University of Twente

Master Thesis

Assessing corporate transition risk: The effects of price elasticity of demand

How the credit risks of the corporate portfolios of banks are affected by the transition towards a low-carbon economy and the influence of price elasticity of demand.

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Executive Summary

This study examines the impact of the low-carbon transition on business credit risk, driven by new European regulations. These regulations require large companies and banks to disclose and assess Environmental, Social, and Governance (ESG) risks, with a particular emphasis on climate-related risks. We introduce a framework utilizing price elasticity of demand (PED) and integrate this feature with carbon pricing, energy consumption, and carbon capture and storage (CCS), covering emissions across Scope 1, 2, and 3. Using scenarios from the Network for Greening the Financial System (NGFS), we modeled financial impacts on six companies—Vattenfall, Tata Steel, Maersk, Vitens, FrieslandCampina, and Boliden—operating in sectors sensitive to transition risks.

Key takeaways

- **The low-carbon transition default risk:** Companies face significant financial challenges from carbon pricing and other transition factors. The impact varies across sectors, depending on emissions types and both product demand and elasticities.
- **Passing on costs mitigates default risk:** Firms with inelastic products can pass on costs and reduce default risk, though this is not viable for all companies.
- **Emission profiles shape risk sensitivity:** Companies with high Scope 1 emissions are highly sensitive to carbon pricing in green scenarios, while those with significant Scope 3 emissions face consistently high risks.

Table 1 presents default risks in the form of Altman Z-scores, scores below 1.1 indicate significant default risk. We only looked at passing on costs as mitigation strategy. Companies with lower Z-scores must adopt alternative strategies to manage the low-carbon transition.

Year	**Vattenfall**	**Tata Steel**	**Maersk**	**Vitens**	**Friesland Campina**	**Boliden**
2023	1.89	5.00	7.92	0.80	1.30	4.58
2050	-0.82	$<$ -1.5	7.89	1.25	-0.68	4.54

Table 1: Z-scores passing on 60% of costs in a global below 2°C scenario.

Contribution

This study is one of the first to combine PED and emissions analysis for a more tailored company-level transition risk assessment. We demonstrate that factors like product elasticity and emission types shape transition risks. We show that passing costs alone is not a viable strategy for 4 of the 6 companies to mitigate transition-related default risk effectively.

Recommendations for further research

- **Incorporating PED into advanced credit risk models:** Integrate PED into advanced models, such as Internal Ratings-Based (IRB) models, for more accurate PD assessments.
- **Exploring additional elasticities:** Research income, cross-price, and green product elasticity for deeper insights into cost pass-on strategies, especially in competitive markets.
- **Include investments in transition risk models:** Future studies should explore whether companies can pass on the financing costs of green investments and include this in credit risk models. This would help clarify the trade-off between short-term financial burdens and long-term cost savings from such investments.

Acknowledgements

The completion of my thesis signifies the end of my time as a student at the University of Twente. Over the course of my master's in Financial Engineering and Management, I have not only learned much on about the the field but also grown personally. I have made friendships and created unforgettable memories. I would like to take this opportunity to express my gratitude for these memorable years in Enschede and for the people who accompanied me on this journey.

Over the past seven months, I have dedicated myself to this thesis at Probability and Partners. I am grateful to the company for providing me with the opportunity to delve into the world of risk management. From the very beginning, I felt welcomed and integrated into the team, and I truly appreciated being involved in the company's activities. I would also like to express my gratitude to the entire team for their support throughout my time there. A special note of appreciation goes to my two supervisors, Erik Kooistra and Gerrit Jan van den Brink, for their guidance in this process. Erik played a pivotal role in shaping the direction of this thesis, and offering valuable support in the development of my model. Gerrit Jan introduced me to the complex world of ESG risks, providing insight into the latest developments and regulations in the field, ensuring the relevance of my work.

From the University of Twente, I would like to thank my supervisors Berend Roorda en Reinoud Joosten. My first supervisor, Berend, has been so cooperative, especially when setting the goals of my research. I truly enjoyed our engaging and constructive discussions, which pushed me to think critically always felt motivated and supported to set out my own course in my work, which I appreciate greatly. My second supervisor, Reinoud, gave very useful feedback, improving my thesis on multiple aspects.

I am proud of this work, as it reflects everything I have learned over the past years. It has allowed me to explore the intersection of credit risk, microeconomics, and climate risk—an area in which I developed an interest during my time in Enschede. This achievement would not have been possible without the support of my family, who constantly motivated me to challenge myself, and my friends, who stood by me throughout this remarkable journey.

Job de Beurs
Utrecht, *17 September, 2024.*

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Nomenclature

AT1 **A**dditional **T**ier 1

BCBS **B**asel **C**ommittee on **B**anking **S**upervision

BRE **B**ond **R**ating **E**quivalent

CCS **C**arbon **C**apture and **S**torage

CET1 **C**ommon **E**quity **T**ier 1

CPI **C**onsumer **P**rice **I**ndex

CSRD **C**orporate **S**ustainability **R**eporting **D**irective

DRI **D**irect **R**educed **I**ron

EAD **E**xposure **at** **D**efault

EBA **E**uropean **B**anking **A**uthority

EBIT **E**arnings **B**efore **I**nterest and **T**axes

ESG **E**nvironmental, **S**ocietal, and **G**overnmental

ETS **E**missions **T**rading **S**ystem

FFE **F**orty **F**oot **E**quivalent

G-SIB **G**lobally **S**ystematic **I**mportant **B**ank

GCAM **G**lobal **C**hange **A**nalysis **M**odel

GHG **G**reen**h**ouse **G**as

GJ **G**igajoule

IRB **I**nternal **R**ating-**B**ased

ITS **I**mplementing **T**echnical **S**tandards

kWh **K**ilo**w**att-**hour**

LGD **L**oss **G**iven **D**efault

MDA **M**ultiple **D**iscriminant **A**nalysis

NDCs **N**ationally **D**etermined **C**ontributions

NFRD **N**on-**F**inancial **R**eporting **D**irective

NGFS **N**etwork for **G**reening the **F**inancial **S**ystem

P&L **P**rofit and **L**oss

PD **P**robability of **D**efault

PED **P**rice **E**lasticity of **D**emand

PV **P**resent **V**alue

RWA **R**isk **W**eighted **A**ssets

SBTi **S**cience **B**ased **T**argets **i**nitiative

VaR **V**alue-**at**-**R**isk

WACC **W**eighted **A**verage **C**ost of **C**apital

WCDR **W**orst **C**ase **D**efault **R**ate

CO2e Carbon Dioxide equivalents

Chapter 1

Introduction

We explore the consequences for banks coming from the the transition to a low-carbon economy. We introduce the concept of transition risk for banks and discuss the regulatory framework that shapes this issue. This chapter outlines the main challenges associated with transition risk and defines the core research problem, accompanied by a discussion of recent developments in the field. We formulate a problem solving approach including a methodology. We conclude this chapter by discussing the scope of this research and presenting the structure of our research.

1.1 Problem context

Financial institutions hold a pivotal role in guiding European markets towards sustainability. As regulations become increasingly strict, banks must adapt their practices by incorporating environmental sustainability into their core operations, by increasing green financing and reducing their carbon footprint. This transformative shift induces significant risks. Institutions must navigate through new financial landscapes and potential instabilities linked with transition towards a low-carbon economy. In 2021, the European Banking Authority (EBA) introduced guidelines aimed at enhancing how financial institutions manage Environmental, Societal, and Governmental (ESG) risks (EBA, 2021). This was quickly followed by the Implementing Technical Standards (ITS), which set clear disclosure requirements for banks about their ESG risks (EBA, 2022). Simultaneously, the European Union's Corporate Sustainability Reporting Directive (CSRD) significantly raised reporting standards, mandating more rigorous sustainability disclosures across all sectors (EU, 2022). As EBA's Pillar 3 mandates take effect, large financial institutions in the EU are required to revise their ESG disclosure practices, enhancing transparency. Among the ESG categories, environmental risks are prioritized due to their measurable nature. The upcoming compliance deadline in June 2024 for financed greenhouse gas (GHG) emissions, which is sooner than for social and governance risks (EBA, 2022). While environmental risks can be measured relatively easily, societal and governmental risks require a more nuanced, qualitative assessment approach due to their wide-ranging implications throughout the value chain. Combined with their measurability and significant impact on the banking sector, we look into the environmental risks.

In the context of environmental risks, banks are required to adapt to climate change, protect biodiversity, prevent pollution, and sustainably manage water and marine resources by integrating these considerations into their risk management frameworks and decision-making processes (EBA, 2021). The EBA highlights climate risk as the key environmental factor connected to broader ESG challenges. Given its broad influence, climate risk not only shapes but also drives the development of other environmental factors. For these reasons we dive deeper into climate risk.

In 2019, the European Central Bank (ECB) stated that climate risks could adversely affect the balance sheets of financial institutions, impacting financial stability, especially if markets fail to price these risks accurately (Giuzio et al., 2019). Regulators divide climate risk up into physical and transition risk. Physical risks come forth out of more extreme climatic events such as floods and wildfires but also the slowly rising sea levels. Transition risk occurs from the transition towards an environmentally sustainable economy (EBA, 2022; Sun et al., 2019). According to a financial stability review in 2021 by the ECB (2021), 70% of credit exposures with high or increasing physical risk over the next decades is in the portfolios of just 25 banks in Europe. Transition risk is spread much wider in the financial system as only 11% of EU based investment funds is considered green (ECB, 2021). Physical risk potentially influences 30% of a banks' corporate exposures, whereas 55% of the investments are made in high-emitting firms and only 1% of the assets align with the EU Taxonomy for sustainable economic activities, a classification system described in Pillar 3 of the EBA to guide sustainable investments (ECB, 2021). A financial stress test covering over 80 financial Dutch institutions, shows portfolio devaluation due to the transition towards a low-carbon economy of up to 11% (Vermeulen et al., 2021). The review and stress test suggest that both physical and transition risk will influence the European financial stability heavily in the future. However, transition risk is more widespread between sectors and faces more methodological challenges. Because of these reasons we will focus this research on transition risk rather than physical risk. Our focus has narrowed from the broad scope of Pillar 3 and CSRD to specifically address transition risk. Figure 1.1 depicts this process.

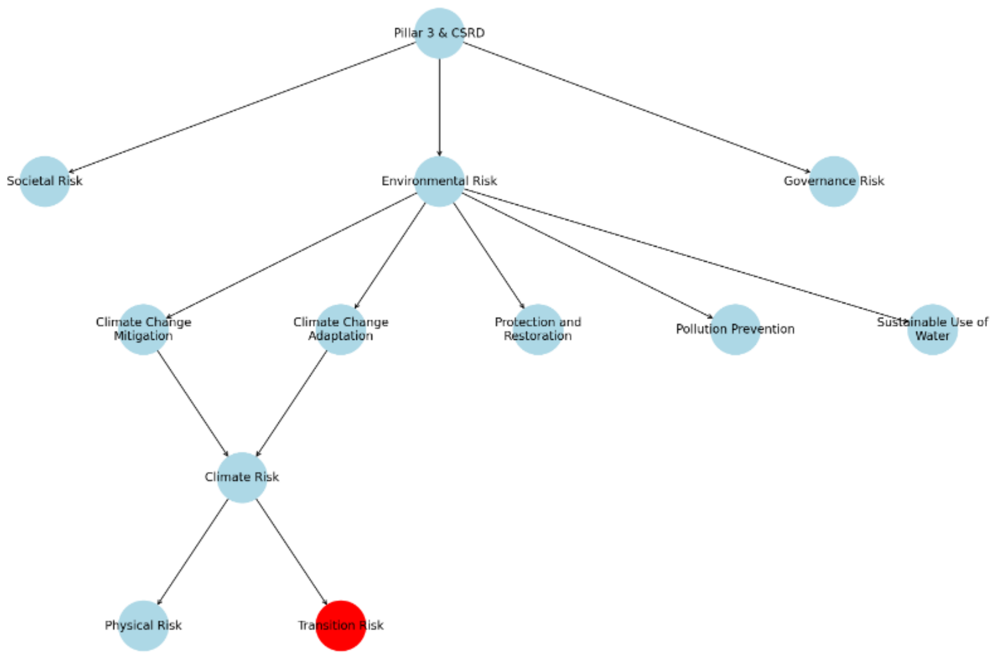

FIGURE 1.1: Area of the research within Pillar 3 and CSRD requirements.

Pillar 3 of the EBA requires banks to describe how ESG risks intersect with traditional risk categories, such as credit-, market-, liquidity- and operational risk (EBA, 2022). In the context of banks, credit risk plays a vital role in the operations of banks and the financial stability. Hence, credit risk can be considered more important than the other risk categories. The integration of ESG considerations, particularly transition risks, into credit risk management can influence the amount of capital banks need to hold, impacting their capital efficiency and profitability. This is highlighted by the fact that credit risk is a key metric used for determining capital requirements from the Basel agreements.

In collaboration with Probability and Partners (P&P), our research aims to quantify how transitioning towards a low-carbon economy affects the credit risk profiles for banks' corporate portfolios. P&P is a risk management consultancy firm based in Amsterdam. P&P operates in four sectors: Banking, Pension funds, Insurance and Asset Management. We conduct this research within the banking sector combining the domains of ESG with credit risk modelling. The ESG/credit risk part of the organization builds and validates models among others for measuring the effect of the transition on credit risk for several financial firms, such as banks. Whilst the first methods have been developed, a deeper understanding of the activated mechanisms is required to be able to capture the consequences for credit risk exposures caused by the transition to a low-carbon economy.

