwide carbon pricing instruments introduced (1990-2024)	(World Bank Group, 2025)
m	Most recent reported Scope 1, 2, and, 3 emissions and carbon prices per climate scenario.	Trucost & NGFS
s	Standard deviation of m, per industry	Calculations

[1] https://www.bloomberg.com, https://www.investing.com, https://www.marketwatch.com

The data collection started with obtaining the tickers of the companies in the corporate bond portfolio of PGGM that are publicly listed. Not all tickers were recognised by Yahoo Finance, but cleaning the data did increase the number of working tickers. Using the cleaned tickers, relevant equity and financial data could be obtained from Yahoo Finance. At the start, a total of 506 companies were considered.

Equity prices were filtered to fit the appropriate time frame. Only adjusted close prices were used to account for stock splits and dividends. This is required for accurate historical equity return calculations. Two companies had missing data regarding the number of outstanding shares. These companies were excluded from the research, leaving 504 unique companies in consideration.

Financial data generally required minimal preparation, although companies not distinguishing between long and short-term debts on their balance sheet were excluded from the research. This is because both are required to obtain a realistic estimate of the debt burden that can be used to calculate the PD. In total, 65 companies were excluded from the research due to missing balance sheet items. Both financial and equity data were converted to Euros. In total 24 unique currencies were present in the dataset. Only Euros are considered because all reporting within PGGM is done in Euros. Moreover, PGGM hedges all of its currency risk through derivatives. Several companies did not report on the currency in which the equity and financial data was reported. These were left out of the research.

Risk-free rates were approximated using 1-year government bond yields, determined by the currency in which the financials of the company are reported. For Euro-reporting companies, an average yield from three high-rated (Netherlands, Germany, Luxembourg) and three low-rated (Greece, Italy, Spain) EU countries provided a representative estimate for the risk-free rate.

No preparation steps were necessary for GHG-pricing instruments, CO_2 emissions, and CO_2 pricing data. The only notable preparation required was the exclusion of three companies due to missing emission data.

After collecting the data, several quality checks were conducted, leading to the exclusion of various companies. First, six companies were removed due to having fewer than 200 equity price observations in the studied year. This is a result of the company not being publicly listed during the entire year. Additionally, three companies had periods with negative market caps, which is impossible as the stock price and number of outstanding shares cannot be negative. This indicated some data quality issues in either the obtained stock prices or number of outstanding shares. A possible explanation could be the fact that these were rather small companies, meaning the data source could be of lower quality. To prevent data quality issues at other firms, further checks were performed on the calculated market caps. The market cap is calculated by obtaining the daily stock price and number of outstanding shares and multiplying these. At a given day, the actual market cap of the company can also be obtained. To ensure data quality, companies having a calculated market cap that deviates with more than 50% of the actual market cap, were removed. As a result 57 companies were disregarded. Furthermore, nine companies were excluded due to stock splits during the observed period. Stock splits introduce challenges in maintaining accurate information on the number of outstanding shares. Finally, a comparison of market cap volatility to share price volatility led to the exclusion of eight more companies.

Afterwards, the regular Merton PDs according to the methodology described in Section 3.2 were calculated. As a result, six additional companies were excluded from the research. These companies either had an outlier PD value (> 99%) or had a NaN-value as PD due to some missing data throughout the process. Consequently, a total of 347 companies remained to be studied. Summary statistics and other information regarding the dataset is provided in the next section.

4.2 Data Analysis

The upcoming sections analyse the dataset at hand. The goal is to provide a relevant context of the data used to validate the model implementation in the next chapter. To do so, each model variable is displayed and anomalies identified during the data exploration process are discussed.

4.2.1 Equity and Financial Data

The size, equity returns, and equity return volatility are key characteristics of the firms of the companies in the portfolio. These characteristics not only provide context about the types of companies included in the dataset but also offers insights into their financial stability. Firstly, larger companies are generally considered more financially stable, as they require significant adverse events to become bankrupt. This stability is also reflected in the equity volatility: the more volatile the equity, the more unpredictable the company's performance, and therefore the higher the risk of insolvency. Additionally, a company with solid equity returns is expected to be more financially stable, as any risks and instabilities are expected to be priced in, leading to lower returns. These claims are supported by Crosbie and Bohn (2002), who state that the nature and maturity of a business influence its asset volatility, which in turn impacts PD. The market capitalizations, asset returns, and asset return volatilities of the companies in the portfolio are illustrated in Figures 4.1 and 4.2.

The majority of the bonds in the portfolio are issued by companies with market caps smaller than €100 billion. For the companies with market caps above €100 billion, two clear outliers exist. Furthermore, the group of companies with a market cap below €100 billion contains numerous outliers between €50 billion and €100 billion market caps. This indicates that most market caps of the issuers in the portfolio are concentrated in the lower billions. This is reflected in the left box plot as the median market cap for the companies with market caps ≤ €100 billion lies at around €8 billion. Figure 4.2 shows the yearly return and volatility over one year of daily data. It can be seen that there are no industries that achieve consistent higher returns than other industries. Similarly, no industry consistently has larger equity returns volatility. Looking at the individual cases, it can be seen that several companies have an equity returns volatility of over 50%, while no company has an equity returns volatility below 15%. It is important to once again state that the equity return volatility is not directly related to the PD of a company, but can give relevant insights of the firm.

4.2.2 Industry Overview

During the analysis of the results, companies are grouped per industry. This is because companies in similar industries have similar business models, leading to similar patterns in emissions and expected exposure to climate risks. Figure 4.3 shows the distribution of companies among the industries. The figure shows that companies are not evenly distributed among the industries. Industrials and Consumer Cyclical contain the largest number of companies. Especially industrial companies are often involved in high-emission activities, increasing their Scope 1 and 2 emissions. Two other industries that are known for their pollution are the energy and utility industries. Significantly less companies are present in these industries, with the energy industry only containing one company. The energy company will remain in the analysis of this chapter to provide a comprehensive overview of the dataset at hand. However, it will be excluded from the results of this research as this could lead to a distorted view.

Throughout this research, results are aggregated on an industry level. Therefore the distribution of companies among the industries plays a key role when interpreting the results.

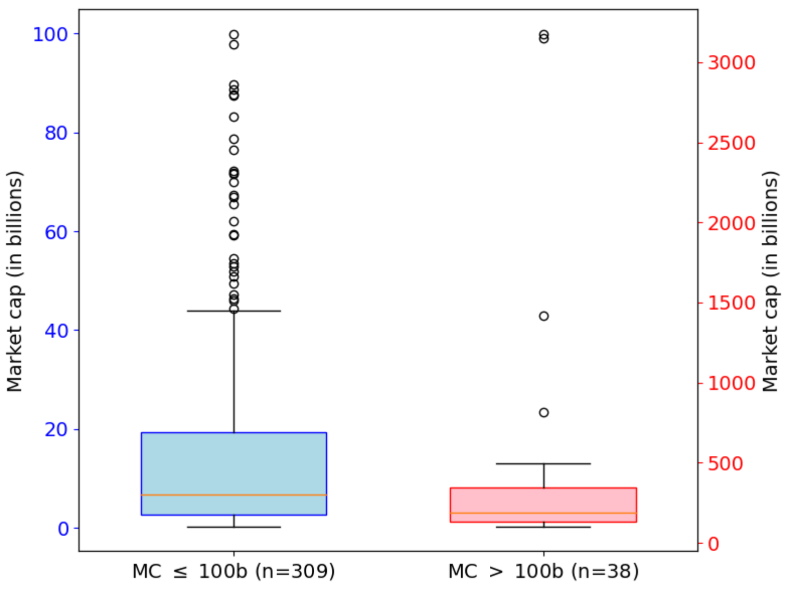

Figure 4.1: Market caps

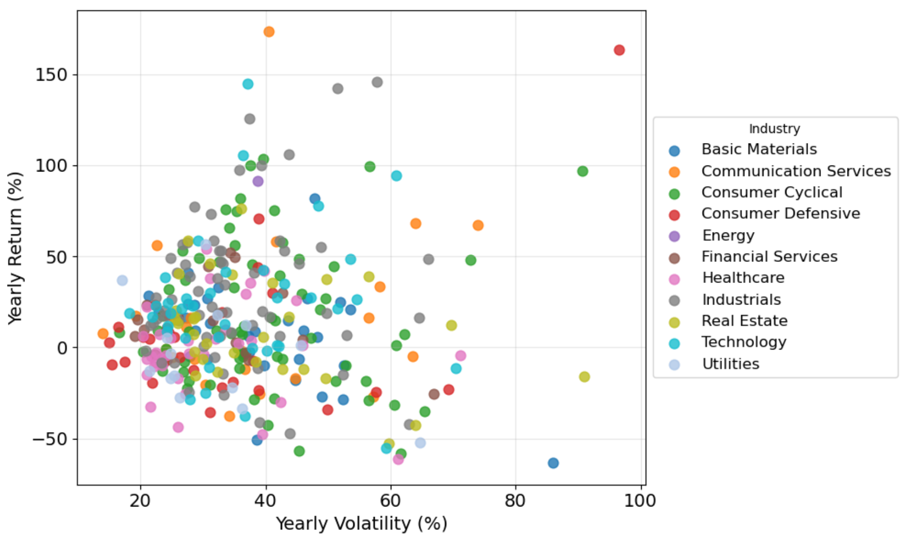

Figure 4.2: Yearly equity returns and corresponding volatility

4.2.3 MIVA and Asset Volatility

As described in Section 3.2, the book value of assets can not be used directly as the asset value when calculating Merton's model. Instead, the market implied value of assets (MIVA) needs to be obtained through an algorithm, described in Appendix B. There can be a significant difference in the book value of assets (BVA), reported on the firm's balance sheet, and the MIVA. The percentage difference between the two is calculated as follows:

$$\%\text{-Difference} = \frac{\text{MIVA} - \text{BVA}}{\text{BVA}}$$

The resulting differences can be found in Figure 4.4.

As can be seen, most companies have a higher MIVA than BVA. This means investors in the market value the assets higher than the actual book value. This is a common observation, as the market value also includes value within a company without a cost basis. For example, goodwill or a valuable idea within the company have no cost bases and therefore no book value. However,

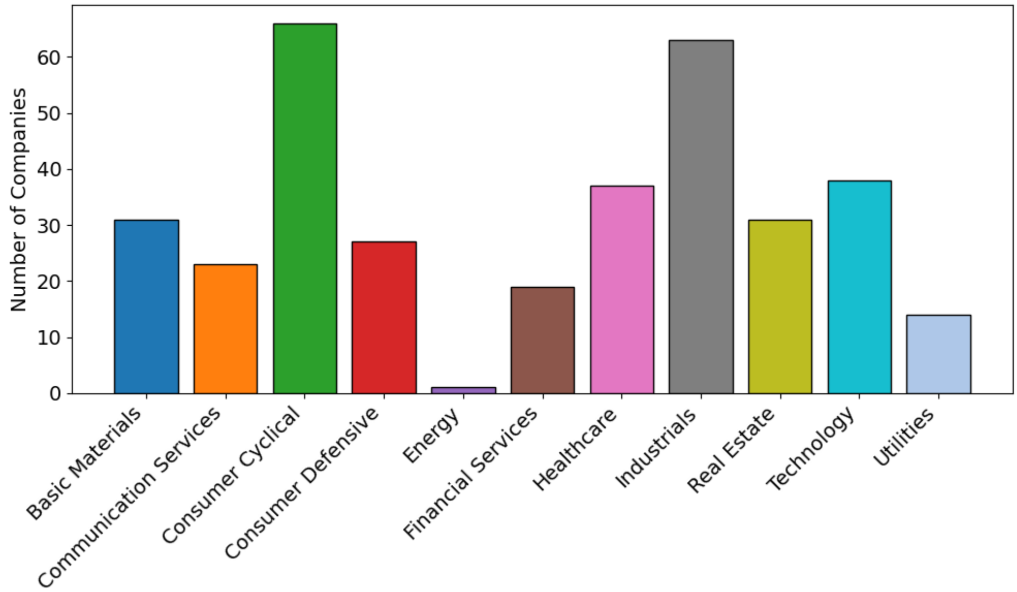

Figure 4.3: Number of companies per industry

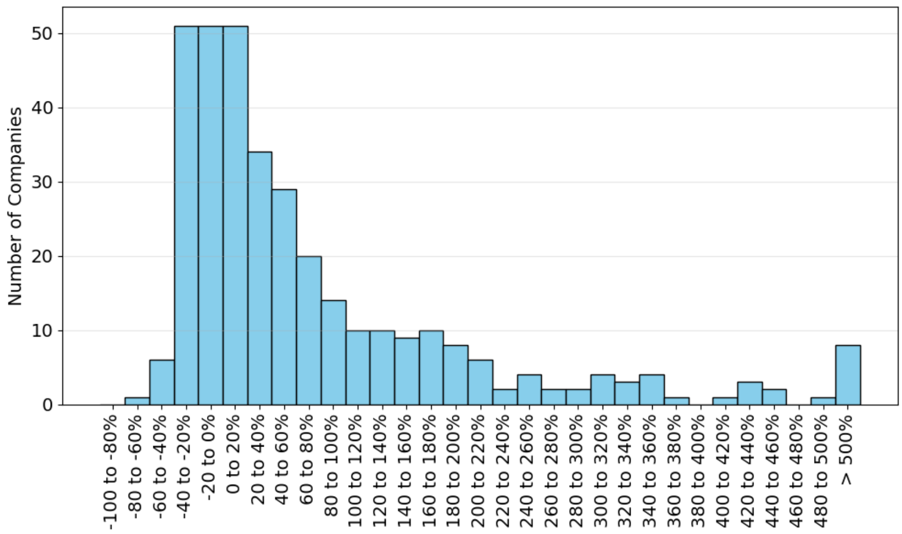

Figure 4.4: Percentage difference between MIVA and BVA

investors in the market do assign a value to these non-tangible assets, often leading to a higher market value of assets than book value. Generally, the higher market value of the assets results in a lower PD. Whether this lower PD properly reflects the actual default risk present within the company is hard to determine. Alternatively, it can be seen that there are 100+ companies with MIVA lower than BVA. This means investors tend to value the assets lower than their cost basis. This could be due to developments in the market that lead to depreciations in asset value, which are not yet reflected in the book value of the assets.

Besides the MIVA, another important variable is the volatility of MIVA returns. This value is obtained through the algorithm in which the MIVA is calculated. The volatilities per industry are displayed in Figure 4.5. Volatility is an important measure for the risk a company bears. Furthermore, it plays a significant role in defining the PD in Merton's model, as discussed in Section 2.2.3. Clear differences in asset volatility, σ_A, are observed across the various industries. Industries such as utilities, financial services, and consumer defensive have notably lower volatility, which makes sense from an economical perspective, given the maturity and proven reliability of their business models. Contrarily, more innovative and thus riskier industries, like technology, experience a higher MIVA return volatility. Again, it is important to note that the box plot for the energy industry is distorted because it includes only a single company. In comparison to the volatility of equity returns, the return volatility of MIVA is lower for the companies. This is likely due to the fact that financial markets contain a large speculation factor, driving large changes in the market cap, while the implied value of assets remains relatively stable.

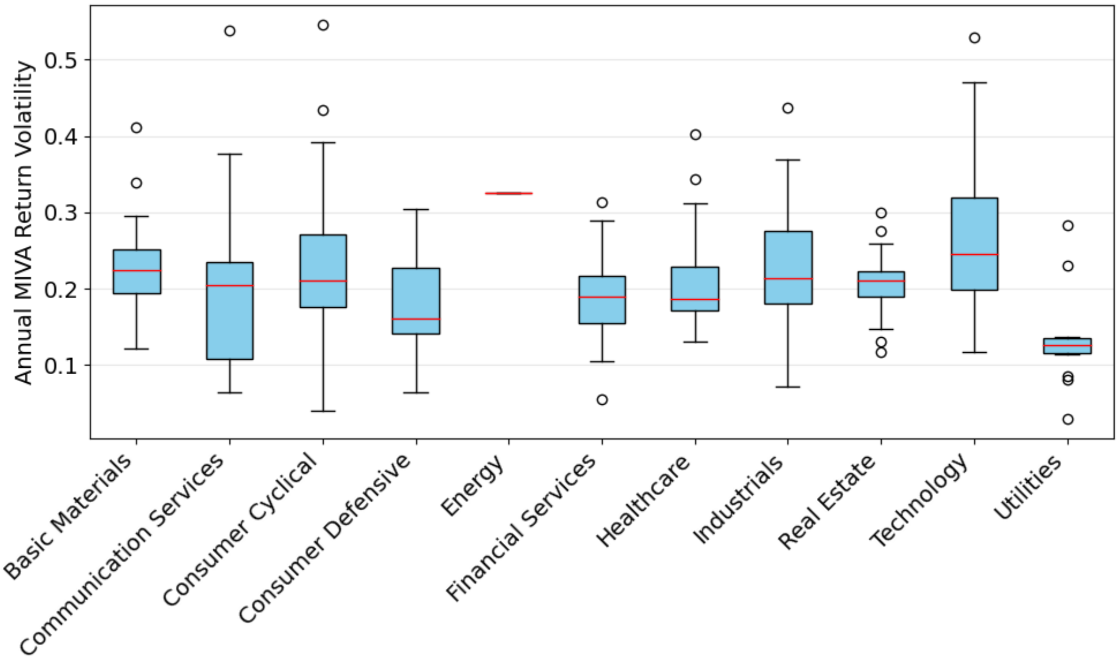

Figure 4.5: Annual MIVA return volatility

4.2.4 Default Threshold

The default threshold is the upper bound at which default is considered at the the time horizon. The closer the MIVA at $t = 0$ sits at the default threshold, the larger the likelihood that asset values lie below the threshold at the time horizon. The debt value as a percentage of MIVA per industry is presented in Figure 4.6. Here, the debt value is the 1-year extrapolated default threshold, calculated according to (3.2), with $k = 0.5$. No individual company has debt exceeding the MIVA (i.e., greater than 100%). This observation could suggest a certain level of stability within the companies. Default occurs when asset values fall below the default threshold. Hence, the smaller the debt as a percentage of the MIVA, the lower the likelihood of default, assuming all other factors remain constant. Nonetheless, it is important to note that other elements, such as the drift and volatility play significant roles. Therefore, there is no one-on-one correspondence between the debt to MIVA ratio and the PD.

4.2.5 Climate Shocks

Summary statistics on the emission data used to determine the climate shocks for each company are presented in Appendix C. As mentioned in Section 3.3, climate shocks are determined by summing the Scope 1 and 2 emissions of the firm, multiplying it by the carbon price for a given scenario and dividing these carbon costs by the MIVA.

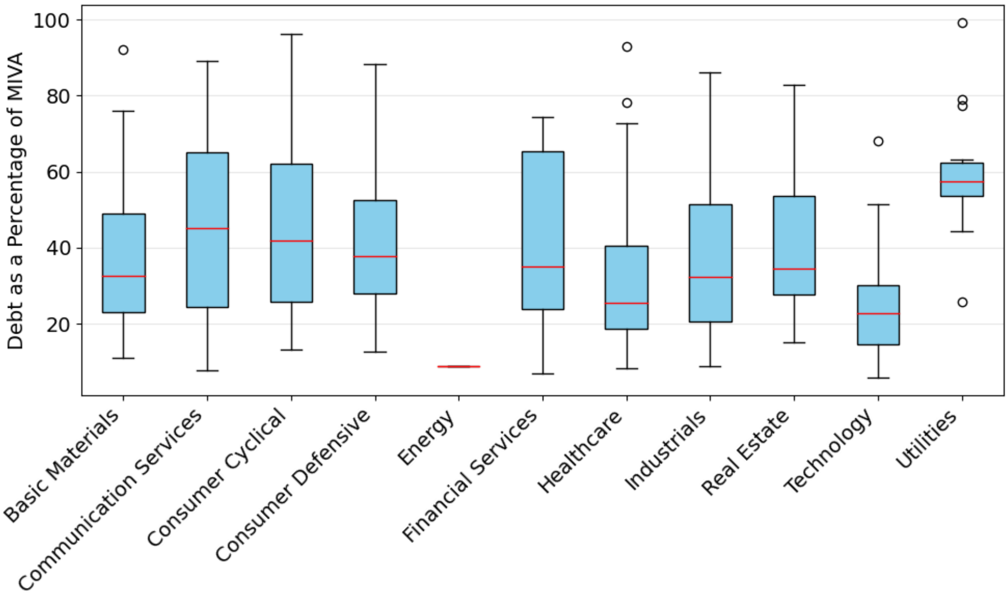

Figure 4.6: Debt to MIVA ratio (%)

Carbon prices are based on the projected carbon price from NGFS (2024). Figure 4.7 shows the projected prices per tonne CO_2 for the NGFS climate scenarios. The prices are projected in five-year intervals from 2020 till 2050. As discussed earlier, this research will focus on the Current Policies, Net Zero 2050, and Below 2 °C climate scenarios. For each scenario, the average yearly carbon price increase is used as the carbon price when calculating $m_{c,z}$. Carbon prices are converted to Euros, using the exchange rate on 01-01-2025, which is 0.97[2]. The resulting carbon prices are given in Table 4.2

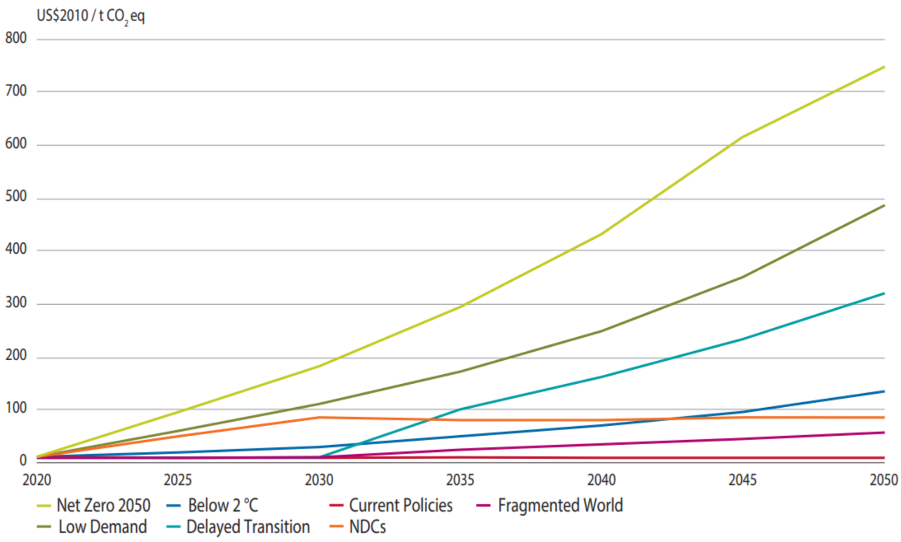

Figure 4.7: Carbon price projections per climate scenario (NGFS, 2024)

Using (3.22) all quantities are put together and the climate shocks can be defined. The sizes of the shocks for each industry are displayed in Figures 4.8, 4.9, and 4.10 for the Current Policies, Net Zero 2050, and Below 2 °C scenarios, respectively.