1.2 Core problem

As the emphasis of regulators on ESG risks grows, banks face the challenge of incorporating ESG factors into their risk management practices. Applying theoretical research can help banks to standardize ESG risk reporting and management operations. Defining a comprehensive methodology for integration of emissions and transition risk presents a complex challenge due to their vast scope and the historically limited data availability. The introduction of the CSRD and EBA Pillar 3 requirements highlights the importance of developing practical methods for quantifying ESG risks. CSRD, which has become effective as of 2023, increases the amount of companies enforced to disclose non-financial matters from approximately 12,000, reporting under the older Non-Financial Reporting Directive (NFRD), to 50,000 (EU, 2022). This enhances the data availability, which aligns with the EBA Pillar 3 which requires banks to disclose financed GHG emissions, due in June 2024. More specifically they need report on their plans and potential methodologies to implement these disclosures (EBA, 2022). With the CSRD extending the scope of ESG reporting and the EBA mandating disclosures on financed emissions, banks are under pressure to adapt swiftly, giving rise to the development of risk management methodologies. In this context, the intersection of GHG emissions, credit risk, and the transition to a low-carbon economy is an important one.

Integrating ESG factors, especially GHG emissions and transition to a low-carbon economy, requires banks to consider each company's unique risks. Current models, often based on sector averages, may inaccurately assess risks due to a lack of specificity. They often use a top-down approach rather than a bottom-up. These models involve assumptions where the adaptability of a business is not taken into account properly. There is a need to understand how companies' mechanisms for coping with transition risk relate to their probability of default (PD), and the magnitude of this relationship. For sound risk management practices, the top-down models used in these cases can be calibrated more precisely on possibly even an individual level. So by gaining more understanding on the differences between companies and sectors, we can model the transition and credit risk exposures more accurately in the future, which is the eventual goal for banks. Hence, we formulate the core problem as follows:

The need for enhanced understanding of the extent and ways in which the transition to a low-carbon economy impacts the finances of companies and consequently their probability of default.

By finding out the significance of the effects of the transition we can see the importance of incorporating bottom-up approaches in standardized risk models. By gaining knowledge about how the finances are affected by the transition, we can build future portfolio wide risk models which can take more characteristics of a company into account to calibrate the more accurately.

1.2.1 Recent developments

The EBA has recently published Pillar 3 requirements on the need for disclosures that encompass Scope 3 GHG emissions (EBA, 2022). Although the direct links between these emissions and credit risk are not explicitly integrated into the proposed regulations, integration makes sense as these two concepts are very much linked. The EBA's alignment with the Network for Greening the Financial System (NGFS) scenarios in their stress testing exemplifies this forward-thinking approach, offering conceptual methodologies to manage climate risk through scenario analysis (EBA, 2021). Most studies employ top-down approaches, using sectorial data to evaluate the credit risk across entire portfolios. This method has been widely adopted by institutions as shown in the study of Vermeulen et al. (2018) for the DNB, the UNEP-FI (2018), and numerous researchers including Battiston and Monasterolo (2020). Top down approaches help address the data challenges often associated with transition risk and emissions (Boungou & Urom, 2023; Jung et al., 2023). In contrast to top-down methodologies, bottom-up approaches offer a more detailed view of credit risks, focusing on individual firms rather than sectors. Mihaylova and Blumer (2022) stress the importance of integrating both top-down and bottom-up methodologies for a comprehensive credit risk assessment. The Basel Committee on Banking Supervision (BCBS) shares this view, highlighting the usefulness of bottom-up approaches which, when carefully correlated, can also be aggregated to assess entire portfolios (BCBS, 2021b). Despite their recognized importance, there is limited bottom-up research on credit risk on an individual company level. For instance, Nguyen et al. (2023) have examined the climate credit risks of 20 banks, rather than the researching the latter's clients, the originators of credit risk. Additionally, Clerc et al. (2020) proposes a bottom-up methodology using scenario analysis with 'infra-sector data' to increase granularity. However these bottom-up approaches still do not examine the how the transition affects a single company and it's PD. Clarkson et al. (2014) looks at company capabilities to manage the transition in valuing companies through the emissions trading system (ETS). However, they did not directly link their findings to credit risk or use scenario analysis in their analysis. These developments highlight the research gap for our problem: the lack of detailed analysis on transition risk in different scenarios for individual companies regarding credit risk risk. Understanding this element is essential for developing reliable top-down PD models in the context of transition risk, a field that is emerging rapidly.

1.3 Research questions

To address the problem discussed in Section 1.2, we define a central research question that will serve as the main research question of this thesis. This question forms the foundation of this research and is articulated as follows:

How can we asses the impact of the low-carbon transition on the probability of default of a business?

To answer this research question we formulate other research questions guiding us through the research. These questions can be used as a building block for the next steps in the research process. The questions are listed below accompanied with a brief motivation.

A *In what ways does the low-carbon transition influence the financial metrics required for defining the default risk of a business?*

Answering this question enhances our understanding of what parts of a business are influenced by the transition and how this affects the profitability of a company. We dive into the definition of the low-carbon transition first and delve deeper into its key drivers. We then elaborate on credit risk standards, identifying key financial metrics used for PD modelling. Next, we explore the different transmission mechanisms of transition on the financials of a business, discovering how the transition can influence the costs and revenue of a business. We see how these consequences potentially affect the financial metrics and the default risk of a business. We conclude by showing the relationship between default risk, credit ratings and the PD.

B *How can long-term scenario analysis be employed to assess the effects of cost increments, revenue changes, and cost pass-on abilities?*

In this part of our research, we develop a framework integrating scenario analysis with the assessment of default risk for a single business. This involves utilizing NGFS scenarios, reflecting potential future transition pathways. We identify relevant scenarios and the indicators to be used for this analysis, leveraging our understanding of the transmission mechanisms for selection. We utilize these scenarios to determine cost increments and future sales increments. Additionally, we develop a method to incorporate business-specific factors, such as the ability to pass on costs, into our framework. Our approach details how financial metrics can be linked with the scenario analysis indicators. We conclude the framework by mapping the to new profit or loss from the transition to a credit risk model. This provides a robust tool for assessing the default risk of businesses in the context of a low-carbon transition.

C *Which key data points and business insights are required for assessing the default risk for single companies?*

To effectively asses the PD for companies it is essential to select appropriate data and business information. This involves choosing relevant companies, representing the sector with a straightforward business model. We consider the GHG emission profiles, select relevant parts of the Profit and Loss (P&L) statement and the balance as well as the products sold and their business models. We review the price elasticity (PED) of demand for the products. We include this to analyze the ability to pass on costs. It is here where we zoom in on a specific company. We do this for six companies operating in different sectors.

D *What is the effect of the low-carbon transition on the probability of default of a business?*

Finally, we apply the developed framework to asses the order of magnitude of default risk and the PD. By comparing historical and projected data under different scenarios, we assess the magnitude of change in PD and find the how default risk evolves over time in different circumstances. These include changes in pricing strategies and PED. This does not only test the efficacy of the framework, but also highlights the potential real-world implications of the low-carbon transition on corporate financial stability.

1.3.1 Research methods and data use

The problem solving approach requires qualitative and quantitative research methods. This section describes the methods we use to answer the research question. The approach encompasses an integration of analytical frameworks, scenario analysis, and empirical data analysis. We combine these to assess the direct and indirect effects of the low-carbon transition on business default probabilities.The different methods are listed below, where RQA means Research Question A and so on.

- *Qualitative research*
  RQA: We use literature review to answer the Research Question A. We gain more in depth knowledge of the low-carbon transition and its drivers. We follow the review by describing several transmission mechanisms using both academic literature and regulatory reports. We conclude the literature review by giving context on credit risk, more specific PD models and the input for these models.

  RQB: We use the foundation from RQA to develop a framework. We use literature of existing transition risk models to find useful scenario indicators. We look into the NGFS scenario possibilities and select appropriate scenarios. We use input from internal stakeholders of P&P for this selection process as well, to secure the relevance for applications in practice. Furthermore, we use literature to explore what influences the ability to pass on costs for a company.

  RQC: We select the companies based on several criteria. criteria are defined using reports of public organizations describing sectors vulnerable to transition risk. Furthermore, we use annual and sustainability reports to gather relevant information. We use academic literature to determine the relevant price elasticities of demand.

- *Quantitative research*
  RQB: We clean and prepare the NGFS data, such that we only use the required components of the data. We want the data to easily integrate into the other quantitative data.

RQC: We prepare the data of emissions and finances of the businesses from the public business reports. We need to structure these data properly and make justifiable modifications to the data such that we use the same data format for every company as input.

RQD: We develop the actual model, integrating scenario and company data. We finalize with evaluation of the results. We compare old PDs with the new PDs, and perform sensitivity analysis on pricing strategies and the PED to see their affects.

1.4 Scope

We discuss the boundaries of our research. Furthermore, we set the theoretical and practical objective for this research. Understanding effects of transition risk on a company is of importance for the entire financial system. Where pension funds, insurers and asset managers look at this problem from an asset and equity perspective, through corporate bonds, shares and derivatives, banks look at it from mostly an asset perspective, because of their loans. We focus on the perspective of a bank, since the regulations for this sector are the most pending. This is the reason we focus on the creditworthiness in the form of PD of the company rather than the effect of transition risks on share prices of a business. However, our research can be interesting for all sectors, especially the part on a companies ability to pass on costs. Numerous ways exist in which the low-carbon transition can influence the creditworthiness of a company, from which we make a selection. The most evident transmission mechanisms of the low-carbon transition and PD can be divided into two categories: profitability and leverage, two factors which have a significant impact on the PD of a company (Campbell et al., 2008). The mechanisms are listed below.

Profitability

- Adding costs to direct emissions: The costs for a company may increase due to carbon tax or a cap-and-trade system for emitting GHGs in their operations.
- Adding costs to indirect emissions: The costs for a company may increase due to the pass through of direct emissions costs of their production inputs from the value chain.
- Ability to change business model: A company must be able to change its old business model to a sustainable profitable business model. If it can, this requires investments. If it cannot, the company has stranded assets which will become worthless.
- Reputational damage: The potential loss of a company's standing and attractiveness to customers due to negative environmental impacts. This can affect the profitability.
- Compliance and legal costs: A company might increase its costs to comply with regulation as this means hiring new lawyers and other staff to set up the reports.
- Passing costs through to customers: The ability of a company to pass on the increased costs mentioned above to the customer is important for the revenue.
- Price elasticity of demand: A company may be able to pass on the costs to the customer; however, this can influence the demand for the product and thus the revenue.

Leverage

- Access to finance: A company which is considered not as green as competitors can have difficulties accessing capital in the usual ways. This means other sources of capital are required, usually against a higher interest, which increases the leverage ratio.
- Competitiveness: The ability of a company to maintain or enhance its market position by adopting advanced, more efficient technologies. If this requires many investments, the debt will increase.
- Investor confidence: The potential loss of a company's standing and attractiveness to investors. This means less supply of capital which can increase interest rates and higher leverage ratios.

For our research we focus on the effects of the transition on the operations of a business and the influence on costs and revenue, thus the profitability. Whilst leverage ratios are important for determining the PD and relevant for transition risk, it is outside the scope of our research. Since we conduct this from the perspective of a bank, we see this as a standard approach of accessing capital, without the leverage complexities. Within the category of profitability we focus on five out of the seven points, we do not cover reputational and legal costs. As the other five points have an interesting interaction, where on the one hand we see costs increasing but strategies to manage these costs differ per company. This means that we focus on the increase of costs due to a company's emissions and its ability of using pricing strategies to mitigate losses. For the latter one we look at the effects on the revenue due to a company's ability to pass on the costs to the customer, which involves PED. The first factor we know that extra costs drive the increments of default risk and that the magnitude of this is influenced by the ability to change a business model. The second and third factor are very much linked, as PED gives is required to asses the ability to pass on costs to customers. It is important to investigate this ability, if a company manages to pass on all the costs, without losing profitability, there would be little to no extra default risk. Hence investigating this ability is essential in saying something about the profitability of a company, and thus their default risk. Furthermore, this ability can differ significantly across sectors and companies within the same sector.

In our research we look into companies operating in vulnerable sectors to transition risk, for whom it is most interesting to observe the magnitude of effects of the transition. Alogoskoufis et al. (2021), a report by the ECB, shows seven NACE-1 level sectors with high level of transition risk, depicted in Figure 1.2. These sectors are: (1) Agriculture, (2) Mining, (3) Electricity and Gas, (4) Water Supply and Waste, (5) Transport, (6) Accommodation and Food, (7) Manufacturing. These are sectors where more than 70% of the firms have a high vulnerability to transition risk. A firms consequently has a high vulnerability to transition risk if their relative emissions fall into the 70th percentile of the scope 1,2 and 3 relative emissions of all companies researched (Alogoskoufis et al., 2021). Scope 1 includes direct emissions, Scope 2 covers indirect emissions from purchased energy, and Scope 3 encompasses all other indirect emissions in the value chain. Hence we will only review companies operating in these sectors. The other criteria for the companies to review is that they have a straightforward business model with a core activity, which delivers their product the the end-consumer. By setting this limitation we can review the addition of costs and PED more easily and focus on the core business rather than also looking at all side business projects.

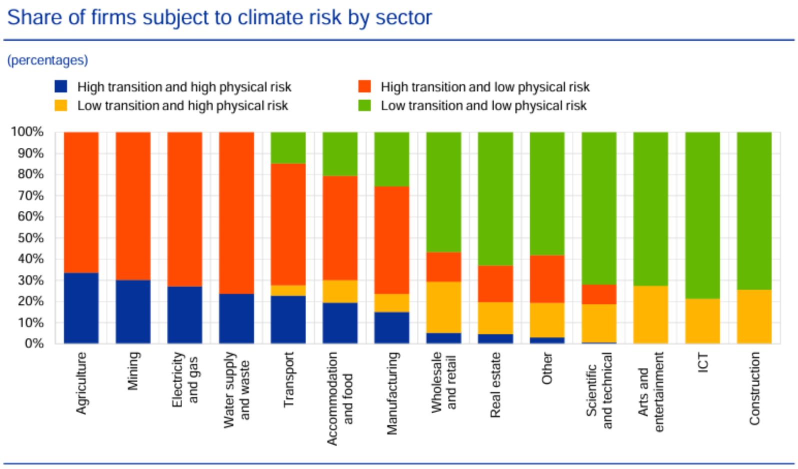

FIGURE 1.2: Overview of sectors vulnerable to transition risk according to the ECB (Alogoskoufis et al., 2021).

Now that we have set the boundaries of our research, we define the theoretical and practical objective of this research.

Theoretical objective: The theoretical objective is to understand the impact of the low-carbon transition on the financial statements of companies. This includes identifying how these transitions affects the costs and the revenue of a firm. Furthermore, we aim to discover a way to include passing-on abilities in a credit risk model. We explore the magnitude of the low-carbon transition and passing-on abilities on the PD of a firm.

Practical objective: The practical objective is to develop a framework that quantifies transition-related credit risk at individual company levels. This framework assesses the impact of the low-carbon transition PD and evaluate how sensitive a company's PD is under different climate scenarios. Furthermore, finding the effect of price elasticities can help practitioners take this into account for model development practices. Additionally, we aim for a framework that it is applicable for evaluating companies not directly studied in this research, thereby aiding in the calibration of top-down transition-related credit risk models.

1.5 Thesis outline

We use this subsection to outline the subjects discussed throughout the chapters of this thesis, to help the reader in maintaining an overview throughout the thesis.

Chapter 2: Theoretical Context
In this chapter we perform our qualitative research, we present the main concepts and definitions regarding the low-carbon transition, financial metrics and credit risk. Furthermore, we answer Research Question A, where we research the aforementioned transmission mechanisms in detail.

Chapter 3: Conceptual Framework Development
Chapter 3 answers Research Question B. We explore the different scenarios and set out a methodology how to integrate these with concepts and mechanisms found in Chapter 2. We summarize the framework in a calculation example. It is here where we aim to establish our theoretical contribution.

Chapter 4: Data selection and Preparation
In the fourth chapter we describe which companies we evaluate and which data we need from them to execute the developed framework. We investigate relevant data and prepare these such that we they are usable in the next phase, and present these results. We answer Research Question C and use this as a building block for performing the actual analysis.

Chapter 5: Model Application and Evaluation
We aim to establish out practical objective in Chapter 5. We combine the input from Chapters 2 and 3 to perform the actual analysis. We present the results and give context to them.

Chapter 6: Conclusion and Discussion
In the final chapter, we give the conclusions of the research. We provide a general overview of the steps taken and the results that are obtained. We discuss the limitations, meaning and relevance of this research design as well as the outcomes of the research. We conclude by recommending future research possibilities.

Chapter 2

Theoretical Context

We conduct a literature review to define key concepts related to transition and credit risk. We begin by defining transition risk and its drivers, aiming to understand their impact on different parts of a P&L statement and the balance sheet. We then explore several credit risk models and their underlying metrics and select a suitable model based on the literature. Our goal is to understand how transition risk affects these metrics and, consequently, the credit risk. This helps us identify the revenue and cost implications of the transition, translating them into financial metrics for the chosen credit risk model. Finally, we outline how these financial metrics can be used for credit risk and PD assessments.

2.1 Transition risk

To measure the effects of transition risk effectively, it is important to define it clearly and understand its drivers. Definitions of transition risk vary, generally referring to the uncertainty of the process of the transition towards a sustainable economy. According to the ECB, transition risk is defined as the potential financial loss an institution may suffer, directly or indirectly, from adjustments toward a lower-carbon and more environmentally sustainable economy (ECB, 2020). The EBA defines it as "the risks of any negative financial impact on the institution stemming from the current or prospective impacts of the transition to an environmentally sustainable economy on its counterparties or invested assets" (EBA, 2022). The BCBS defines transition risk as "the risks associated with the adjustment process towards a low-carbon economy" (BCBS, 2021a). Transition risk itself thus encompasses a wide range of impacts resulting from the shift towards a sustainable economy. To enhance measurability, the EU set goals of achieving a 55% reduction in GHG emissions by 2030 relative to 1990 levels, and reaching net-zero emissions by 2050 (European Commission, 2024). Henceforth, we define transition risk as the risk of financial losses that institutions may incur due to adjustments in their counterparties or asset investments, driven by the transition toward achieving a 55% reduction in GHG emissions by 2030 and net-zero emissions by 2050.

2.1.1 Drivers of transition risk

Several factors, known as risk drivers, push the risks associated with the EU's environmental goals. Institutions categorize the drivers for the transition in various ways. The EBA outlines three primary drivers for transition risk: policy changes that alter asset values in carbon-intensive sectors; technological advancements that depreciate existing technologies and necessitate asset repricing; and shifts in consumer and investor behavior that can increase operational costs and affect demand (EBA, 2021). The EC's guidelines expand on these drivers, agreeing on policy and technological risks and adding legal risks, which stem from potential litigation related to inadequate efforts in climate impact mitigation or adaptation. Additionally, the guidelines differentiate consumer behavior into two separate risks: market and reputational risks. Market risks come from shifts in consumer and business preferences towards greener products and services, and reputational risks occur when companies fail to maintain their reputation due to perceived environmental impact (European Commission, 2019). The Task Force on Climate-Related Financial Disclosures (TCFD) categorizes these drivers into four primary groups: policy and legal risks, technology risks, market risks, and reputational risks. These categories represent areas where changes related to the sustainability transition could challenge financial stability and operational viability (TCFD, 2017). Since we perform our research in the context of a bank, we follow the categorization of the EBA. Figure 2.1 shows how the risk drivers affect different players in the economic environment. The figure describes the causal relationships between transition risk drivers and financial landscape, shown in the form of companies, households and financial institutions. As mentioned before, we focus on how the drivers affect revenue and the P&L statement. These consequently affect bankruptcies and higher loan default ratios for banks. We briefly discuss the relationship between some of the transmission channels and the drivers and illustrate these relationships with examples.

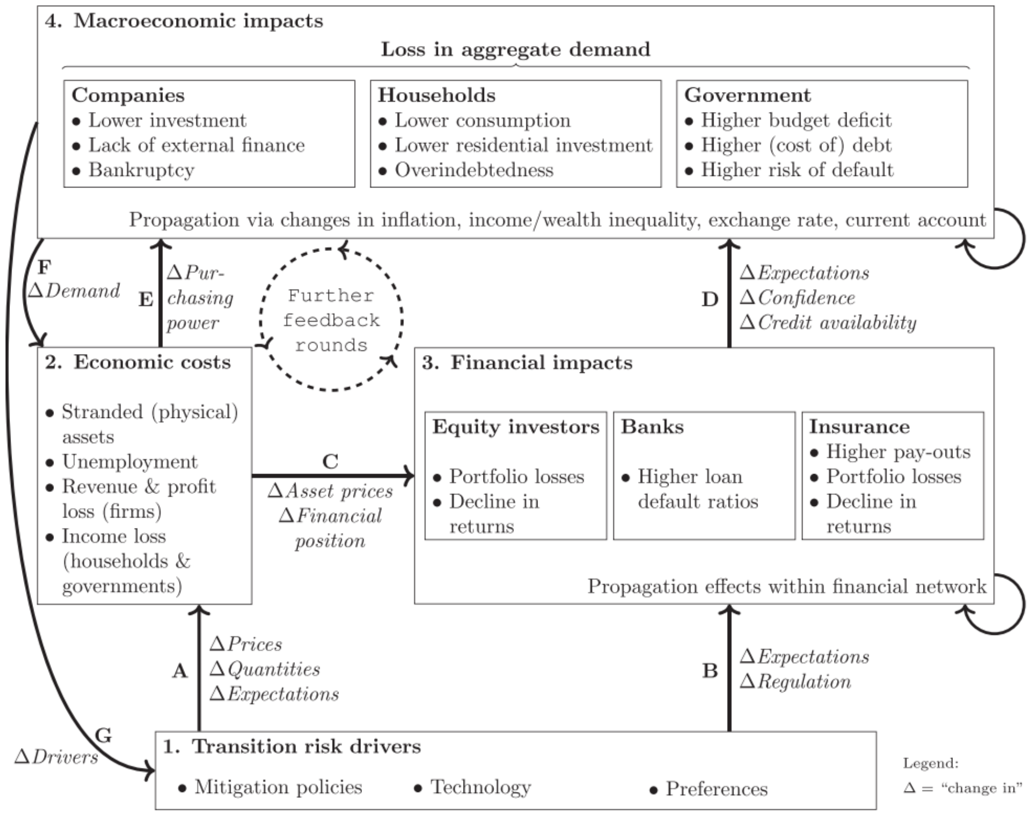

FIGURE 2.1: Schematic view of chain of causation from risk drivers to impacts (boxes) via transmission channels (arrows) (Semieniuk et al., 2021).

Policies and regulations

Climate-related policy changes can impact profitable business models. For example, the revised Energy Efficiency Directive of 2023 mandates EU countries to reduce energy consumption by 11.7% by 2030 compared to 2020. This directive, part of the EU's sustainable economy strategy, requires annual energy savings of at least 0.8% in 2021-2023, 1.3% in 2024-2025, 1.5% in 2026-2027, and 1.9% in 2028-2030 (European Union, 2012). Unlike the previous directive, the new one enforces binding targets, compelling businesses to measure and disclose emissions more extensively. In Spain, for example, large companies must undergo energy audits, with non-compliance fines up to €60,000 or 10% of turnover (Nabitz & Hirzel, 2019). Transitioning from fossil fuels to renewable energy is costly (Elavarasan et al., 2020; Kumar & Pal, 2020). Besides increased reporting and energy costs, policy actions also lead to higher operational costs and to new capital expenditures (Clarkson et al., 2004; Malinauskaite et al., 2020). Companies might anticipate these regulations, as seen in China, where varying local regulations prompted polluting firms to relocate to less regulated areas, avoiding investment in energy-saving technologies (J. Shen et al., 2017). Climate policies have higher priority in the EU compared to other regions, exemplified by the US leaving the Paris Agreement in 2022. In India, only 5.2% of credit supports energy production, and just 17.5% focuses on renewable energy, despite the country's goal to be carbon neutral by 2070 (Colenbrander et al., 2022). Regulatory differences can influence financial institutions, potentially leading to relocation (Beylin, 2020). However, EU ESG regulations often affect other markets due to efficiency benefits (Bradford, 2019). These policies drive transition costs, harming company profitability and increasing credit risk for banks.

Technological advancements

Businesses heavily reliant on older technologies, face competitiveness risks due to technological advancements. Berman et al. (2021) show that for the financial services industry the impact of external innovations on new entrepreneurial firms and established incumbents is asymmetric. Technological development offers a competitive advantage to new emerging fintech firms, who are able to adapt to new technologies easily. Established companies have heavily invested in the existing way of doing things. Their business models, operational processes, and infrastructures are deeply rooted in the current and low-tech industry standards and practices. This imposes implementation challenges of the new technologies into their business models. Another risk of technological advancements is the risk of significant write offs on past investments. As the development of low-carbon technologies accelerates and these become more economically viable, they increasingly lead to the stranding of traditional, carbon-intensive assets, forcing industries to reassess and potentially devalue their long-standing investments (Firdaus & Mori, 2023; Kavlak et al., 2018). Figure 2.1 depicts this in Box 2, in the form of stranded assets. Technological advancement is however also a crucial aspect of reduction emission strategies, such as carbon capture technologies and renewable energy sources (van der Ploeg & Rezai, 2020). Technology interacts heavily with policies, as new technologies open space for new policies and policies drive new technological innovations (Schmidt & Sewerin, 2017; Stirling, 2014). We analyze the costs of the most important technological advancements for carbon reduction technologies in Section 3.2. The costs additions for investments in new technologies and the pressure that comes from competitive issues impacts the profitability of these companies negatively. This increases the default ratios for banks.

Consumer and investor behaviour
Behavioural changes are linked to both consumers and investors. From the investor side, some Dutch pension funds are withdrawing from the fossil fuel sector. ABP, the largest Dutch pension fund, announced it will no longer invest in the fossil fuel industry. According to their annual report, between 2021 and 2022, they reduced their investments in the fossil industry by €7.5 billion (ABP, 2022). These decisions potentially limit companies' access to capital. Note that investing in sustainable businesses is most common in Europe. In the second quarter of 2023, Europe had more than seven times the amount of assets in sustainable funds than the United States (Statista, 2023). On the consumer side, demand is shifting towards more sustainable forms of transportation, manufacturing, and energy use. According to Ipsos (2020), 69% of the global population has made changes in their use of products and services due to concerns about climate change. Shifts in demand towards sustainable products significantly alter market dynamics. The lowest price is less of a priority to consumers who prefer green consumption (Zhang & Zheng, 2022). Demand preferences interact with technological development and policy directions. Demand impacts the pace and direction of technological change and policies. Mobilization against nuclear energy is an example of this, holding back technological development (Boudet, 2019). This restriction of quantities is Transmission Channel A in Figure 2.1. However, it generally drives the adaptation of companies. As consumers prefer eco-friendly options, companies that adapt may experience growth, while others may face difficulties. This shift affects pricing strategies and demonstrates demand elasticity, where consumer response changes with price fluctuations or increased environmental awareness, which is Transmission Channel F in Figure 2.1. These changes bring uncertainty to the market and can impact the market shares of companies, harming their revenues and profitability. This increases the risks banks face from these companies. We explore the effects of such pricing strategies, in the form of passing on costs to consumers, and demand elasticity in Section 3.3.