It is observed that significant differences exist in between industries. The three industries

[2]https://finance.yahoo.com

Table 4.2: Average Yearly Forecasted Carbon Price Increase (€/tonne CO_2) per NGFS Climate Scenario (NGFS, 2024)

Scenario	Carbon Price (€/tCO_2)
Current Policies	0.32
Net Zero 2050	24.25
Below 2 °C	4.20

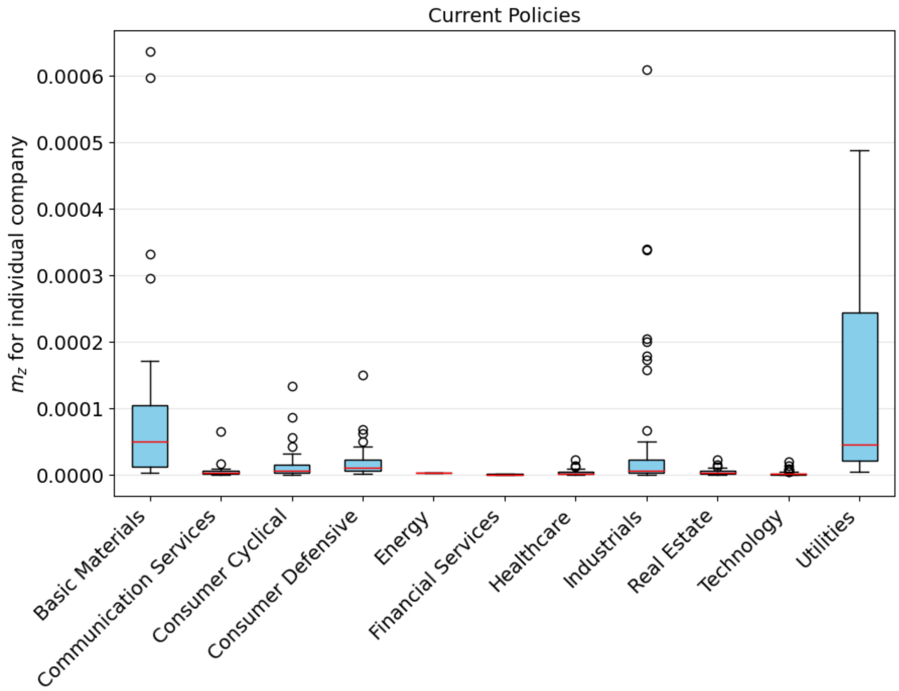

Figure 4.8: Climate shocks under the Current Policies scenario

that have the largest shocks are "Basic Materials", "Industrials", and "Utilities". The first two have relatively many outliers, resulting in some large shocks. The utilities industry however, in general has many companies with large climate shocks. When comparing the two scenarios, absolute differences in the shocks are vast. Shocks range up to 5% in the Net Zero 2050 scenario, whereas the highest shock in the Current Policies scenario barely exceeds 0.06%. This shock size is calculated according to (3.22), meaning it refers to the percentage point difference in market value of the assets. The distribution of the shock sizes among the different industries does not change between the different climate scenarios, because emissions are assumed to remain equal within each scenario. As a result, the only differences between the climate scenarios stem from the carbon price and shock intensities. These values are fixed per scenario and do not vary by industry. Consequently, the relative difference in shock sizes between industries remains similar, regardless of the climate scenario.

4.2.6 Energy Industry

As stated earlier, the dataset includes one company from the energy industry. When comparing under different climate scenarios, the climate shock for this company is relatively low compared to other industries. This is counterintuitive, given the characteristics of the energy industry and expected vulnerability towards climate risks. This section will briefly explain this observation.

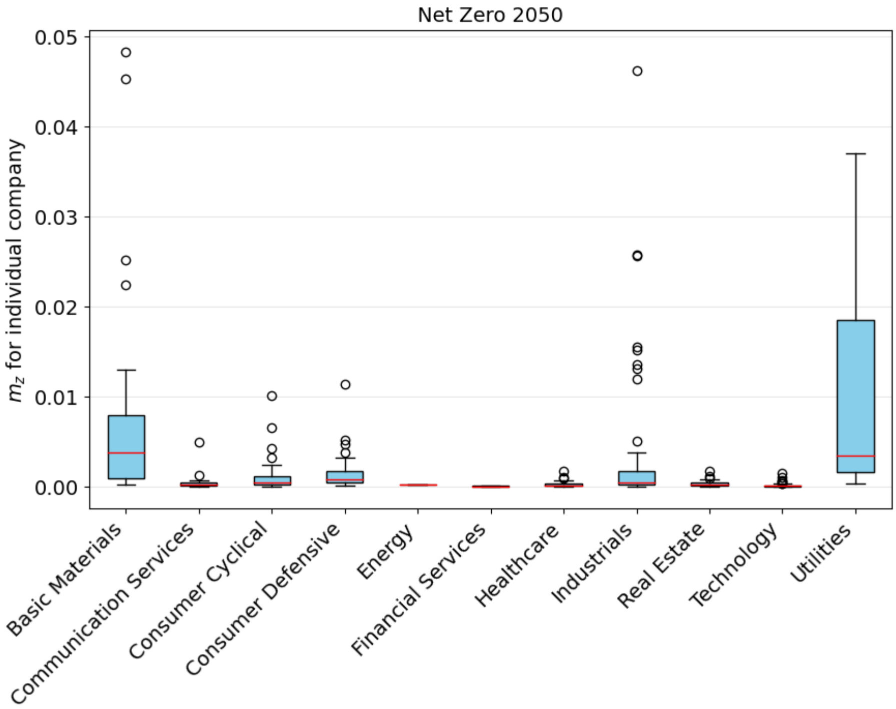

Figure 4.9: Climate shocks under the Net Zero 2050 scenario

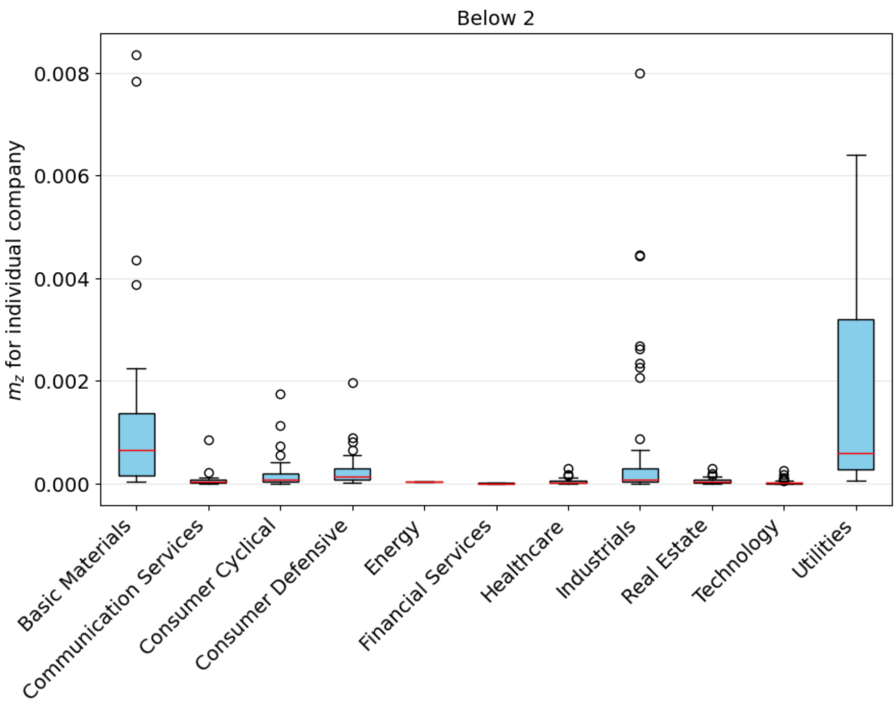

Figure 4.10: Climate shocks under the Below 2 °C scenario

However, to prevent the company from distorting the results, by being perceived as representative of the entire energy industry, it is excluded from the analysis in the remainder of the research. As a result, 346 remain to be studied.

The energy company in the portfolio owns properties with coal mines operated by other firms. It generates revenue through commissions rather than direct energy production. This business model results in lower Scope 1 and 2 emissions, contributing to a relatively low shock size assigned in the methodology of this research. It could be argued however that companies leasing mines might also face climate risks. Currently this is not captured in the methodology as Scope 3 emissions are excluded from this research. Further discussion on this topic can be found in Chapter 6.

4.3 Conclusion

This chapter builds on the initial findings presented in the previous chapter to further address the fifth research question: "How can an extended structural default risk model be implemented in a case study?". The methods underlying the real-world implementation of a climate-adjusted structural default risk model were presented in the previous chapter. This chapter delved into the data collection and preparation steps, after which a detailed analysis of the data is performed.

First, an overview of the required data to implement the methods for obtaining the regular and climate-adjusted PDs is shown. These are summarised in Table 4.1. Afterwards, the necessary preparation and filtering steps that have been performed to assure adequate data quality have been highlighted.

Second, the cleaned and prepared dataset is analysed. In the analysis, emphasis is put on the model parameters. No significant data issues were uncovered during the analysis, except for the Energy industry only containing a single company. Therefore, this industry is removed from the case study as it could lead to distortion in the results of this research.

Chapter 5

Results

This chapter presents the results of the empirical validation of the model through a case study on PGGM's corporate bond portfolio. The goal is to give a comprehensive overview of the outcomes that are relevant in answering the main research question of this study: "How can climate risks be integrated into structural default risk models through the underlying channels that cause default, to quantify their impact on firm default risk?". The preceding chapters have (1) highlighted previous work and background information related to the goal of this research, (2) described the methods performed in this research to form an answer to the main research question, and (3) described the data underlying the empirical validation of the model implementation. These efforts allowed for empirically validating the model of which the results are presented here. The results of the case study are twofold. First, the regular and climate-adjusted PDs of the companies in the portfolio are presented. This is done to reason on the actual impact of climate risks on the corporate bond portfolio of PGGM. Second, the results of validating the model implementation are presented. To do so, a sensitivity analysis is performed that displays the model behaviour under varying input parameters.

5.1 Regular PDs

The average PD per industry according to the regular Merton model implementation, described in Section 3.2, is shown in Table 5.1. Note that the PDs are rounded up to three decimals and PDs below $1 \cdot 10^{-3}$% are considered to be 0.

The first thing that stands out is that the distribution of the regular Merton PDs is severely right-skewed. This is evidenced by the fact that, for all industries, the 75th percentile is smaller than the mean. Consequently, the mean PD per industry gives a distorted view. An explanation for this observation is the relative financial stability of the companies included in the study. Most companies have a PD that is close to, or essentially zero. In fact, all industries except one have more than half of the companies with a PD of 0%. The only exception to this is the Consumer Cyclical industry (0.002%). When looking at the upper quarter of the data, the first notable PDs start to arise. Here Consumer Cyclical (0.413%) has the clear highest 75% PD, after which Communication Services (0.154%), Utilities (0.146%), and Basic Materials (0.138%) come. Although most companies have a PD equal to 0%, the PDs within the top 5% of each industry are quite significant. Only the Technology industry has a 95% PD below 3%, at 0.181%. Considering the maximum PDs, it is observed that the Technology (1.982%) and Financial Services (7.998%) have no company with a PD larger than 10%. The industries with the highest maximum PD are Industrials (28.961%), Basic Materials (26.669%), Healthcare (23.729%), and Consumer Cyclical (23.640%). Overall, the standard deviation of the PDs is rather high with all industries having a

Table 5.1: Regular Merton PDs per Industry

Industry	**#**	**Mean**	**Std. Dev.**	**Min**	**50%**	**75%**	**95%**	**Max**
Basic Materials	31	1.181%	4.927%	0.000%	0.000%	0.138%	4.116%	26.669%
Communication Services	23	0.949%	2.378%	0.000%	0.000%	0.154%	6.671%	9.156%
Consumer Cyclical	66	1.425%	4.202%	0.000%	0.002%	0.413%	5.699%	23.640%
Consumer Defensive	27	1.026%	3.500%	0.000%	0.000%	0.000%	6.395%	16.612%
Financial Services	17	0.677%	2.051%	0.000%	0.000%	0.039%	4.272%	7.998%
Healthcare	37	0.948%	3.986%	0.000%	0.000%	0.000%	3.337%	23.729%
Industrials	63	1.100%	4.206%	0.000%	0.000%	0.009%	6.578%	28.961%
Real Estate	30	0.843%	2.723%	0.000%	0.000%	0.055%	5.793%	12.989%
Technology	38	0.069%	0.326%	0.000%	0.000%	0.000%	0.181%	1.982%
Utilities	14	1.891%	4.344%	0.000%	0.000%	0.146%	11.897%	12.532%

standard deviation in PD of over 2%, except for the Technology industry (0.033%). This indicates there is quite some variability within the PDs which is supported by the relatively large maximum PDs for each industry. A significant difference between the maximum PD and 95th percentile PD within an industry may indicate the presence of outliers. This is observed within the Basic Materials, Industrials, and Healthcare industries, which show differences of 22.553, 22.383, and 20.392 percentage points, respectively, between the maximum PD and the 95th percentile PD.

Differences in PD exist between the companies within an industry. In the Basic Materials industry for example PDs range by 26 percentage points. This could be attributed to several characteristics of the individual companies such as its capital structure, asset volatility, or geographical exposure. Differences in PD between industries exist, although they do not differ vastly. Several industry-specific financial and economic characteristics can be identified that explain these differences. First the Utilities industry has a capital-intensive nature, which can make them vulnerable to economic downturns. Consumer Cyclical firms are sensitive to economic cycles, meaning demand for their products decreases significantly in economic downturns. Conversely, the Financial Services, Real Estate, Healthcare, and Communication Services industries have moderate PDs, reflecting their relative stability and essential service demand. The Technology industry has the lowest average PD, minimal standard deviation, and lowest maximum PD, indicating its low perceived default risk. This could be driven by high profitability margins and strong investor support. This in turn could lead to resilience against economic fluctuations and therefore default risk.

To provide a better view of the PDs in the upper scale, Figure 5.1 shows the distribution of the 50 highest PDs. The Consumer Cyclical industry is the most prominently represented industry in this group. This aligns with the finding that it has the highest 75th percentile PD value. This could partially be explained by the large number of companies in this industry. However, the Industrials industry contains three fewer companies, but has ten less companies in the top 50 PDs.

Furthermore, it can be seen that the PD drops fast, with only 11 out of 346 companies having a PD of more than 10%.

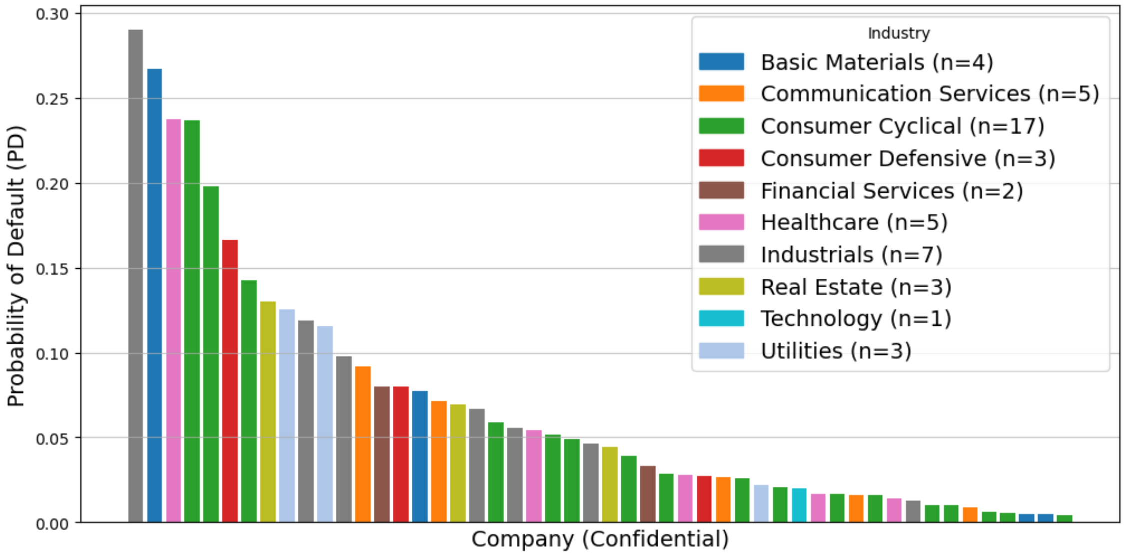

Figure 5.1: 50 Largest regular Merton PDs

5.2 Climate-Adjusted PDs

This section analyses the climate-adjusted PDs. To do so, the percentage point change in PD and the percentage increase of the PD when considering climate risks are calculated. These are calculated as follows:

$$\Delta PD(c,z) = (PD^{*}(c,z) - PD(c)) \cdot 100$$

and

$$\text{\%-Increase} = \frac{PD^{*}(c,z) - PD(c)}{PD(c)} \cdot 100$$

Here $PD^{*}(c,z)$ is the climate-adjusted PD for company c under climate scenario z and $PD(c)$ refers to the regular Merton PD of the company. The shift in mean PD per industry, averaged over the different climate scenarios is displayed in Table 5.2. Differences smaller than $1 \cdot 10^{-3}$% are regarded as 0. According to the model, the Utilities industry is affected the most by the introduction of transition risks in the PD calculation. In this industry, the mean PD increases by almost 35%, corresponding to a percentage point difference of 0.661. This suggests that the carbon emissions in relation to the asset value of the company is fairly high, resulting in a larger transition risk impact. It can also be seen that the Industrial and Basic Materials industries experience a shift in PD of around 2.11% and 1.70% respectively. The effect on PD for the introduction of climate risks is almost negligible for the other industries. This finding is somewhat counterintuitive, given the widely acknowledged implications of climate change, as presented in Chapter 2. This is partially caused by the fact that the changes in PD in Table 5.2 are averaged over all climate scenarios. This leads to slower-transitioning scenarios diminishing the transition risks that are present in faster-transitioning scenarios. Nevertheless, even accounting for this, larger changes would have been expected. Chapter 6 touches upon this further and reflects on the model implementation and data used to proxy climate risks. Especially for the Real Estate industry low impact of climate risks might be surprising considering the CO_2 emissions that come from construction. However, it could indicate that mainly administration and advisory firms in the real estate industry are within the portfolio.

Table 5.2: Difference in Mean PD per Industry Averaged over all Climate Scenarios

Industry	**Mean Regular Merton PD**	**Mean Climate PD**	**%-Point Difference**	**%-Increase**
Basic Materials	1.181%	1.201%	0.020	1.693%
Communication Services	0.949%	0.950%	0.001	0.105%
Consumer Cyclical	1.425%	1.426%	0.001	0.070%
Consumer Defensive	1.026%	1.028%	0.002	0.195%
Financial Services	0.677%	0.677%	0.000	0.000%
Healthcare	0.948%	0.948%	0.000	0.000%
Industrials	1.100%	1.123%	0.023	2.091%
Real Estate	0.843%	0.843%	0.000	0.000%
Technology	0.069%	0.069%	0.000	0.000%
Utilities	1.891%	2.551%	0.661	34.902%

As mentioned, Table 5.2 averages the shifts in PD over the three climate scenarios that are considered in this research. In reality, the climate scenario that is considered has an effect on the magnitude of the change in PD. Table 5.3 shows the average and maximum percentage point difference in PD per climate scenario for each industry.

The table indicates that the climate scenario significantly impacts the change in PD when climate risks are considered. Within the slow-transitioning Current Policies climate scenario, no shifts in PD are observed, except for the Utilities industries. However, even in this industry, the effect is almost negligible. As a result, the output of the model suggests that if current policies and jurisdictions remain unchanged, transition risks will be minimal. However, as discussed in previous chapters, climate risks are expected to intensify, likely resulting in newer and more strict climate policies. Consequently, the Current Policies scenario is expected to underestimate climate risks, which is reflected in Table 5.3.

In the fast-transitioning Net Zero 2050 scenario, more significant shifts in PD are observed. Under this scenario, the Utilities industry experiences the largest average shock, slightly exceeding 1.75%, which is nearly double the average regular PD for companies in this industry. The Industrials and Basic Materials industries also face notable shocks under this fast-transitioning scenario, consistent with the findings presented in Table 5.2. Conversely, the Financial Services, Health Care, Real Estate, and Technology sectors experience no shift in PD when averaged across all individual companies. Additionally, the Financial Services and Technology industries do not experience a shift in PD when looking at the maximum values. Similar to the Current Policies scenario, the Below 2 °C scenario shows almost no effects when considering the average change in PD. However, the Utilities (3.148), Industrials (0.073), and Basic Materials (0.011) industries do experience shifts when looking at the maximum change in PD.

Table 5.3: Average and Maximum Percentage Point Difference in PD per Climate Scenario

Industry	Mean Regular Merton PD	Current Policies		Net Zero 2050		Below 2 °C	
		Avg	Max	Avg	Max	Avg	Max
Basic Materials	1.181%	0.000	0.000	0.059	0.546	0.001	0.011
Communication Services	0.949%	0.000	0.000	0.002	0.032	0.000	0.001
Consumer Cyclical	1.425%	0.000	0.000	0.002	0.020	0.000	0.000
Consumer Defensive	1.026%	0.000	0.000	0.004	0.097	0.000	0.002
Financial Services	0.677%	0.000	0.000	0.000	0.000	0.000	0.000
Healthcare	0.948%	0.000	0.000	0.000	0.003	0.000	0.000
Industrials	1.100%	0.000	0.000	0.068	2.952	0.002	0.073
Real Estate	0.843%	0.000	0.000	0.000	0.001	0.000	0.000
Technology	0.069%	0.000	0.000	0.000	0.000	0.000	0.000
Utilities	1.891%	0.001	0.014	1.752	22.020	0.229	3.148

It is important to note that in the implementation of this research, there are absolute differences in the impact of climate risks between different climate scenarios, as can be seen in the table. However, the relative change between industries is almost identical for the scenarios. This is because in the current implementation there is no distinction in the carbon emission reduction between industries or certain accelerating effects for particular industries under a climate scenario. Therefore, the only difference in climate risk per scenario is caused by the different carbon prices and shock intensities. As these quantities are independent of industry, company or other portfolio characteristics, the patterns between the scenarios per industry are not that different. There can however still be slight differences, which are likely caused by some non-linear model behaviour discussed further in Section 5.3.