In conclusion, transition risk is driven by policy changes, technological advancements, and shifts in consumer behavior. Policy changes, particularly in the EU, are the main driver, dictating the transition's pace and nature. Policies can accelerate or hinder progress towards a sustainable economy. Technological developments and changes in consumer and investor behaviors, often influenced by policies, also significantly influence market dynamics. We want scenarios to capture these dynamics. Our focus is on EU policies as the primary driver used in scenario analysis. We also consider technological advancements, in the form of carbon capturing systems. Consumer behaviour is addressed by looking at the ability of businesses to pass on costs to consumers. These factors collectively worsen the financial position of businesses, leading to higher default ratios for banks (Transmission Channels B and C in Figure 2.1).

2.2 Credit risk

We discuss the basic principles of credit risk, outlining various credit risk models and introducing concepts such as the probability of default. Additionally, we examine relevant regulations. The Basel Committee defines credit risk as the potential for a bank borrower or counterparty to fail to meet its obligations according to agreed terms. We adopt the same definition, given the Basel Committee's role in setting international banking regulation standards. Lending activities are the main source of credit risk for banks. Additional sources, including but not limited to, are interbank transactions, foreign exchange transactions, and financial products such as options and swaps (BCBS, 2000). Banks can encounter three types of credit losses: expected, unexpected, and stress losses, illustrated in Figure 2.2. The expected loss refers to the anticipated credit loss that the bank expects on its credit portfolio within a certain time frame. This is typically covered by provisioning and pricing policies and is considered the normal cost of business. In contrast, the unexpected loss represents portfolio risk (Dolfin et al., 2019). The capital requirements proposed by the BCBS are intended to absorb these unexpected losses. The shaded area on the right-hand side of the curve indicates the likelihood that losses will exceed the sum of expected and unexpected losses. In other words, it represents the probability that the bank will be unable to meet its credit obligations using profits and capital. This is the Value-at-Risk (VaR) level. This level represents the maximum potential loss over a specific time period, which will only be exceeded with a probability equal to 1 minus the confidence level (CL). Losses exceeding VaR are often called 'stress losses', it is the part of the unexpected losses which is too expensive to hold capital against additionally leading to solvency issues (Gonzalez et al., 2012).

Current EU regulation aligns with the Basel III agreements, specifying the capital a bank must hold. This is expressed as a percentage of the risk weighted assets (RWA). These are calculated by assigning different risk levels to a bank's assets to ensure that the bank holds capital corresponding with the riskiness of its assets, as defined by the BCBS. The requirements include:

- At least 4.5% Common Equity Tier 1 (CET1).
- Up to 1.5% Additional Tier 1 (AT1) capital.
- Combined, CET1 and AT1 form total Tier 1 capital, which should be at least 6% of RWA.
- An additional 2.5% CET1 should be held as a conservation buffer.
- 2% Tier 2 capital to replenish conservation buffer, which includes subordinated debts and general loan-loss reserves.
- A counter-cyclical capital buffer, varying from 0 to 2.5%, should also be maintained.

All these requirements aim to help a bank absorb unexpected losses (Barakova & Ottolini, 2021; BCBS, 2019a, 2019b). The largest banks in the world are classified as Globally Systematic Important Banks (G-SIBs), which need to hold additional capital. These banks have large impacts on the financial stability, that capital problems influence the entire financial system. G-SIBs banks must hold extra CET1 capital on top of the minimum regulatory requirements. This additional buffer is intended to provide greater loss-absorbing capacity in times of financial stress. The required additional CET1 capital ranges from 1% to 3.5% of RWA, depending on the bank's systemic importance (FSB, 2023). These requirements show the relationship between assets and capital for banks.

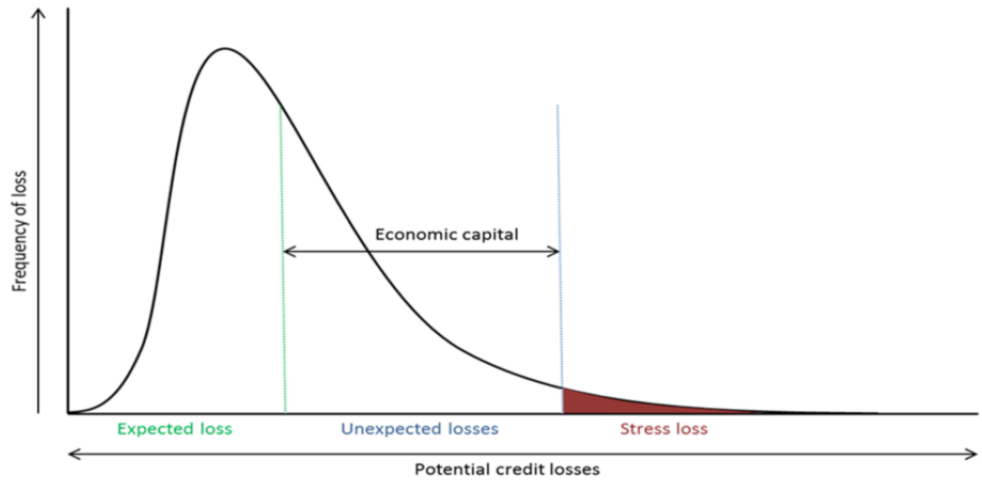

FIGURE 2.2: Frequency of loss as a function of potential credit losses (Dolfin et al., 2019).

To determine the necessary capital reserves a bank must maintain, it is essential to compute the VaR. The VaR is the sum of the expected and unexpected losses. It is used to determine the capital reserves a bank must maintain in addition to adhering to regulatory requirements. According to Hull (2018), the one-year VaR, as well as the expected and unexpected losses, can be determined as follows:

$$\text{Value at Risk} = \sum_i WCDR_i \cdot LGD_i \cdot EAD_i.$$

This is a summation over all companies i in the portfolio, multiplying the Worst Case Default Rate (WCDR), Loss Given Default (LGD), and Exposure at Default (EAD). The WCDR is determined using a confidence level (CL). The total expected loss from defaults in a portfolio can be calculated with the following formula.

$$\text{Expected Loss} = \sum_i PD_i \cdot LGD_i \cdot EAD_i.$$

The total expected loss for a bank is the sum of all expected losses for each company in the portfolio. Since the VaR is the summation of expected and unexpected loss, we obtain the following calculation method for the unexpected loss:

$$\text{Unexpected Loss} = \sum_i (WCDR_{CL,i} - PD_i) \cdot LGD_i \cdot EAD_i.$$

By subtracting the PD from the WCDR, we obtain the unexpected losses, which represent the amount of capital held. We will briefly describe the terms used in these equations below.

- **Probability of default**
  PD quantifies the likelihood, expressed as a percentage, that a borrower defaults on its obligations. This metric initiates a credit loss in the formulas above. Banks calculate this percentage using their own models. Several different methods exist, which we describe in Section 2.2.1.

- **Exposure at default**
  EAD represents the total amount of credit exposure at the moment a borrower defaults. This value is used to determine the overall potential loss in financial assessments and is expressed in monetary units. As the loan approaches maturity, the exposure amount decreases due to loan payoffs, conditional an installment plan has been agreed upon.

- **Loss given default**
  LGD measures the expected percentage of a loan that will not be recovered in the event of a default. It affects the amount of loss a lender would face in such a case. LGD is expressed as a percentage of the EAD. The more a company recovers from defaults, such as through collateral or cash, the lower this percentage.

- **Worst case default rate**
  This rate reflects the highest expected default rate under hypothetical stress scenarios, often used in stress testing. For company i, the WCDR is computed based on the PD and a copula correlation between borrowers, ρ (Hull, 2018). It is expressed as a percentage and it is essential for understanding the potential impact of extreme financial conditions on credit portfolios, hence it is used for unexpected losses. The hypothetical stress scenarios are related to the VaR by the confidence level which is chosen. Most often, the confidence level set by regulators is 99.9%, which means there is a 0.1% chance that the losses will exceed the expected and unexpected loss (BCBS, 2005). This is referred to as a 99.9% VaR, indicating a 0.1% probability of experiencing the stress loss scenario depicted in Figure 2.2.

These formulas are based on the model illustrated in Figure 2.2, which underpins the Internal Rating-Based (IRB) approach. This approach, approved by the Basel agreements, is used by banks to calculate their capital requirements. The IRB approach can be used in two ways, the foundational IRB (F-IRB) approach and the Advanced IRB (A-IRB) approach. In the F-IRB approach, the PD and thus the WCDR are determined by banks themselves. The EAD and LGD are prescribed by the BCBS. In the A-IRB approach, the EAD and LGD may be modelled by banks themselves, provided the methodology for this is approved by regulatory bodies (BCBS, 2024; Hull, 2018).

We select PD as the metric for credit risk because it drives defaults. PD is a key component in the Basel Committee's credit risk framework, informing both expected loss calculations and capital requirements determination. Its analytical clarity makes it essential for assessing borrowers' financial health and the risk profile of banking portfolios.

2.2.1 Probability of default models

Several methodologies can estimate default risk in the form of probability of default. These can be categorized into three different approaches: accounting-based, market-based, and rating agency methods. Accounting-based models use financial statement data to assess default risk. Models like the E. Altman (1968) Z-score, Ohlson (1980) O-score and Zmijewski (1984) probability model analyze accounting metrics for profitability, working capital and liabilities to assess the default risk. This analysis estimates the likelihood of default and provides insight into a company's ability to meet its financial obligations. Market-based approaches use real-time market data and asset pricing models to evaluate default risk. This allows for swift responses to the market changes in comparison to accounting based models. Market based models include the Merton model, Moody's KMV model, credit default swap (CDS) spreads, and bond spreads. The Merton (1974) model, based on option pricing theory, estimates default probabilities by viewing a company's equity as a call option on the company's assets, with the company's debt as the strike price, and then use the Black-Scholes formula to solve. Whilst the Merton model only builds on debt and volatility, Moody's KMV model characterizes the entire business for both equity and assets, allowing more complex capital structures (Kealhofer, 2003). Moody's KMV uses an empirically-calibrated default point instead of the total debt. Furthermore they incorporate a proprietary function to estimate the assets and volatility for the probabilities of default, instead of the strict Merton model assumptions. This default risk based focus, rather than a debt valuation focused measure, makes the KMV model the preferable model (Kealhofer, 2003). CDS spreads and bond spreads are effective indicators of credit risk. CDS spreads represent the cost of protection against default, similar to an insurance. On the other hand, bond spreads indicate the extra yield that investors require for assuming credit risk. An increase in either type of spread suggests a heightened perception of risk and a higher probability of default (Abinzano et al., 2020). Rating agencies such as Moody's, Standard & Poor's, and Fitch Ratings measure default risk through credit ratings. They consider quantitative and qualitative factors including financial metrics, industry dynamics, and management quality. Credit ratings provide standardized assessments of default risk, aiding investment decisions (Weissova et al., 2015). The credit rating agencies use historical default data to empirically map credit ratings to real-world PDs, rather than the theoretical risk neutral probabilities used in the Merton model. A higher credit rating implies a lower PD (Hull, 2018).

Research comparing the effectiveness of different approaches in predicting default risk yields varying results. Kealhofer (2003) found that accounting-based models, particularly those incorporating KMV methodology, are more effective than credit ratings. Hillegeist et al. (2004) found that market-based measures like the Merton model provide valuable insights compared to accounting scores such as the Altman Z score. Hillegeist et al. (2004) introduce a combination of market and accounting data into a Black-Scholes-Merton probability (BSM-Prob) model. Abinzano et al. (2020) show the consistent behaviour of CDS spreads for default risks, also for longer time horizons in comparison to several accounting and other market based metrics. Das et al. (2009) found that accounting metrics explain these reliable CDS spreads at least as well as structural models that make use of market data, such as Merton distance to default model. Combining the two information sources explains even more of the spread. Bandyopadhyay (2006) illustrate that accounting credit risks remain an practical way to give context on the probability of default, by developing an alternative Z-score. The Altman Z-score provides reliable result and is suitable for researching a phenomenon and its effect of defaults, without requiring complex modelling (E. I. Altman et al., 2017). Table 2.1 presents the advantages and disadvantage, the comparison between the accuracy of the models comes from Abinzano et al. (2020).

Sophisticated models like the BMS-Prob and KMV are more accurate and produce a better fit for defaults than accounting models (Abinzano et al., 2020). However, they also are more complex and come with data challenges. Accounting models focus on a company's financial statements and operational performance to estimate default probabilities. They provide reliable and insightful results, which can easily be tailored to an individual company. We want to describe the effect of the transition on the probability of default, rather than estimating the probability of default the most accurate way possible. We choose to use a accounting-based default model because of their relative simplicity and reliability.

Category	Models	Advantages	Disadvantages	Source
Accounting-Based	Altman Z-score, Ohlson O-score, Zmijewski score.	Uses financial statement data to assess default risk. Provides insight into financial obligations.	May not reflect current market conditions. Less responsive to immediate economic changes. Less accurate.	E. Altman (1968), Ohlson (1980), Zmijewski (1984).
Market-Based	Merton model, Moody's KMV, CDS spreads, Bond spreads, BMS-Prob.	Reflect real-time market data, can handle complex capital structures. More accurate.	Require advanced mathematical and financial modeling, less transparent.	Merton (1974), Kealhofer (2003), Das et al. (2009).
Credit Rating	Moody's, Standard & Poor's, Fitch Ratings.	Provide standardized risk assessments, includes both qualitative and quantitative analysis.	Potentially slow to react to quick market changes, may have biases. Accuracy depends on default sample.	Weissova et al. (2015), S&P Global Ratings (2022), Hull (2018).

TABLE 2.1: Probability of default modelling categories.

2.3 Accounting models

In this section we explore the different methods for finding the PD for a company. We start by presenting the most relevant models and follow this by a comparison. Setting out the differences between the methods, allows us to choose the most suitable PD model.