Overall, the magnitude of climate shocks aligns with the definitions of the NGFS scenarios, with larger shocks occurring in more fast-transitioning scenarios. The Utilities industry experiences the most significant shift in PD when climate risks are taken into account. Under the Current Policies scenario, no industry faces significant shifts in PD due to climate risks.

Finally, it is notable that large differences between the average and maximum climate impact are observed within the Net Zero 2050 scenario. For instance, the average shock for the Consumer Defensive industry (0.004) is almost equal to the average shock for this industry under the other climate scenarios. However, the maximum shock of (0.097) could be quite impactful. This suggests that the impact of climate risks within the Net Zero 2050 scenario is strongly skewed. This phenomenon is mainly present within the Utilities industry, where the maximum percentage point difference in PD lies at 22.020. Therefore, the results of the model suggest that, on average, the effects of transition risks are rather limited. However, exceptions exist where the impact could be enormous. This is illustrated further in Table 5.4, which presents summary statistics per industry for the Net Zero 2050 scenario.

The table shows that within the Net Zero 2050 scenario, there is considerable variability in the

Table 5.4: Percentage Point Difference in PD per Industry Under the Net Zero 2050 Scenario

Industry	**#**	**Mean**	**Std. Dev.**	**Min**	**50%**	**75%**	**95%**	**Max**
Basic Materials	31	0.059	0.138	0.000	0.000	0.014	0.362	0.546
Communication Services	23	0.002	0.007	0.000	0.000	0.000	0.009	0.0322
Consumer Cyclical	66	0.002	0.004	0.000	0.000	0.002	0.008	0.020
Consumer Defensive	27	0.004	0.019	0.000	0.000	0.000	0.007	0.097
Financial Services	17	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Healthcare	37	0.000	0.000	0.000	0.000	0.000	0.000	0.003
Industrials	63	0.068	0.378	0.000	0.000	0.001	0.252	2.952
Real Estate	30	0.000	0.000	0.000	0.000	0.000	0.000	0.001
Technology	38	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Utilities	14	1.752	5.859	0.000	0.000	0.085	9.045	22.020

actual impact of transition risks across industries. The minimum shift in PD for each industry is negligible, and this holds true for the 50% of companies with the lowest shifts. Again, the shifts in PD are severely skewed, with notable changes beginning to occur at the 95th percentile. Only the Utilities and Basic Materials industries experience significant shifts at the 75th percentile. Furthermore, the model suggests that the extent to which climate risks will materialise is highly company-specific. For most companies, no notable shifts are observed. However, those that do experience a shift may face large implications, with shocks exceeding 22 percentage points. The fact that more than half of the companies experiences no shock is not expected and is attributed to the methodology and data used in this research. This is discussed in further detail in Chapter 6.

To provide a better view of the most impactful shifts, Figure 5.2 presents all instances where the shift in PD is larger than 0.1 percentage points. Consistent with previous findings, the Utilities, Industrials, and Basic Materials industries are the only industries represented among the largest shifts. The figure shows considerable variability within the group of 14 largest shock sizes. Specifically, the company within the Utilities industry that experiences a shift of 22 percentage point has the largest impact. Shifts of this magnitude can have numerous real-world effects, including the deterioration of credit ratings.

To analyse the effect of climate risks in relation to the credit rating of the firms, Figure 5.3 shows the average shift in PD per credit rating. These ratings state something about the real-world PD of the company. Investors use this as one of the characteristics to reason on the default risk a firm possesses. Therefore, it is interesting to see whether there is some correlation between credit rating and shift in risk-neutral PD as a result of climate risks. Note that the outlier of 22.02 percentage point is not included in the figure, as this would have given a distorted view.

Some trend can be observed, indicating that the lower the credit rating, the larger the shift in PD. This provides some evidence suggesting that a higher real-world PD correlates with a greater effect on the risk-neutral PD when climate risks are considered. Nonetheless, the data is

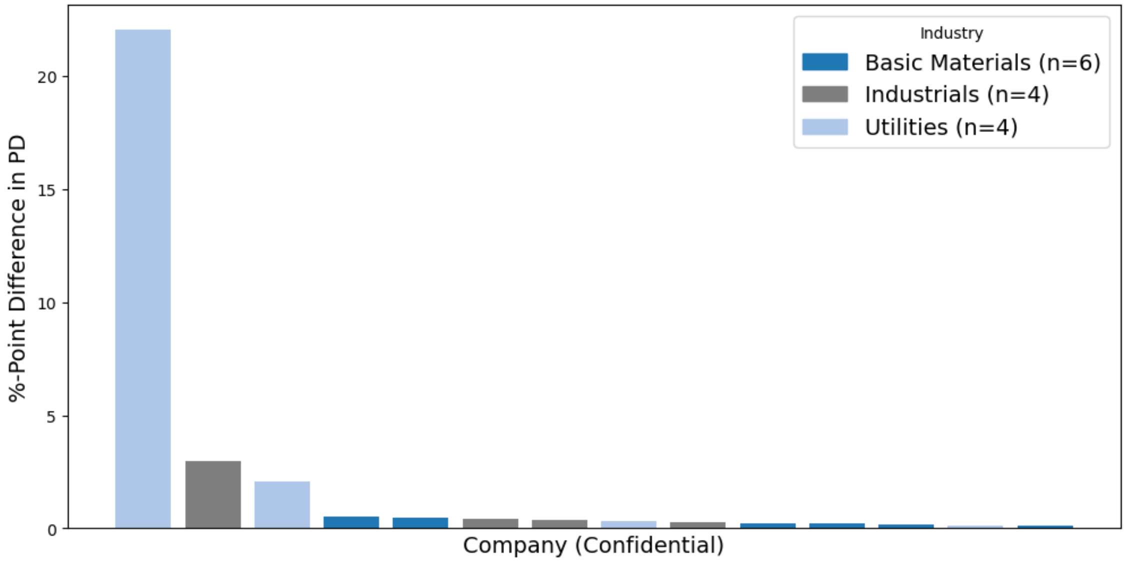

Figure 5.2: Percentage point differences in PD (≥ 0.1)

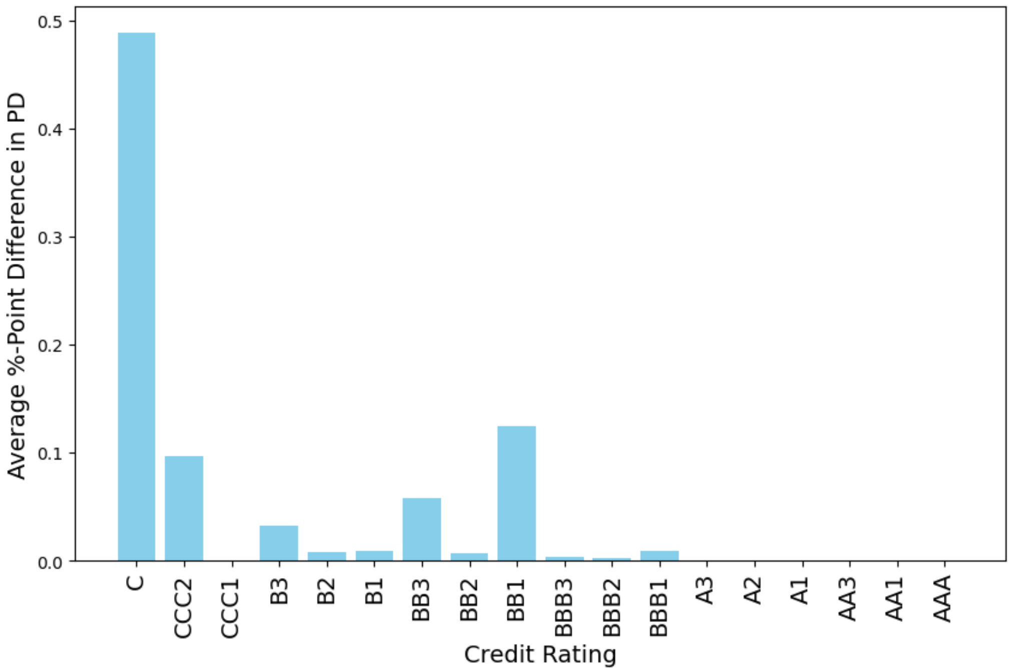

Figure 5.3: Average percentage point difference in PD per credit rating

too limited to draw definitive conclusions on this relationship. In addition to reasoning on the relation between shifts in climate PD and credit ratings, it is important to consider the potential for changes in credit ratings as a result of the adjustments in PD. Unfortunately, there is no direct correspondence between the regular Merton risk-neutral PDs and the credit ratings of firms. Consequently, it is not possible to determine what percentage of firms would experience a change in credit rating when considering the climate-adjusted PD. When analysing companies with the maximum shifts in PD, such as the firm that experiences a 22.02 percentage point increase in PD due to climate risks, it is likely that such a shift could lead to a change in credit rating. This particular company is rated fairly high at AA2, which suggests that a change in PD of this magnitude would likely influence its credit rating. Such changes in credit rating could impact the investment decisions of asset managers. This topic is further explored in Chapter 6.

5.3 Model Implementation Evaluation

In the final section of this chapter, the model implementation itself is reflected upon. To do so, the asset value channel behaviours stated in Section 3.4 will be analysed to see whether the model exhibits behaviour expected from theory. This helps in justifying whether the results obtained in the previous sections are valid. The analyses performed in this section will be done by the means of a stylised company with input parameters given in Table 5.5.

Table 5.5: Variables of Stylised Example

Variable	Value
r	5%
D	80
A	100
σ_A	20%

To find the 1-year regular Merton PD of this fictive company, (2.15) can be used:

$$\begin{aligned} PD &= \Phi\left(-\frac{\ln(\frac{A}{D}) + (r - \frac{1}{2}\sigma_A^2)T}{\sigma_A\sqrt{T}}\right) \\ &= \Phi\left(-\frac{\ln(\frac{100}{80}) + (0.05 - \frac{1}{2}0.2^2)\cdot 1}{0.2\sqrt{1}}\right) \\ &= \Phi\left(-\frac{0.253}{0.2}\right) \\ &= \Phi(-1.2657) \\ &= 0.1028 = 10.28\% \end{aligned}$$

5.3.1 Shock Intensity

As mentioned earlier, it is expected that an increase in the expected number of shocks increases the PD for a company. To verify this, Figure 5.4 shows the development of the PD for increasing values of λ.