Altman Z-score

The most well-known accounting based default risk model is the Altman Z-score, introduced in E. Altman (1968). The method was originally designed for manufacturing companies. A default is predicted with a formula derived from a multiple discriminant analysis (MDA) of five accounting ratios. This analysis results in a Z-score, which indicates the probability of default within two years. Table 2.2 gives the interpretation of the Z-scores per version of Altman the Z-score. The five most important variables which came out of the discriminant analysis, form the basis of the original Altman Z-score.
The variables are:

- X_1 : Working capital/Total assets.
- X_2 : Retained earnings/Total assets.
- X_3 : Earnings before interest and taxes/Total assets.
- X_4 : Market Value of Equity/Book value of total liabilities.
- X_5 : Sales / Total assets.

The original Z-score from E. Altman (1968) specifically for manufacturers who where publicly traded was:

$$Z = 0.012 \cdot X_1 + 0.014 \cdot X_2 + 0.033 \cdot X_3 + 0.006 \cdot X_4 + 0.999 \cdot X_5.$$

Altman revised the Z-score for private and non-manufacturers companies. He changed the numerator of the X_4 from market value of equity to book value of equity. By using the same dataset, E. Altman and Hotchkiss (2006) revised the Z-score model, with a different variable X_4 in into the Z'-Score model which is the following:

$$Z' = 0.0717 \cdot X_1 + 0.847 \cdot X_2 + 3.107 \cdot X_3 + 0.420 \cdot X_4 + 0.998 \cdot X_5.$$

Altman also came up with a four variable Z"-score, which excludes the fifth variable. The Sales/Total assets ratio could bring in an industry effect, since this variable is industry sensitive. This score is made for non-manufacturing companies (E. Altman & Hotchkiss, 2006).

$$Z" = 6.56 \cdot X_1 + 3.26 \cdot X_2 + 6.72 \cdot X_3 + 1.05 \cdot X_4.$$

The original Altman Z-score is designed for public manufacturing companies and incorporates market value metrics. The Z'-score, modified for private companies, replaces market value with book value to adjust for the lack of public data. Meanwhile, the Z"-score is tailored for non-manufacturing and emerging market firms, focusing on broader financial structures and eliminating sales from its calculations. The effectiveness of these models has been shown, where the Z-score still applies for pubic companies and Z"-score is preferred above the Z'-score, due to is higher accuracy (E. I. Altman, 2018; E. I. Altman et al., 2017; Shi & Li, 2023).

Score type	**Score range**	**Financial condition**
Original Z-score (Public manufacturing companies).	Z > 3	Low risk of bankruptcy.
	2.7 < Z < 3	Be on alert.
	1.81 < Z < 2.7	Good chance of default.
	Z < 1.81	High risk of bankruptcy.
Z'-score (Private companies).	Z' > 2.9	Low risk of bankruptcy.
	1.23 < Z' < 2.9	Grey area, be on alert.
	Z' < 1.23	High risk of bankruptcy.
Z"-score (Private and public, manufacturing and non-manufacturing companies).	Z" > 2.6	Low risk of bankruptcy.
	0.9 < Z" < 2.6	Grey area, be on alert.
	Z" < 0.9	High risk of bankruptcy.

TABLE 2.2: Interpretations of Altman Z-Score Outcomes for Different Company Types(E. Altman & Hotchkiss, 2006; E. I. Altman, 2005).

Ohlson O model

Ohlson (1980) uses nine variables rather than the five used in Altman to come to predict the default risk, these variables are a combination of financial ratios and dummy variables. The time horizon for this measure is one year. The O-score is found by performing a linear regression of the following variables:

- **SIZE**: The logarithm of the ratio of total assets to the GNP price-level index. The index assumes a base value of 100 for 1985.
- **TLTA**: Total liabilities divided by total assets.
- **WCTA**: Working capital divided by total assets.
- **CLCA**: Current liabilities divided by current assets.
- **NITA**: Net income divided by total assets.
- **FUTL**: Cash flows from operations divided by total liabilities.
- **INTWO**: A dummy variable that is one if net income was negative for the last two years, zero otherwise.
- **OENEG**: A dummy variable that is one if total liabilities are greater than total assets, zero otherwise.
- **CHIN**: Change in net income, calculated as $\frac{NI_t - NI_{t-1}}{|NI_t| + |NI_{t-1}|}$, where NI_t is net income at time t.

We observe similarity with the variables used in the Altman Z-score, namely the WCTA, which is equal to X_1, the NITA which is similar X_2 and TLTA, which inverse is similar to X_3 of the Z-score. Some of the variables have an positive impact on the O-score, others a negative. The Ohlson (1980) O-score is calculated the following way:

$$\begin{aligned} O = &-1.32 - 0.407 \cdot \text{SIZE} + 6.03 \cdot \text{TLTA} - 1.43 \cdot \text{WCTA} \\ &+ 0.0757 \cdot \text{CLCA} - 2.37 \cdot \text{NITA} - 1.83 \cdot \text{FUTL} \\ &+ 0.285 \cdot \text{INTWO} - 1.72 \cdot \text{OENEG} - 0.521 \cdot \text{CHIN}. \end{aligned}$$

For a one-year time horizon, a higher O-score indicates an increased probability of default, suggesting financial distress. Lower scores suggest lower default risk.

Frydman Kao Altman (FKA)

The work by Frydman et al. (1985) created a foundation for a new type of models. They introduced a recursive partitioning for classification of bankruptcy, which boils down to a decision tree with financial ratios as nodes. They analyzed 20 financial ratios and came to a model to predict default of 200 firms based on four ratios. Figure 2.3 depicts the decision tree and the ratios with decision points used in the article. The decision tree based approach allows for capturing complex and non-linear relationships which are features that traditional statistical methods do not have. This method forms the basis for machine-learning based approaches. However, these require large data samples and then still can be unstable (Ptak-Chmielewska, 2016). Hence this methodology is not very suitable for individual assessments without large datasets to train.

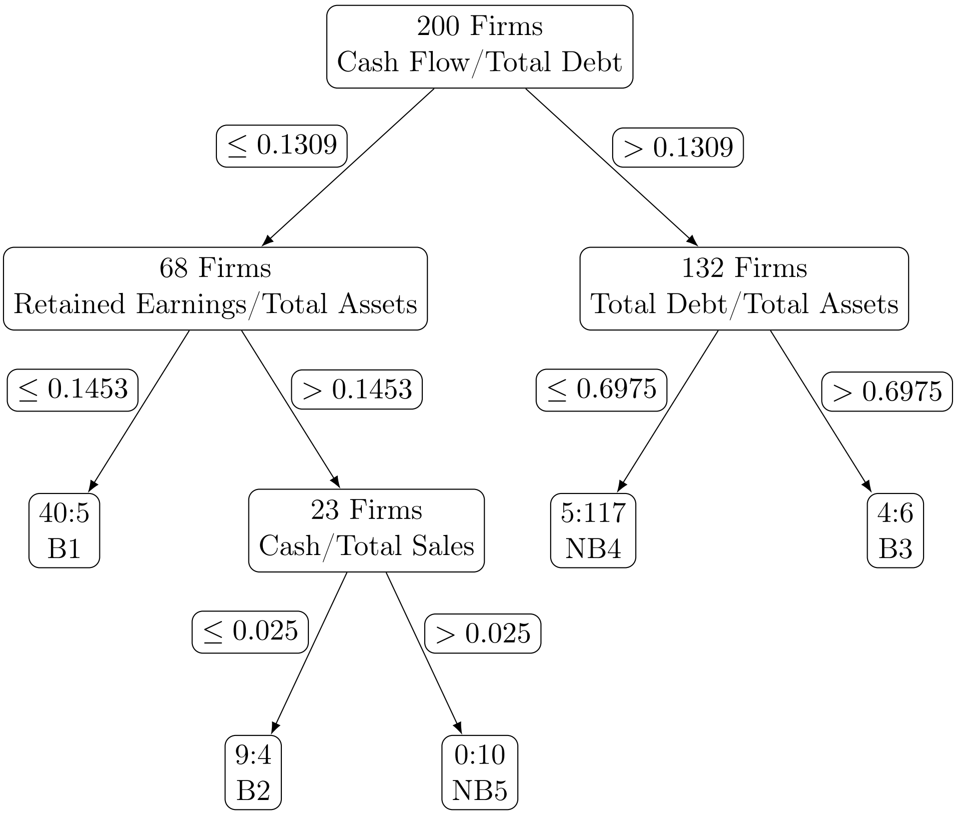

FIGURE 2.3: Decision Tree from Frydman et al. (1985).

Hannan and Hanweck (HH) model

The model introduced by Hannan and Hanweck (1988), often used in the banking sector, focuses on assessing the default risk of banks rather individual firms. The theoretical framework is based on three financial ratios: equity divided by assets, expected return on assets and the estimated variance of assets, all in context of banks. The default risk of the bank, or risk for insolvency of a bank is given given by the probability of losses exceeding equity. They use Tchebysheff's inequality for a symmetrical distribution to come with the following measure for PD (Abinzano et al., 2020):

$$PD = \min\left(1, \left(\frac{\sigma_R}{E(R) + \frac{E}{A}}\right)^2\right).$$

In this case σ_R is the standard deviation of the return on assets, and $E(R)$ is the expected return on assets. E represents the equity and A the assets of the bank. This models thus focuses on insolvency for a bank and is not tailored to individual companies.

Zmijewski's model

Zmijewski (1984) model uses probit analysis, useful for binary regression. To predict a one year default risk, the model employs three financial ratios. These parameters came forth from data using 40 defaults and 800 non-defaults, this set up is mostly used in academia (Grice & Dugan, 2003). The model straightforward and has been validated in multiple studies, making it a robust tool for financial analysts seeking to assess the insolvency risk of firms with minimal computation complexity. The function is given by:

$$X = -4.3 - 4.5 \cdot X_1 + 5.7 \cdot X_2 - 0.004 \cdot X_3.$$

Where:

X_1 : Net income / Total assets.

X_2 : Total liabilities / Total assets.

X_3 : Current assets / Current liabilities.

The outcome X filled into a probit function, which is the cumulative distribution function of the standard normal distribution, which maps the X score to a number on the interval $[0, 1]$. An outcome higher than 0.5 means little default risk, a score below this threshold means default risk. For the X-score this means $X < 0$ gives a financially a healthy company, $X \geq 0$ means a company is in distress.

Taffler Z-score

The Taffler (1983) model, was developed to predict the PD for manufacturing companies in the UK between 1969 and 1976. The Taffler model uses four different financial ratios as input of a linear discriminant analysis, just like the Altman Z-score, for the prediction of a Z score. The Taffler Z-score formula is given by:

$$Z_{\text{Taffler}} = 3.20 + 12.18 \cdot X_1 + 2.50 \cdot X_2 - 10.68 \cdot X_3 + 0.0289 \cdot X_4.$$

Where:

X_1 : Profit before tax / Current liabilities.

X_2 : Current assets / Total liabilities.

X_3 : Total assets / Current liabilities.

X_4 : Post-tax net income / Total assets.

Under the Taffler model, a T value below 0.2 indicates that a company is in the distress zone and at risk of bankruptcy, while a T value above 0.2 signifies financial stability and a low risk of bankruptcy (Marsenne et al., 2024).

Grover G-score

The Grover G-score was developed by reassessing the Altman Z-score. Thirteen new financial ratios were added and using the same method on 70 companies, of which half went into default, the following score was created (Marsenne et al., 2024). The G-Score formula is given by:

$$\text{G-Score} = 0.057 + 1.650 \cdot X1 + 3.404 \cdot X2 - 0.016 \cdot X3.$$

Where:

$X1$: Working capital / Total assets.

$X2$: Earnings before interest and taxes / Total assets.

$X3$: Net income / Total assets.

Grover's model categorizes bankrupt companies with a score less than or equal to -0.02 as ($G \leq 0.02$), while companies classified as non-bankrupt if $Z \geq 0.01$.

Springate S model

The Springate S model employs a linear discriminant analysis in its formulation. With the following formulation, the model aims to predict a default:

$$\text{S-Score} = 1.03 \cdot X1 + 3.07 \cdot X2 + 0.66 \cdot X3 + 0.4 \cdot X4.$$

Where:

$X1$: Working capital / Total assets.
$X2$: Profit before interest and tax / Total assets.
$X3$: Profit before tax / Current debt.
$X4$: Total sales / Total assets.

According to Tristanti and Hendrawan (2020) the applicable cutoff values are 0.862 and 1.062. If the value of S $<$ 0.862, the company is in financial distress, when 0.862 $<$ S $<$ 1.062, it is in the "grey" zone, where the problems need to be addressed promptly. When S $>$ 1.062, the company is in good financial health.

The Pompe & Bilderberg model

Pompe and Bilderbeek (2005) examined how individual variables affect default risk prediction in small- and medium-sized industrial Belgium firms. They found no specific order in the predictive power of financial ratios like liquidity and profitability. These categories have similar predictive powers years before bankruptcy. Predicting default is harder for younger firms. They used MDA and Neural Network (NN) to assess bankruptcy, yielding similar results, and compared these models' outcomes with individual variables using a dichotomous classification test. Both methods used two sets of predictor variables: one from stepwise selection and another from factor analysis, with models containing 8 or 9 variables. The paper did not provide a detailed discriminant function or NN layout. It aimed to review the order of financial ratio categories, individual variables' predictive power, and firm age's effect on default predictability. As full models aren't presented, they can't be used in our study. Moreover there is no comparative literature to assess their performance.

We acknowledge the existence of other accounting default risk models, but we have selected to our belief the most relevant ones, which were covered and more importantly compared extensively in the literature. Table 2.3 presents a comprehensive overview of the features which are used. Here we combined some similar ratios and added a check mark if the inverse of the ratio is used in the model to gain the overview. For comprehension we added a check mark at ratios that use liabilities where the actual model uses debt. Even though these concepts are different, they describe similar statistics hence we combined these definitions. The table provides a comprehensive summary of the section by showing which features are used per model. For the Pompe & Bilderberg model we use the eight variables for the older firms using the stepwise selection. As we look into older firms and the model using stepwise selection outperformed the other model (Pompe & Bilderbeek, 2005).

Financial Ratio	Altman Z	Altman Z'	Altman Z''	Ohlson O	FKA	HH	Zmijewski X	Taffler Z	Grover G	Springate S	P&B model
Working capital/Total assets	✓	✓	✓	✓					✓	✓	✓
Retained earnings/Total assets	✓	✓	✓		✓						✓
EBIT/Total assets	✓	✓	✓						✓		
Market value equity/Book value liabilities	✓										
Book value equity/Book value liabilities		✓	✓								
Sales/Total assets	✓	✓								✓	
Total liabilities/Total assets				✓	✓		✓			✓	
Current liabilities/Current assets				✓			✓				✓
Net income/Total assets				✓			✓	✓	✓		
Cash/Total sales					✓						
Expected return on assets						✓					
Equity/Total assets						✓					
Variance of return of assets						✓					
Profit before tax / Current liabilities								✓		✓	
Current assets / Total liabilities								✓			
Total assets / Current liabilities								✓			
Cash Flow/Debt				✓	✓						
Size				✓							
Net income dummy variable				✓							
Total Liabilities vs Total assets dummy variable				✓							
Change in net income				✓							
Debtors / Total assets											✓
Cash flow / Total assets											✓
Income taxes / Added value											✓
Added value / Total assets											✓
Net liquidity / Current assets											✓

TABLE 2.3: Comparison of financial ratio usage in different models.

2.3.1 Comparison of the models

To select a model, we compare the performance of the models and look at the suitability. Since we do not test the performance of these models, we need literature for the selection procedure. Furthermore, most of the described models are the base models of which new updated version exist, but most comparisons have been performed using the base models. To verify the performance of the models we take a look at Abinzano et al. (2020), which tested the performance among other of the Z-score, O-score, Zmjiewski's model and Hannan and Hanweck model. They applied these models to companies of the New York Stock Exchange from 1986 to 2016, excluding banks, finance companies and insurers. For one-year time horizon on a dataset with all types of default, Zmijewski (1984) X-score came out best, followed by Ohlson (1980) O-score, E. Altman (1968) Z-score and at last the Hannan and Hanweck (1988) model. For a two-year time horizon, the Z-score outperformed the O-score. For a dataset which only includes non default events and severe default events, the Ohlson O-score gains significant performance, the other models change slightly. Elviani et al. (2020) compared the Ohlson O-score, Zmjiewski X-score, Altman Z-score and the Springate model to each other. They came to the conclusion that the latter two are the most appropriate and accurate model in predicting bankruptcy of trade sector companies in Indonesia. Marsenne et al. (2024) compared the O-score, Z-score, Taffler model, Grover model and Zmjiewski's X-score for prediction default for an airline, showing that the Taffler model came out the best and the Springate model the worst. Helastica and Paramita (2020) performed an analysis on the Grover, Zmjieweski and the regular Altman model for 8 companies. The accuracy of the Zmjieweski was the highest, followed by Grover and Altman.

Model	**Industry**	**Accuracy**	**Underlying Model**	**Individual Level**	**Sources**
Altman Z	Public manufacturing	Moderate	MDA	Yes	Shi and Li, 2023
Altman Z'	Manufacturing	Moderate	MDA	Yes	Shi and Li, 2023
Altman Z"	General	High	MDA	Yes	Shi and Li, 2023, E. I. Altman, 2018
Ohlson O	General	Moderate to High	Logistic Regression	Yes	Abinzano et al., 2020, Elviani et al., 2020
FKA	General	Moderate	Decision Tree	No	Frydman et al. (1985)
HH	Banks	Moderate	Inequality Formula	No	Hannan and Hanweck (1988)
Zmijewski X	General	Moderate	Probit Regression	Yes	Abinzano et al., 2020, Elviani et al., 2020
Taffler Z	Manufacturing	High	MDA	Yes	Marsenne et al., 2024
Grover G	General	Moderate	MDA	Yes	Helastica and Paramita, 2020
Springate S	General	Moderate	MDA	Yes	Elviani et al., 2020, Marsenne et al., 2024
P&B model	Industrial	Unknown	MDA or NN	Yes	Pompe and Bilderbeek, 2005

Table 2.4: Summary of financial distress prediction models.

Overall the results of these comparisons are contradictory, not defining a clear best performing model. The differences are set out in Table 2.4, where we note that the accuracy's are compared to each other and not related to other better performing non-accounting models. All papers do mention that these accounting score should be used to identify the financial situation, distress or healthy, of a company rather than the exact PD of a business. Our choice for a suitable PD model is the Altman Z"-score, for several reasons. The accuracy compared to other models is reasonably stable and good (E. I. Altman et al., 2017; Marsenne et al., 2024; Shi & Li, 2023), the model is applicable to all type of firms, whilst the well performing Taffler model is developed for manufacturing firms. Furthermore, the Altman score is the most well known score, making interpretability for stakeholders more easy than other less known models in the sector. At last, the financial ratios used in the Altman Z"-score are well known, using clear definitions which help in our search for suitable data.

2.3.2 Key metrics of the Altman Z"-score

We describe the several metrics or accounting ratios used in the Altman Z"-score, from now on Z-score, to show what can influence these metrics and thus the result of the Z-score. We start by once again presenting the formula for the Z-score, from where we can explain each ratio and their different components.

$$Z = 6.56 \cdot X_1 + 3.26 \cdot X_2 + 6.72 \cdot X_3 + 1.05 \cdot X_4.$$

Where:

X_1 : Working capital/Total Assets.

X_2 : Retained earnings/Total Assets.

X_3 : EBIT/Total assets.

X_4 : Book value of equity/Book value of total liabilities.

X_1: Working capital/Total assets

This ratio is commonly found in corporate studies as it is a measure of the net liquid assets of the firm relative to its total capitalization. Working capital is defined by E. Altman (2013) as the difference between current assets and current liabilities. The term current refers to all assets that are expected to be converted to cash and all liabilities that are anticipated to be settled within a year. A higher working capital means that the firm has a higher liquidity. A firm which has operating losses, will have shrinking current assets in relation to the total assets. The total assets of a company represent everything a company owns and uses for it's operations. This consists of current and non-current or long-term assets. Forms of current assets are cash, inventory and accounts receivable. Examples of long-term assets are machinery, buildings and patents. This ratio can be seen as a liquidity ratio: the higher the ratio, the higher the liquidity.

X_2: Retained earnings/Total assets

Retained earnings are the cumulative earnings of a company throughout its lifetime after accounting for dividend payments, which are retained for reinvestment. E. Altman (2013) brings up two considerations for this account. First of all, it can be subject to manipulations through reorganization and dividend declarations. We should thus be aware of this when selecting companies and possibly make required adjustments. The other consideration is the fact that in retained earnings, an age factor arises, since it is a cumulative.

However, this does make sense as younger companies are more likely to default (Lisboa et al., 2021). This ratio can also be considered as a form of leverage ratio as firms with higher retained earnings, will likely have financed their investment using their own money rather than creating debt (E. Altman, 2013).

X_3: EBIT/Total assets
EBIT is a commonly used measure in accounting, meaning earnings before interest and taxes. It is a measure of the productivity of a firm, excluding leverage or tax factors. This ratio shows the ability of a firm to generate earnings based on it's assets. According to E. Altman (2013) it is the most powerful profitability type measure for prediction of default, reflected by the coefficient in the formula.

X_4: Book value of equity/Book value of total liabilities
The book value of equity represents the net assets value of a company, it is the total assets minus the total liabilities of a firm. A higher equity means that the financial position of a company is stronger, as the total assets are larger than the total liabilities. The total liabilities, the denominator of this ratio, encompass all current and long term liabilities of a company. Long-term liabilities can be long-term debt, deferred tax obligations, whilst short-term liabilities consist among other of deferred revenue, accounts payable and short-term debt. The ratio shows how much the firm's assets can decline in value before the liabilities exceed the assets and the firm becomes insolvent (E. I. Altman et al., 2017).

The purpose of our research is to find how these financial ratios are exactly influenced by the transition. We see that decisions from regulations such as carbon price increases can effect yearly profits, either once or recurring. Furthermore, the new investments also increase costs and require new loans which create extra liabilities for the company. The consequences are either a smaller numerator or a larger denominator, which reduces the ratio. Due to the plus signs in the formula, the Z-score reduces as well. Figure 2.4 shows how the different ratios can be affected by actions taken due to the low-carbon transition.

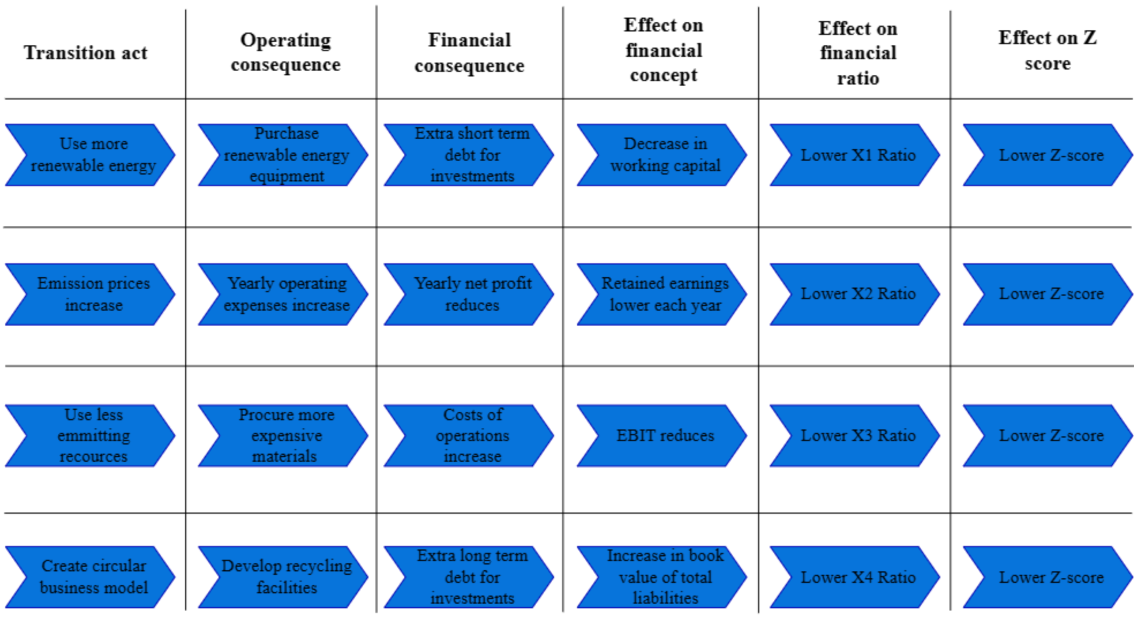

Figure 2.4: Potential effects of transition of Z-score.

2.3.3 Mapping the Altman Z-score

Even though the Altman Z-score is a well known measure, it does not give an exact PD. It provides insight in the default risk of a company, which is less precise than a PD. As this research aims to find the order of magnitudes rather than an exact PD, this matters not. However, to make results more recognizable for managers, we can map these results to credit ratings. We can map these credit ratings to a PD, using historical default rates. In this part of the research we explain the theoretical background of mapping the Z-score to a PD and show the steps involved. In Chapter 5 we elaborate more on how we use these mappings in presenting the results.

E. Altman and Hotchkiss (2006) and E. I. Altman (2005) show how the Z-score is directly translated into a U.S. bond rating equivalent (BRE). A BRE is a translation of a numerical or qualitative score, such as the Z-score, into a standardized credit rating that reflects the creditworthiness and default risk of a bond. The BRE aligns with the familiar rating scales used by major credit rating agencies like S&P, Moody's, and Fitch, allowing for a consistent comparison of credit risk across different issuers and securities. By mapping specific score ranges to corresponding credit ratings, based on empirical analysis of a large sample of U.S. firms with rated bonds. This mapping is done for the newest variant of the Z-score for non-manufacturers and emerging markets. We note that the Z-scores used for mapping have a constant of 3.25 added. The 3.25 is added in the emerging markets model to account for major accounting differences between emerging market countries and the United States. In the original Z-Score model, a score of zero corresponds to a BRE of D. The new constant standardizes this by mapping a score of 1.75 to a BRE of D. However, this constant is not included in our model as we do not look at emerging countries. In order to map properly, we reduce 3.25 from the Z-scores in the mapping table. This ensures the BRE aligns with the boundaries in Table 2.2. Table 2.5 shows our modified mapping table based on E. Altman and Hotchkiss (2006) and E. I. Altman (2005).

Safe Zone		Gray Zone		Distress Zone	
Z-Score	Rating	Z-Score	Rating	Z-Score	Rating
> 4.90	AAA	2.40 - 2.60	BBB-	0.50 - 0.90	B-
4.35 - 4.90	AA+	2.00 - 2.40	BB+	-0.05 - 0.50	CCC+
4.05 - 4.35	AA	1.70 - 2.00	BB	-0.75 - -0.05	CCC
3.75 - 4.05	AA-	1.50 - 1.70	BB-	-1.5 - -0.75	CCC-
3.60 - 3.75	A+	1.25 - 1.50	B+	< -1.5	D
3.40 - 3.60	A	0.90 - 1.25	B		
3.15 - 3.40	A-				
3.00 - 3.15	BBB+				
2.60 - 3.00	BBB				

Table 2.5: Z-score and equivalent bond rating.