Clearly, the PD increases when the number of shocks increases. This behaviour makes economic sense because the shocks add more uncertainty to the value of assets. This uncertainty is reflected in the PD of the company. Moreover, the negative shocks cause the value of assets to drop and therefore increase the likelihood that they lie under the default threshold at maturity.

5.3.2 Mean Jump Size

Another variable for which the influence on the asset value channel behaviour should be studied is the mean jump size, m. The figure below shows how the PD changes for different values of m.

Again, an decrease in PD is observed when jumps become less negative. A more negative jump size results in shocks being more negative, resulting in poorer asset performance.

5.3.3 Jump Size Uncertainty

The uncertainty in jump size is governed by s which is the standard deviation of the distribution from which the jump sizes are sampled. As stated in Section 3.4, the effect of s on the asset value

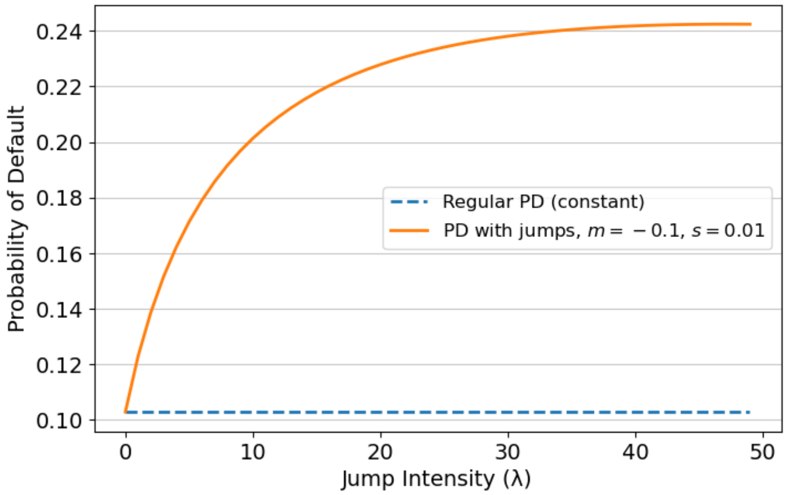

Figure 5.4: PDs for different shock intensities

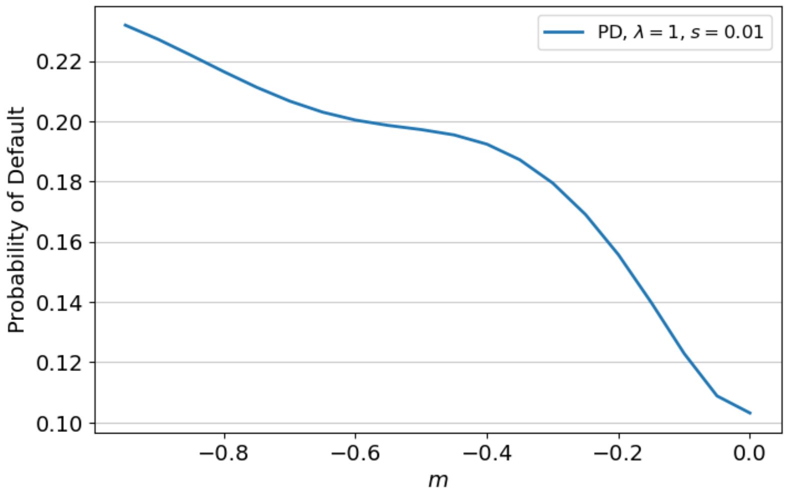

Figure 5.5: PDs for different jump sizes

channel behaviour is not as straightforward as for the other variables. However, when looking at Figure 5.6, it can be seen that there is a clear increase in PD for larger values of s. The jump diffusion model has its roots in option theory. An option increases in value when the uncertainty increases. For larger values of s, more uncertainty is present in the value process. Hence, one would expect the PD to increase.

5.3.4 Possibility of Positive Jumps

The log-normal distribution used to sample jump sizes does not strictly give negative jumps. In the jump diffusion model, a negative jump occurs when the jump size Y is less than one. This is because in (3.12), $Y - 1$ is added to the GBM of the jump-diffusion model. Thus, the probability of a negative jump occurring is represented by the quantity $P(Y < 1)$. This probability changes per company as the CDF of the log-normal distribution is shaped by the company-specific m and s. The probability of a negative jump does not strictly have to be 1, as the PDF of the log-normal distribution can have some leakage towards positive jumps. Figure 5.7 shows the distribution of companies across different probability intervals for experiencing negative jumps.

The figure shows that all companies have $P(Y < 1) \geq 0.5$, meaning each company has a larger

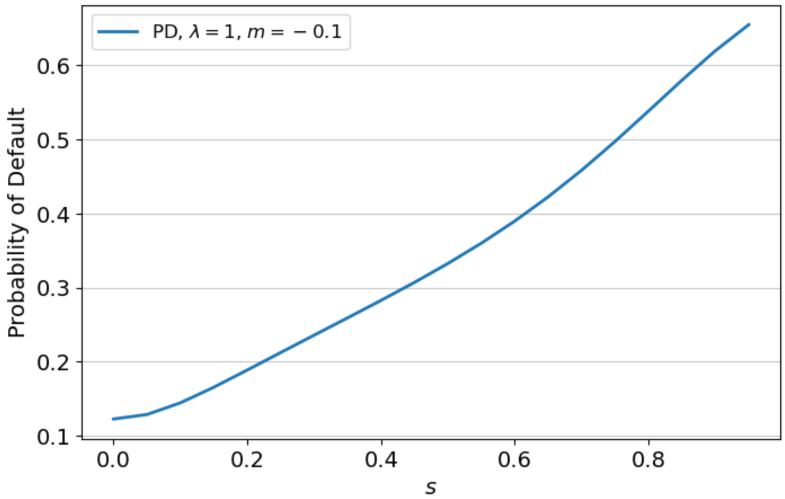

Figure 5.6: PDs for different jump uncertainties

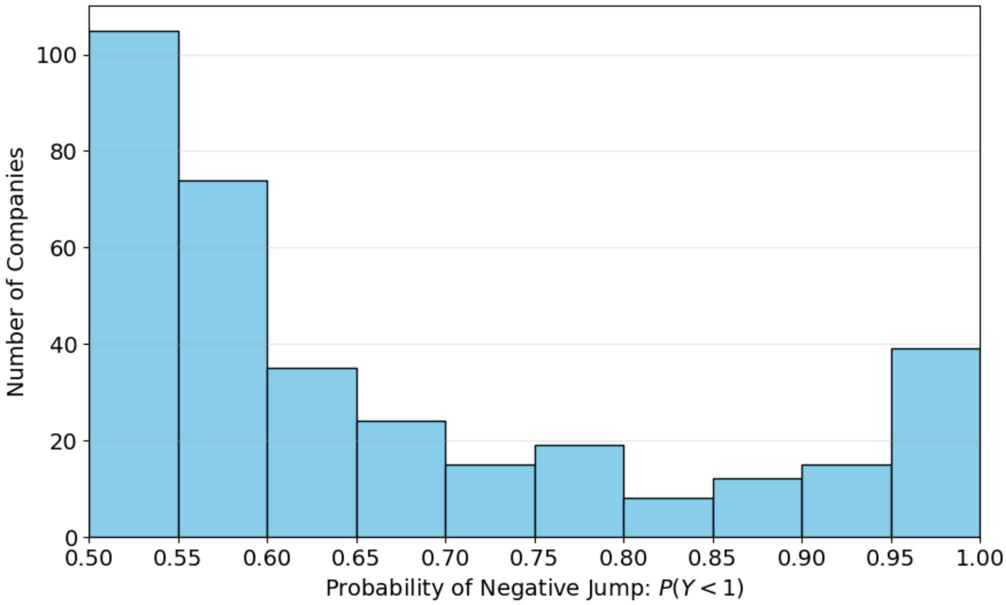

Figure 5.7: Probability of negative jumps

chance of observing negative than positive jumps. Moreover, the more extreme the emissions of the company and therefore the more extreme the shock, the further away the distribution lies from the leakage point and thus the larger the probability of a negative jump. Hence, companies that face bigger transition risks are expected to experience fewer positive jumps than those with smaller transition risks.

To explain why this could make economic sense, imagine a set of companies within the same industry. In this research, transition risks are quantified by the additional costs induced due to for example a carbon tax. If each company is treated independently, it would be expected that negative jumps occur. This is because an increase in costs negatively affects the asset values of the company. However, when looking at the industry as a whole, it is expected that some shifts occur between competitors. High-emitting companies could face reputation risks, meaning customers shift to competitors with lower emissions. On average, this would influence low-emitting companies more positively, meaning there could be possibilities for positive shocks. This topic is touched upon further in Chapter 6.

5.4 Conclusion

This chapter displayed the results of empirically validating the model through a case study. It shows that the difference in PD, as a result of taking into account climate risks, is industry and climate-scenario dependent. The results show that on average the Utilities industry is affected the most. Moreover, the Industrials and Basic Materials industries are impacted quite significantly by climate risks. Especially the fast-transitioning Net Zero 2050 climate scenario brings forward shocks in the PD. This is in line with the expectations as carbon prices are higher in this scenario and pricing instruments are expected to be introduced further.

However, for the majority of companies, the model suggests that the effect of climate risks on the PD is negligible. This is especially the case under the Current Policies scenario, but even holds for the Net Zero 2050 scenario. This is attributed to the data used and scope of the model, which is discussed further in Section 6.2. Furthermore, according to the model, no clear correlation is found between the credit rating of the firm and the shift in PD as a result from climate risks. However, in the extreme cases where companies experience significant shifts in risk-neutral PD, there is quite some potential to experience a shift in credit rating.

When evaluating the behaviour of the model implementation through a sensitivity analysis, the results are as expected. Chapter 6 will highlight the model implementation further. Moreover, it will go deeper into what the results mean in practice and whether they are economically relevant.

Chapter 6

Conclusion & Discussion

This research studies the incorporation of climate risks into structural default risk models, to address the need for better quantification of the impact of climate risks on firm default risk. Existing studies often overlook the underlying channels through which climate risks influence default risk. This study extends a structural default risk model to include climate risks and evaluates it using PGGM's corporate bond portfolio. The aim is to enhance the understanding of the channels through which climate risks influence default risk. By demonstrating the ways climate risks affect default probabilities, this research can help academics, regulators, and financial institutions make more informed decisions to better align financial risk management with broader sustainability goals. This chapter concludes the research by reflecting on the results, acknowledging limitations, and offering recommendations for future research.

6.1 Conclusion

The research goal that this research aims to achieve is defined in Chapter 1. It is to quantify the impact of climate risks on firm default risk and provide a deeper understanding of the channels through which this impact occurs. To address this research goal, the following main research question is formulated:

How can climate risks be integrated into structural default risk models through the underlying channels that cause default, to quantify their impact on firm default risk?

At the beginning of this research, the central research question was dissected into five smaller research questions. These have been answered throughout the previous chapters of this research. This section will continue by addressing the main research question. The answer to the main research question is twofold. First, an answer will be given on how climate risks can be integrated into structural default models, based on the findings of this research. Moreover the model implementation is validated. Second, attention will be put on the quantification of climate risks. The impact of climate risks on PGGM's corporate bond portfolio and the economic relevance of the results are discussed.

6.1.1 Integrating Climate Risks in Structural Default Risk Models

Climate risks can be incorporated into structural default models through various channels. Previous research has explored the integration of physical and transition risks through asset value, asset volatility, drift rate, and debt level channels. This research focuses on the asset value channel due to its direct influence on the PD and the flexibility it offers in the available approaches to incorporate climate risks.

Two primary approaches can be considered in the asset value channel: (1) directly applying a shock to the asset value, and (2) modifying the process the asset value follows. This research focuses on the latter approach, as it more accurately reflects the uncertainty of climate risks by allowing climate risks to occur at random points in time. Moreover, modifying the value process of the assets offers an endogenous treatment of climate risks, allowing for a deeper understanding of how climate risks affect default risk. The literature review reveals that the integration of climate risks in this manner is limited in previous academic research. Transition risks have not been incorporated into the actual asset valuation process, and physical risks have only been considered to a very limited extent.

This research uses Merton's jump diffusion model to quantify climate risks through the asset value channel. This model introduces random shocks with a Poisson distribution frequency and log-normal shock sizes, resulting in a modified analytical PD formula incorporating three additional parameters: λ (shock intensity), m (mean of logarithmic jump sizes), and s (standard deviation of jump sizes). By linking these parameters to climate-related characteristics, such as the carbon emissions of a company or the frequency with which carbon pricing instruments are introduced, the integration of climate risks in the calculation of the default risk can be made explicit.

Chapter 3 demonstrates a particular way in which the model defined in this research can be implemented. A case study is performed on PGGM's corporate bond portfolio to assess the incorporation of transition risks through the asset value channel. Shock sizes, dependent on corporate carbon emissions, are calculated using the carbon prices derived from NGFS climate scenarios. This results in the definition of m. By taking the standard deviation of m per industry, values for s are obtained. A base value for the shock frequency, λ, is determined from the historical frequency of the introduction of carbon pricing instruments. Then for faster-transitioning scenarios λ is assigned higher values. Although this research is limited to transition risks, this approach could be suitable for incorporating physical risks as well. For instance, the number of shocks could correspond to the occurrence of extreme weather events within a given period, while shock sizes could be determined based on the exposure of the region where the company operates.

To validate the mechanics of the model implementation, this research formalises the effect of interest within the asset value channel that the climate parameters bring forward. Findings indicate that an increased number of shocks raises the PD, more negative jumps increase default probability, and higher uncertainty in jump sizes increases PD. Furthermore, the current implementation allows for positive jumps, but each firm faces more negative than positive jumps. Firms with more extreme climate shocks have increased expectation of negative jumps, which is in line with economic principles. The observed validity of model behaviour is crucial in accepting climate-adjusted PDs that result from the model. Moreover, it indicates that adjusting the asset value channel could be a promising way to explore further in the study of incorporating climate risks in structural default risk models.

In summary, this research contributes to academic literature by introducing a novel method for integrating climate risks into firm default risk modelling. It specifically focuses on the underlying channels through which default occurs, with a particular emphasis on the asset value channel. Validity checks show that model behaviour is as expected and in line with economic expectations. A specific instance of the model is implemented through a case study in which PGGM's corporate bond portfolio is studied.

6.1.2 Financial Impact of Climate Risks

According to the model created in this research, climate risks could potentially become material within investment portfolios when quantified through the asset value channel. The significance of the impact depends on several characteristics, most notably the climate scenario under which the climate risks are studied, as the climate scenario governs the shock intensity and carbon prices. When looking at the portfolio as a whole, the model shows that the impact of climate risks is relatively small, even for fast-transitioning climate scenarios. For instance, over 50% of the companies experiences no shift in PD under the fast-transitioning Net Zero 2050 scenario. This is not in line with theory, but can be explained by the model only considering the asset value channel. It is expected that this channel cannot capture the full implications of climate risks as these can become material through various other channels. Moreover, Scope 3 emissions were left out in the shock definition as these are not expected to be taxed. Section 6.2 will further highlight these shortcomings. However, when looking at individual companies, significant shifts in PD can be observed. This information helps asset managers in determining where climate risks are likely to become material within the portfolio. Furthermore, it does show that the asset value channel is capable of quantifying climate risks. Overall the observed shifts in PD could have two main practical implications for PGGM and asset managers in general.

First, risk-neutral PDs are used for valuing financial instruments, particularly CDSs. Therefore, a shift in the risk-neutral PD due to climate risks directly influences the CDS spreads associated with a company. The CDS spread is the cost of insuring against a company's default. An increase in the CDS spread thus translates to a higher market-perceived risk of default for that company. Asset managers use CDS spreads as real-time forward-looking market signals about a company's default risk, functioning as early warning systems. According to the results of this research, if market participants explicitly consider climate risks, the risk-neutral PD rises, and a shift in the CDS spread is expected. This makes it more expensive for asset managers to hedge against the company's default risk and could indicate future financial distress for the company, as higher CDS spreads raise borrowing costs. Furthermore, if market participants are not yet explicitly considering climate risks, there is a risk that when they all begin to do so at once, it will lead to significant adjustments in CDS spreads and financial markets. This is a scenario that is considered in stress tests from regulators.

Second, a change in the perceived risk of the company can force asset managers to adjust their asset allocations. This is because asset managers typically operate under mandates that limit the amount of risk investments can bear. These mandates are often linked to credit ratings supplied by external rating agencies. Although these ratings are based on real-world PDs, it is expected that the impact of climate risks on risk-neutral PDs propagates towards real-world PDs. This is partly shown in Chapter 5 and is also anticipated from economic theory. As stated earlier, an increase in the risk-neutral PD leads to a shift in the CDS spread, which in turn raises the interest the company must pay when borrowing money. Moreover, the increased market-perceived default risk can cause a change in investor behaviour, potentially leading to a sell-off of the company's debt and equity. Both developments can worsen the company's financial situation, potentially affecting the real-world PD and causing a shift in the company's credit rating. Such a shift could then affect investment decisions to remain compliant with existing mandates. It should be noted that not enough evidence is provided in this research to conclude that climate risks have more impact on companies with lower credit ratings. Moreover, the lack of calibration between risk-neutral PDs and credit ratings causes no clear conclusion to be drawn on the percentage of companies that change credit rating due to taking into account climate risks. However, as some of the companies with the largest shifts in PD are fairly high rated, there is potential for the rating to shift.

Because of these two implications, this research shows that the change in risk-neutral PD, resulting from climate risks, could potentially have an impact on PGGM's business operations. Furthermore, it demonstrates the economic relevance of the impact of climate risks on default risk and asset managers in general.

6.2 Discussion

This section will discuss the approach designed in this research and the results that are brought forward. To do so, limitations and simplifications are pointed out.

6.2.1 Data

The primary data sources for this research include Yahoo Finance for equity and company financial data, Trucost for emission data, and NGFS for climate scenario information.

Several issues were present when working with the data from Yahoo Finance. Mainly missing data proved to be a challenge. Particularly data regarding the number of outstanding shares, balance sheet items, and currency information for smaller firms. While these issues were mitigated through data quality checks and filtering, it remains a limitation as using an alternative data provider might have resulted in the inclusion of more companies and perhaps different data values. As the companies with missing data were often relatively small, there is a risk of the results being biased towards larger firms.

Secondly, Trucost, a commercial entity owned by S&P Global, supplies emission data for public companies worldwide. This data is crucial for determining the climate shock size in the jump diffusion model. Nevertheless, other emission data suppliers may employ different methodologies or consider additional factors, which could influence the shock sizes. Consequently, the results of this research may be biased towards Trucost's methodologies. Currently, Scope 3 emissions are not considered in defining the climate shock as these are not included in carbon pricing instruments. Scope 3 emissions capture indirect up- and downstream emissions in the supply chain of the company. Hence, Scope 3 emissions provide a lot of information about the business model of the firm. Therefore, they could serve as important proxies for future climate risks as new legislation might be imposed that focuses specifically on Scope 3 emissions. These developments go hand-in-hand with companies have to report more on their Scope 3 emissions, also bringing forward various costs. Furthermore, only emission data was considered to define the climate shock, whereas other transition risk measures, such as water usage or innovation levels, could enhance its definition. Additionally, the lack of geo-information can be seen as a limitation. Having this data would have allowed to vary the transitions risks per region due to different jurisdictions. Moreover, the geo-locations could have been a first step in quantifying physical risks.

Thirdly, NGFS data is used for the definition of climate scenarios. Although this is considered an industry standard, it is important to acknowledge that the NGFS's definition of climate scenarios could contain inherent biases due to the methodologies it uses. Currently, most focus lies on the carbon price under a climate scenario. However, fast-transitioning climate scenarios could also impose drastic changes to business models. These effects can have large impact on the organization and bring forward additional risks. Having data on these effects could potentially lead to better quantification of climate risks and more accurately describe the transition risks under such fast-transitioning climate scenarios.

Lastly, due to the constraints of using Merton's model, only public companies were included in the research. This constitutes to part of the corporate bond portfolio of PGGM, meaning not a totally comprehensive view is provided in this research on the effect of transition risks on firm default risk within PGGM's corporate bond portfolio.

6.2.2 Methodology

The approach developed in this research to quantify the impact of climate risks on firm default risk is subject to several limitations. To start, the approach is based on Merton's default model, which itself is derived from the Black–Scholes option pricing model. Therefore, the assumptions within the Black–Scholes framework also apply here. Key assumptions in Black-Scholes include constant risk-free rates, which often does not align with reality as central banks frequently adjust these rates to manage inflation. In this research, risk-free rates are associated with the currency in which a company reports its financials, representing the region where most business activities occur. This makes the definition of the risk-free rate more realistic, but does not tackle the constant risk-free rate limitation. Additionally, the model assumes a fixed debt structure, represented entirely by a zero-coupon bond. In reality however, debt structures are not fixed and consist of complex combinations of various debt instruments. Finally, the assumption of a costless and frictionless market without dividend payments is not in line with actual market conditions. In reality, companies do pay dividends and transaction costs exist.

Regarding the implementation of the regular Merton model, a point of discussion is the dependency on k. This variable governs the fraction of long-term debt that is considered in the definition of the default threshold. It is set at 0.5 as this is standard in the industry. However it should be noted that there is a potential bias of the results towards this specific value of k.

When considering the Merton jump diffusion model and the specific approach developed in this research, several other limitations come forward. First, all uncertainty components in the jump diffusion process are assumed to be independent. This means the diffusion dz, the Poisson process N governed by λ, and the jump sizes $Y \sim e^X$ (where $X \sim N(m, s^2)$) are all independent from each other. As stated in Chapter 2, however, this assumption may not hold for climate risks, which are expected to increase in frequency and severity. It is plausible that there could be positive or negative correlations between shock intensity and sizes.

Second, as jump sizes are assumed to be distributed log-normally, there is a possibility of positive jumps occurring. A motivation for the occurrence of positive jumps has been provided in Section 5.3. Although it could make economic sense to allow for positive jumps, there are contexts in which only negative jumps are more preferred. Changing the jump size distribution disallows the use of the analytical formula of the PD under the jump diffusion model.