Credit ratings can be mapped into default rates. This is the percentage of entities that have historically defaulted over a given time period. This can be interpreted as a PD, as this is the probability that a single entity will default over a given time period. Mapping this should be done with caution, as the credit ratings cover ranges of Z-scores. Furthermore, all mappings are based on historical data and are purely useful for more recognizable results. We use the global corporate cumulative average one-year default rates over 1981-2023 of S&P Global Ratings (2023) for the mapping of credit ratings to PD. The default rates are used as proxy for the PD. The Altman Z-score has a 1 or 2 year horizon, hence we use a one-year horizon PD. The data presents cumulative default rates, but this is negligible in one year horizon as this is the smallest horizon. We note that the mapping does not continue lower than CCC, whereas our credit ratings include CCC-. Credit score of D generally stands for default of a company.

Rating	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB
Default rate	0.00	0.00	0.02	0.02	0.04	0.05	0.05	0.09	0.14
Rating	BBB-	BB+	BB	BB-	B+	B	B-	CCC/C	
Default rate	0.21	0.28	0.45	0.88	1.86	2.73	5.33	25.98	

TABLE 2.6: European corporate cumulative average one-year default rates by rating 1981-2023 S&P Global Ratings (2023).

We have established how to interpret the Z-scores in the context of a PD, however this involves two mapping procedures, including several assumptions. This causes a loss of accuracy, hence we find the Altman Z-score the best format for the results. Mapping it into a PD can be used to provide more results which are easier to recognize and interpret for managers.

2.4 Conclusion on theoretical context

To assess the impact of the low-carbon transition on a business's probability of default, a systematic approach is required. This involves understanding transition risk, selecting appropriate credit risk models, analyzing key financial ratios, and interpreting the results. Transition risk, driven by policy changes, technological advancements, and shifts in consumer and investor behavior, can significantly affect a business's financial health. We focus on policies as the main driver of transition risk. We explored various credit risk models and found that accounting-based models, particularly the Altman Z-score, are most suitable for this analysis. Mainly due to its practicality, reliability, and applicability across various industries. The Altman Z-score uses key financial ratios to evaluate default risk in the form of a Z-score. We have shown how potential transition acts can influence the Z-score, to gain understanding on the mechanisms within the Z-score. Mapping these Z-scores to U.S. bond rating equivalents and historical default rates provide a clear framework for translating financial health into recognizable credit ratings and default probabilities. By interpreting these mapped default probabilities, we can evaluate the likely impact of the low-carbon transition on individual default risks, which affect the credit risks of the portfolio of a bank.

Chapter 3

Conceptual Framework Development

We now present the conceptual framework of this thesis. It includes climate scenarios, cost increment modelling, and changes in revenue through price elasticities of demand. We explain how these factors are combined and modified to determine new accounting ratios for the Altman Z-scores. We begin by describing various climate scenarios to enhance result interpretation. Next, we explore how these scenarios can be used to model cost increments, followed by finding how passing on costs to customers influence the profitability of a company. These preliminary results necessitate modifications for inflation, currency, and present value calculations. We review how to integrate these results in the financial metrics described in the Chapter 2. To make a comprehensive summary, we provide a calculation example. We lay the foundation for the modelling practices throughout the research. Defining the conceptual framework aims to answer the research question: *How can long-term scenario analysis be employed to assess the effects of cost increments, revenue changes, and cost pass-through abilities?*

3.1 NGFS scenarios

Utilizing climate scenarios to assess the transition's impact on a company's creditworthiness is common practice. We use the NGFS database due to its proven suitability and reliability in the financial sector (Monasterolo et al., 2023). Although Koninklijk Nederlands Meteorologisch Instituut (KNMI) scenarios are available, they primarily focus on ecological aspects rather than financial considerations, making the NGFS database a more appropriate choice for our transition risk analysis. The NGFS provides short-term models ranging up to 5-years, which have less uncertainty. However, we want to look at long-term effects as well. Hence, we use the long-term scenarios. The NGFS set includes several models which can be used. We selected the Global Change Analysis Model (GCAM) 6.0 model. Is it an integrated assessment model to simulate and analyze global energy, economic, land use, and water systems under different climate policies. In our case it is modelled with the NGFS policy scenarios. We choose this model over others, such as the MESSAGEix-GLOBIOM and REMIND-MAgPIE, as it uses partial equilibrium approach rather than a general equilibrium. This feature allows for focusing on a single market, utilizing price elasticity of demand assuming *ceteris paribus* on other marktets. Its flexible demand responses enable more sector-specific research. The GCAM model's ability to capture the evolving energy system helps assess transition risks, as the future electricity generation mix varies over time within each scenario. Other models use general equilibrium with fixed demand, making them less suitable for detailed analysis. These models have a larger scope, not looking at sectors specific but at the entire economy, suitable for cross sector analysis (Bertram et al., 2020). Additionally, P&P has previously used these scenarios, which is convenient for comparison and modelling practices. The NGFS presents data on seven policy scenarios, categorized into four quadrants: 1) orderly transition, 2) disorderly transition, 3) too little too late, and 4) hot house world. Figure 3.1 illustrates the scenarios, with each quadrant representing the effect on transition and physical risk. Our focus is on the vertical transition risk axis.

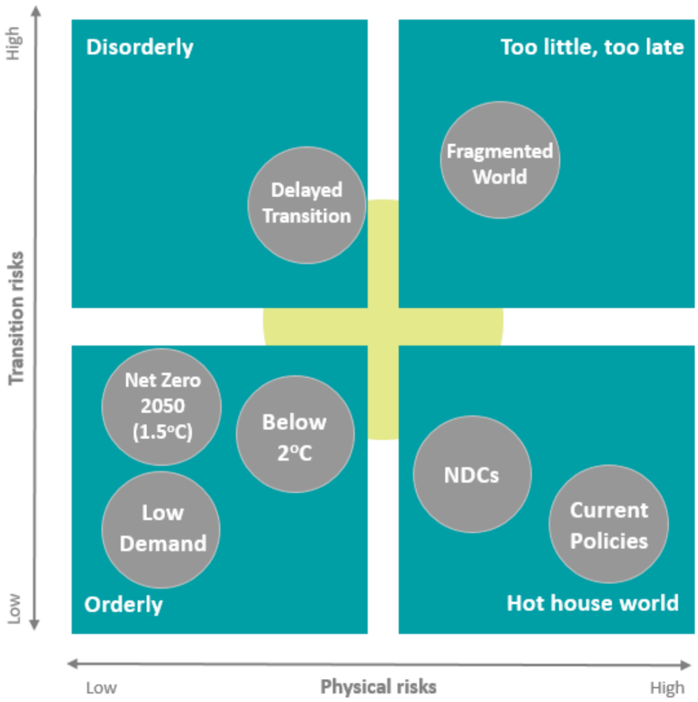

FIGURE 3.1: Scenario framework from NGFS (2023).

We use the definitions given by the latest report of the NGFS (2023) on these scenarios, to outline the differences between these scenarios. It is essential to understand the differences to be able to interpret the outcome of the scenario analysis. As these scenarios will form the foundation of modelling costs increments and revenue changes.

Orderly Transition

Orderly scenarios assume that ambitious climate policies are introduced early and become gradually more stringent. Both physical and transition risks are relatively subdued. This quadrant has three different scenarios.

> *Low Demand* explores the global efforts needed to be able to limit global warming to below 1.5°C by 2050 in an orderly fashion, aligned with the Paris Agreement, driven by lower energy demands. Given delays of some policies, this scenario uses the most ambitious targets.
>
> *Net Zero 2050* limits global warming to 1.5°C through stringent climate policies and innovation, reaching global net zero CO2 emissions around 2050. For some jurisdictions such as US and the EU this means net zero for all GHGs.
>
> *Below 2°C* gradually increases the stringency of climate policies, giving a 67% chance of limiting global warming to below 2°C. Additionally, countries with net zero targets reach 80% of them.

Disorderly Transition
Disorderly scenarios assume that climate policies are delayed or divergent across countries and sectors. These scenarios are associated higher transition risks, as carbon prices might need to rise sharply and abruptly. They have relative smaller physical risks compared to the hot house world and too little to late scenarios, as the global temperature rises slower. There is only one scenario in this quadrant.

> *Delayed Transition* assumes annual emissions do not decrease until 2030. Strong policies are needed to limit warming to below 2°C. In this scenario the negative emissions from for instance carbon capture are limited.

Hot House World
Hot House World scenarios have the assumption that global warming cannot be limited. This results in the fact that temperature thresholds are exceeded, leading to severe physical risks but limited transition risks. We have two different scenarios in this quadrant.

> *Nationally Determined Contributions (NDCs)* includes all pledged targets by countries, even if is not implemented yet.

> *Current Policies* assumes that only currently implemented policies from nations are preserved.

Too Little, Too Late
Too little, too late scenarios assume that a late and uncoordinated transition fails to limit physical risks whilst also raising transition risks.

> *Fragmented World* assumes a delayed and divergent climate policy response among countries globally, resulting in both high transition and physical risks. Countries without net zero targets follow current policies, other countries achieve 80% of their targets.

Understanding these scenarios helps in predicting the transition risks and knowing what scenario is most applicable for a decision-making process. Now that we have established the different scenarios, we show how to use them in practice. The NGFS scenario explorer allows users to select variables, regions, and time horizons. We use data from 2020 to 2050 for the EU-15 region, consisting of 15 pre-enlargement EU member states. This region is the largest EU-based region in the NGFS dataset. If the data is unavailable, we use the EU-12 region, the second-largest EU-based group. The data are provided in 5-year intervals. We used linear interpolation to create yearly data between these points. We used data from 2020 to 2050, after which we cleaned them by removing 2020 till 2022 and setting 2023 as the base year. This year is also the base for our accounting data from annual reports. Linear interpolation is used to estimate yearly data points between the provided 5-year intervals, ensuring a more detailed and continuous dataset.

The NGFS notes that there is no base scenario or most realistic scenario, as all scenarios are what-if analyses. Hence, it is insightful to compare these scenarios so managers can determine which is most applicable at any given time. We use the below 2°C scenario as a base scenario for comparisons in sensitivity analysis. This scenario is chosen for its plausible transition risks and balanced interpretation of policies and medium technological advancements. Table 3.1 presents the assumptions for all scenarios. The table maps out key features of the scenario narrative and their macro-financial risk implications stemming from transition or physical risk. Given that the world is not on track to meet the Paris

Agreement goals of 1.5°C according to the UN (United Nations Framework Convention on Climate Change, 2023), the less ambitious goal of well under 2°C is a suitable base scenario. It provides a more nuanced and realistic view than low-demand or net-zero scenarios, while still assuming 80% of net zero goals are achieved.

Category	**Scenario**	**End-of-century warming**	**Policy reaction**	**Technology change**	**Carbon dioxide removal**	**Regional policy variation**
Orderly	Low Demand.	1.4°C.	Immediate.	Fast.	Medium use.	Medium.
	Net Zero 2050.	1.4°C.	Immediate.	Fast.	Medium-High use.	Medium.
	Below 2°C.	1.7°C.	Immediate and smooth.	Moderate.	Medium use.	Low variation.
Disorderly	Delayed Transition.	1.7°C.	Delayed.	Slow/Fast.	Low-medium use.	High.
Hot House World	NDCs.	2.4°C.	NDCs.	Slow.	Low use.	Medium.
	Current Policies.	2.9°C.	None - Current Policies.	Slow.	Low use.	Low.
Too-Little Too-Late	Fragmented World.	2.3°C.	Delayed and Fragmented.	Slow/ Fragmented.	Low-medium use.	High.

Table 3.1: Overview of NGFS scenarios by key assumptions. Green means "lower risk", yellow means "moderate risk", red means "higher risk" (NGFS, 2023).

The different NGFS scenarios form an important basis for modelling the cost increments and revenue changes. Not only provides it different scenarios, but also allows it for quantifying non financial data such as emissions and energy usage. Observing the effect of different policies on the default risk, allows managers to make decisions accordingly. By using NGFS scenarios, which are policy-driven scenarios, we effectively use policies as main driver for transition risk, as the variables in these scenarios change based on the assumed consequences of the different policies.

3.2 Cost increase

In this section, we describe how we quantify costs incurred from the transition. We explore how transition risks can lead to increased operational costs. We utilize the scenarios described in the previous sections to quantify the extra costs. We handle the following key factors leading to cost increases: carbon pricing, energy consumption, supply chain emissions, carbon capture and storage (CCS), and stranded assets.

Carbon Pricing
The EU employs a cap-and-trade system for CO2 equivalent (CO2e) emissions, where the total emissions are capped, and emission rights can be traded. CO2e measures the impact of greenhouse gases in terms of equivalent CO2 warming potential. Firms can buy the right to emit 1 tonne of CO2e, incentivizing emission reductions as costs increase with emissions. From 2021 to 2030, the EC reduces total emission rights annually by 2.2% , increasing the price of these rights, known as the carbon price (European Commission, 2023). Companies in the EU can purchase these rights annually, and prices are expected to rise post-2030 as emission reduction measures become more challenging. The Market Stability Reserve cannot fully stop this rapid price increase, as it adjusts supply automatically to stabilize the market (Enerdata, 2023). The NGFS (2020) provides carbon price projections for the EU and globally across several scenarios. We link Scope 1 emissions, emitted from owned or controlled resources, to these projected carbon prices to model increased costs. The price, given in 2010 US dollar per tonne of CO2e, reflects the cost of emitting carbon based on different policies, including cap-and-trade prices and taxes.

Figure 3.2 presents interpolated carbon pricing data in 2010 US dollar per tonne of CO2e, adjusted for inflation by multiplying the amount by the 2023 consumer price index (CPI) divided by the 2010 CPI, resulting in a factor of $\frac{304.7}{218.1} = 1.397$ (Minneapolis, 2024). By applying this adjustment to each scenario's Scope 1 emissions, we calculate the increased costs. We determine a firm's Scope 1 emissions using their current emissions and targets, then linearly interpolating between these points. Each line represents one of the NGFS scenarios presented in Section 3.1. We use the seven specific scenarios and not the four quadrants in which they are categorized.