Third, the jump diffusion model, like the regular Merton model, operates within a risk-neutral framework. Within this framework, all risks are assumed to be hedgeable. Merton assumes that shocks are idiosyncratic, corresponding to zero-beta events uncorrelated with market behaviour, and therefore hedgeable. Nonetheless, in climate risk modelling, scenarios may arise where the zero-beta shock assumption is invalid. For example, global weather-related damages have reached $275 billion in 2022 alone, and significant natural disasters such as earthquakes or hurricanes in densely populated areas could impact global financial markets. Transition risks, such as stranded assets and business model disruptions, may also cause significant financial distress with market-wide effects. As climate-related shocks become more correlated across industries and regions, the hedging assumptions underlying the risk-neutral framework may require re-evaluation.

Finally, the current model implementation only considers the asset value channel to quantify climate risks. Within the asset value channel, Scope 1 and 2 emissions together with carbon prices are used to determine the shock size. Various aspects of climate risks are not considered in this limited focus of the model. Hence, the model might not be able to capture the full consequences of climate risks, which is reflected in the results. There might be industries that will face severe transition risks, but not through reduced asset values as a result of carbon taxes.

6.2.3 Climate Scenarios

The parameters λ, m, and s are influenced by the chosen climate scenario. The frequency of shocks is initially based on the historical introduction of carbon pricing instruments. However, these instruments are not applied on a global level, meaning that not all companies in the portfolio are affected. This could potentially lead to an overestimation of transition risks within the portfolio. Another limitation is the model's inability to capture the non-linear nature of transition risks within a climate scenario. As a result, scenarios without orderly transition paths, like the Delayed Transition scenario, are excluded from the research. To make sure the model is capable of accurately dealing with these scenarios, time-dependency must be present in the definitions of λ and m. However, this causes the definition of the analytical formula for the PD under the jump diffusion model to become invalid. When studying disorderly climate scenarios in the current model implementation, short-term transition risks are overstated because the total transition pathway is averaged over the entire time frame.

6.2.4 Model Risk

Model risk is a significant consideration in financial modelling. It refers to the potential flaws in the model itself or misinterpretation of its outcomes. Generally, as model complexity increases, so does the potential for model risk. Merton's basic model already consists of several complex relationships, which are further complicated in the jump diffusion model. Although numerous measures and checks are implemented to ensure accurate model implementation and result interpretation, the increased model risk remains. Moreover, it is often the case in financial modelling that simpler models perform more accurately than complex models, as increased model complexity can introduce additional noise. This should be acknowledged, as the climate extension in this model leads to a more complex approach compared to the regular Merton model.

6.3 Future Research

This section discusses avenues for future research based on the findings of this research and its limitations, pointed out in the previous sections. Given the novelty of the field this research contributes to, there are still numerous directions for future research that could be fruitful.

To begin, future research directions could further explore the translation of climate risks to financial shocks. As previously stated, the main focus of this research is to develop an approach to incorporate climate risks through the underlying channels of default. To validate the approach, a case study was performed where climate risks are translated to financial shocks by linking them to certain model parameters. Several improvements can be made in this translation to represent climate risks more realistically. Future research could develop a better translation mechanism and directly leverage the approach of this research to incorporate these financial shocks in the PD calculation.

Furthermore, when developing more sophisticated climate shocks, extensions can be made to incorporate physical risks. The approach developed should allow for the inclusion of physical risks, but this was not directly tested due to data limitations. It would be interesting for future work to incorporate physical risks through the approach and compare the validity of the model and its results with the results of this work.

When studying the climate risks through Merton's jump diffusion model, several future research directions exist. First, further research can be done in changing the jump size distribution. For example, distributions that only allow negative jumps or extreme value distributions. Second, future research could look at making λ, m, and s time-dependent to allow for representing climate scenarios with non-linear transition pathways. Specific focus could then be put on finding an analytical formula for the PD under this time-dependent jump diffusion model. Third, efforts could be put on finding the analytical definition of the effects of interest within the asset value channel, as described in Section 3.4.2. This research shows the relations for $\frac{\partial PD^*}{\partial \lambda}$, $\frac{\partial PD^*}{\partial m}$, and $\frac{\partial PD^*}{\partial s}$ through a stylised example, rather than obtaining their analytical definitions.

Future research could also look at a employing a different methodology to adapt the asset value channel and make it suitable to incorporate climate risks. Although the model jump diffusion model aims at being more realistic than the standard Merton model, it still contains several characteristics that could be more realistic. Examples are the constant risk-free rate, the simplified debt structure, and the possibility to only default at maturity. Future studies can utilise a different extension of the Merton model that tackles several of these assumptions.

Besides the asset value channel, the study of other channels through which climate risks affect firm default risk could also be valuable to study. This research limits itself to the asset value channel, but existing academic research has shown that climate risks can be incorporated through different channels. By studying other channels a beginning can be made on developing industry-specific approaches to quantifying climate risks. The channel through which climate risks become visible could be dependent on the business model of the company. This research takes a single approach for each company, but future research could look at employing more granular methods that focus on the channels that tend to be most vulnerable for the specific industry of the form.

Finally, it would be beneficial to have more insights on the probability of a certain climate scenario becoming reality. Having analysed the transition risks per scenario, a key figure missing is the likelihood of a climate scenario occurring. Having insights on this helps in further defining the financial materiality of the transition risks within the portfolio. Determining the likelihoods of the climate scenarios is challenging and far broader than financial research, however, its outcomes would definitely benefit in putting the results of this research in perspective.

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Appendix A

Search Queries

Table A.1: Search Queries on Incorporating Climate Risks in Structural Default Models

Query	Database	#	Date Range
TITLE-ABS-KEY ((("climate" OR "environment*" OR "sustainab*" OR "carbon" OR "physical" OR "transition") AND ("risk*")) AND ("structural credit risk*" OR "structural credit model*" OR "structural credit*" OR "structural default"))	Scopus	12	2005-2024
("climate risk" OR "environmental risk" OR "transition risk" OR "physical risk" OR "carbon risk") AND ("structural credit risk" OR "structural credit model" OR "structural credit" OR "structural default")	Springer	10	2008-2024
("climate risk*" OR "environmental risk*" OR "transition risk*" OR "physical risk*" OR "carbon risk*") AND ("structural credit risk*" OR "structural default" OR "structural credit*")	JSTOR	3	2006-2023
"structural credit risk" → "climate"	SSRN	18	2004-2023
"structural credit risk" → "environment"	SSRN	22	2004-2024
"structural default" → "climate"	SSRN	12	2004-2024
"structural default" → "environment"	SSRN	20	2001-2024

Appendix B

MIVA Algorithm

Algorithm 1 Obtaining the MIVA and corresponding σ_A

$T \leftarrow 1$
$C \leftarrow$ Currency in which company financials are reported
$r \leftarrow$ 1-Year government bond yield, dependent on C
$E^{obs} \leftarrow [E_0^{obs}, E_1^{obs}, \ldots, E_\tau^{obs}]$, observed equity values during financial year
$D \leftarrow [D_0, D_1, \ldots, D_\tau]$, interpolated debt thresholds during financial year
$A \leftarrow E^{obs}$, assume MIVA equals observed equity values as starting point
$R^A \leftarrow$ Daily equity returns according to (3.5)
$\sigma_A \leftarrow$ `numpy.std`$(R^A) \cdot$ `numpy.sqrt`(τ)
$\sigma_A^{old} \leftarrow$ `numpy.std`$(R^A) \cdot$ `numpy.sqrt`$(\tau) + 1$
`threshold` $\leftarrow 1 \cdot 10^{-5}$
while $|\sigma_A - \sigma_A^{old}| >$ `threshold` **do**
    `new_assets` $\leftarrow$ `[]`
    for $t \in [0, \tau]$ **do**
        $E_t^{obs} \leftarrow E^{obs}[t]$
        $D_t \leftarrow D[t]$
        $A_t \leftarrow A[t]$
        if $t = 0$ **then**
            $A_t \leftarrow \arg\min_{A_t} |E_t^{Merton} - E_t^{obs}|$
        else
            $A_{t-1} \leftarrow A[t-1]$
            $A_t \leftarrow \arg\min_{A_t} \left(|E_t^{Merton} - E_t^{obs}| + 0.01 \cdot |A_t - A_{t-1}|\right)$
        end if
        `new_assets`$[t] \leftarrow A_t$
    end for
    $A \leftarrow$ `new_assets`
    $R^A \leftarrow$ Daily asset returns according to (3.5)
    $\sigma_A^{old} \leftarrow \sigma_A$
    $\sigma_A \leftarrow$ `numpy.std`$(R^A) \cdot$ `numpy.sqrt`(τ)
end while
return A, σ_A

Appendix C

Emission Data

Table C.1: Scope 1 Emissions (tonne CO_2)

Industry	**Mean**	**Std. Dev.**	**Min**	**25%**	**50%**	**75%**	**Max**
Basic Materials	5310184	12453636	7493	214869	457872	3283190	62714022
Communication Services	204791	289328	305	12118	57719	305034	993347
Consumer Cyclical	487568	1778298	137	36072	102102	372308	14270000
Consumer Defensive	838364	1038100	4602	81968	368909	1036836	3561979
Energy	1558	0	1558	1558	1558	1558	1558
Financial Services	3590	5468	216	932	1674	3686	23637
Healthcare	202031	220780	1886	56332	120725	288624	846547
Industrials	2384024	6530488	26	26640	112792	677321	36782148
Real Estate	66065	136651	14	9711	22424	47139	606970
Technology	61566	148090	25	2383	9935	58852	828619
Utilities	19848693	42983820	90846	450600	2553253	22126571	162074556

Table C.2: Scope 2 Emissions (tonne CO_2)

Industry	Mean	Std. Dev.	Min	25%	50%	75%	Max
Basic Materials	1191679	1960781	5323	110895	510263	1531973	9966879
Communication Services	1000700	1524256	5	19324	253703	1291617	5141350
Consumer Cyclical	692825	2060302	3674	38424	128622	436684	15672712
Consumer Defensive	552002	709694	9384	72203	209665	772044	2274577
Energy	7634	0	7634	7634	7634	7634	7634
Financial Services	19192	21867	3015	4995	9630	20187	68809
Healthcare	212610	220760	4005	54105	139852	341643	1154012
Industrials	220755	714538	86	24858	49009	135836	5432100
Real Estate	315478	750618	183	32191	61376	205596	3451583
Technology	359422	1313127	132	10394	32273	167389	8078298
Utilities	721100	1422701	4203	46794	139414	378086	4323044

Table C.3: Scope 3 Emissions (tonne CO_2)

Industry	Mean	Std. Dev.	Min	25%	50%	75%	Max
Basic Materials	2515886	3626019	34977	436428	1183712	3236980	17035621
Communication Services	1686165	2278118	43681	112745	647240	2027921	9381632
Consumer Cyclical	2946051	6490276	21624	383585	744912	1759040	30038604
Consumer Defensive	7193806	13607383	128581	688707	2531394	8124016	67591679
Energy	4628	0	4628	4628	4628	4628	4628
Financial Services	203654	253374	13719	32419	67742	294141	773737
Healthcare	1875569	2456271	26334	329951	1227022	2790196	12621316
Industrials	1084940	1352893	51761	234417	638574	1334015	5422589
Real Estate	242070	528014	9614	40595	85033	190066	2739950
Technology	1923413	6904560	9488	136125	392051	868501	42687646
Utilities	1279287	991131	76728	504967	944578	2124244	3320355