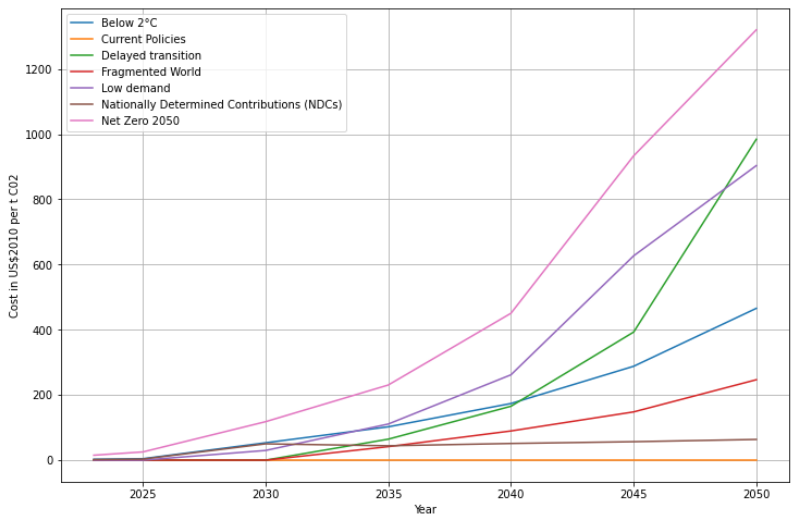

FIGURE 3.2: Price of emitting one tonne of carbon equivalent in US$ 2010 (NGFS, 2023).

Energy usage
Scope 2 emissions mainly come from a firm's energy sources, which can be reported accurately. These are indirect emissions from electricity, steam, heat, or cooling (U. S. E. P. Agency, 2020). The NGFS (2020) models energy prices per scenario. Electrification increases operational costs (Wei et al., 2019), which we model through electricity prices. Bio-energy and fossil fuels remain cheaper, but fossil fuel use will decrease to cut emissions.

We project future electricity for companies by adjusting current use with the percentage change in consumption for each year. New costs are calculated by multiplying new electricity prices with new consumption. We use NGFS data for final energy consumption and industrial electricity prices, shown in Figures 3.3 and 3.4. Final energy includes all industries and the residential sector. We apply the same method to gas prices and consumption, as gas usage is still considerable. Despite lower future gas consumption, the cost of the new energy mix will rise. Figures 3.5 and 3.6 show NGFS gas prices and usage. Prices are in US$2010 per Gigajoule (GJ), and consumption in Exajoule (EJ). We use the percentage change in energy consumption as a proxy for Scope 2 emissions.

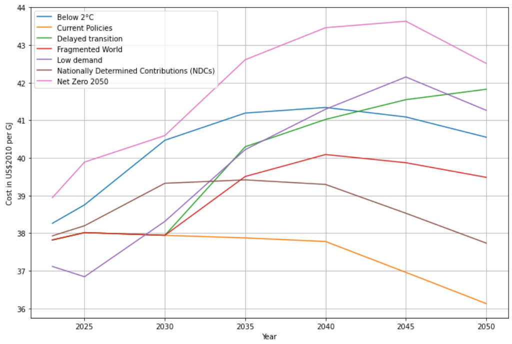

FIGURE 3.3: Electricity prices in US$2010 per GJ (NGFS, 2023).

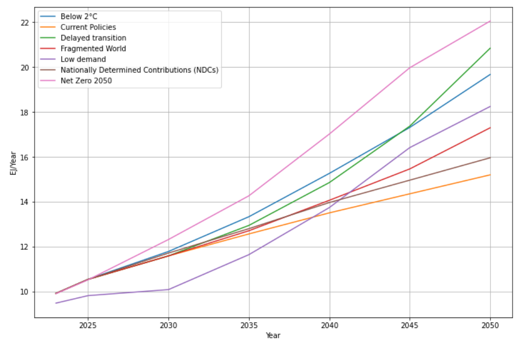

FIGURE 3.4: Electricity usage in EJ per year (NGFS, 2023).

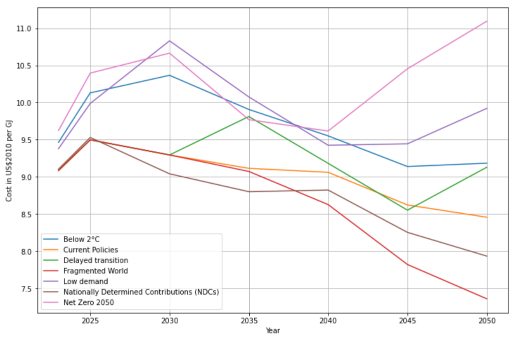

FIGURE 3.5: Industrial gas prices in US$2010 per GJ (NGFS, 2023).

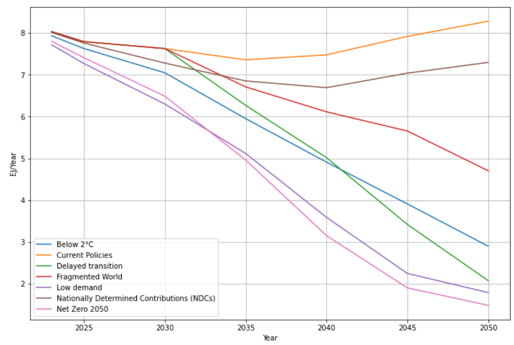

FIGURE 3.6: Gas usage in EJ per year (NGFS, 2023).

Supply chain emissions

Scope 3 emissions include all the other emissions throughout the value or supply chain of a business. Scope 3 emissions often constitute the largest portion of a company's total greenhouse gas emissions across all three scopes. However, they come from outside the operations of the business itself. Companies under the CSRD are required to report on Scope 3 emissions, to understand their emissions impact across the value chain. This enables companies to focus efforts where they can have the greatest impact. Given the wide range of Scope 3 emissions, accurately finding proxies for these emissions can be challenging. Therefore, our analysis focuses on purchased goods and services, as this category typically makes a significant contribution to a company's overall Scope 3 emissions in the downstream part of the value chain (CDP, 2023). The other large category of Scope 3 emissions is the use of products sold, especially for the energy and utility sectors. We tackle this issue in the next paragraph on CCS. The focus on purchased goods and services entails that we research the costs of conventional versus greener alternatives.

Carbon capture and storage
Carbon sequestration is the process of capturing and storing atmospheric carbon particles. Some companies do in fact emit GHG in their production process regardless of their energy usage, such as cement producers (L. Shen et al., 2014). For some sectors, such as the energy sector, the Scope 3 emissions come from the use of their product. To become net-zero in 2050, these companies will need to invest in carbon capturing techniques. Other business see that CCS as a way to reduce their net emissions without changing their business model. These technologies are still in development and can vary, hence their costs vary as well. This depends on whether you only measure costs of capturing, or also transportation and storage (Rubin et al., 2015). To price CCS correctly, we follow a study by Sievert et al. (2024), which compares the costs of capture and storage for three main technologies. These technologies are (1) Liquid Solvent which uses chemicals,(2) Solid Solvent, which uses solid materials and (3) Ambient Weathering process, which utilizes naturally occurring minerals. We create an average of the costs per tonne CO2 of these technologies, due to the uncertainty on which technology has the most promising future. In Table 3.2, we show an overview of the initial prices and production learning rates from Sievert et al. (2024), which we can use for calculations. We use the initial price per tonne CO2 that is captured and stored. Than we use the projected experience rates, making the technology cheaper. The experience rates are different for the initial price to 10 MT/CO2, and from 10MT/CO2 to 1GT/CO2. The experience rate is the efficiency improvement per doubling of cumulative production. The formula for a unit price CO2 captured per ton in dollars is given by:

$$C_n = C_0 \times \left(\frac{n}{N}\right)^{-\text{learning rate}}.$$

Where:

C_n is the cost at capacity n.

C_0 is the initial cost.

n is the current capacity.

N is the initial capacity.

Learning rate is $-Log_2$ (1 - Experience rate).

	Chemicals	**Solids**	**Natural**
Initial capacity in tonne CO2/year	500,000	4000	1000
Initial costs in US$ per tonne CO2	670	1282	2481
Learning rate if production is 10Mt CO2/year	7%	8%	10%
Learning rate if production is 10Mt CO2/year - 1GT/year	5%	5%	7%

TABLE 3.2: Costs and experience Rates for Different CCS Technologies (Sievert et al., 2024).

We can then use the prediction of the NGFS (2023) scenario analysis, which estimates the amount of CO2 which is captured and stored for several scenarios. Figure 3.7, shows the global CCS capacity per year per scenario. We used global rather than EU-15 as this is more realistic for determining the market price. We can use the formula and Table 3.2 to estimate the costs of one Mt CO2 captured and stored per year per scenario, depicted in Figure 3.8. We adjust the costs for inflation, using the same technique as with previous prices, by using the US$2022. This gives a multiplication by $\frac{304.7}{292.7} = 1.041$ (Minneapolis, 2024).To determine a company's CCS needs, we examine their sustainability reports. This typically involves capturing residual emissions from operations or end consumers, covering Scope 1, 2, and 3 emissions. The Science Based Targets initiative (SBTi) suggests carbon capture is essential for achieving net zero (SBTi, 2024). If a company aims to be net zero by 2040, we calculate the remaining emissions and linearly interpolate the necessary captured emissions. Emissions are not captured linearly; each new machine boosts capacity in jumps, and spreading costs over the years justifies this assumption. After achieving net zero, CCS capacity remains the same. The costs per tonne of CO2 captured decrease, reducing total costs from the net zero point.

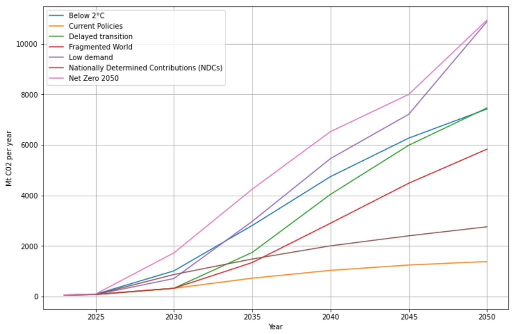

FIGURE 3.7: Global CCS capacity (NGFS, 2023).

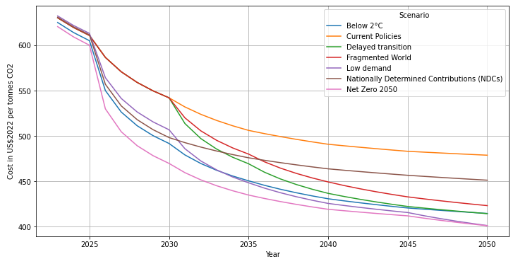

FIGURE 3.8: Average cost CCS in US$2022 per tonne CO2 based on global capacity.

Stranded assets

A constrained carbon future will strand reserves, especially in carbon-intensive sectors with fossil fuel reserves. McGlade and Ekins (2015) estimate that one third of oil, half of gas, and over 80% of coal reserves should remain unused from 2010 to 2050. Equipment value decreases, but due to data issues, we do not cover this. Companies will need to write off these assets, reducing total assets. Gradual write-offs will decrease asset value over the years. Sudden regulation could cause immediate write-offs, but we do not consider this due to prediction issues. To evaluate stranded asset costs, we estimate our fossil fuel production share and apply global decline projections of the NGFS scenarios. Emptied oil fields lose value, but companies will keep investing in new fields. We spread the projected asset value decline over the stranding period for yearly write-offs, reflecting this as an expense in the P&L statement. The asset value decline comes from the percentage decline in fossil fuel EU-15 production, assumed for the company as well. This production includes energy with and without CCS technology, as seen in Figure 3.9. This reduces operational profits yearly. This method can be applied to coal, gas, and oil reserves.

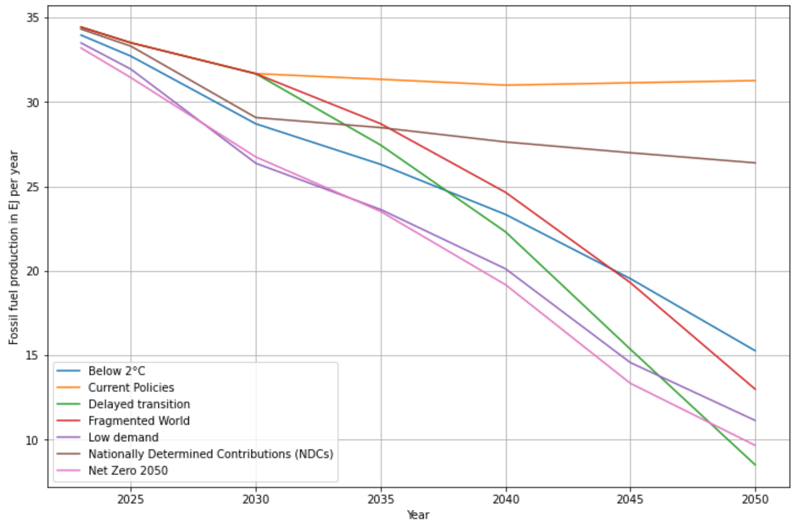

FIGURE 3.9: Fossil fuel production for EU-15 region in EJ per year.

Final remarks on cost factors

We have established 5 cost factors which we use to determine the increased costs of a firm, using the NGFS scenarios and public data from the firms. Table 3.3 gives an overview of the section above, describing how we can quantify the costs and how it affects either the P&L statement or the balance sheet. Modelling the cost increments is the basis for determining the new accounting ratios used in the Altman Z-score. Per scenario the costs found by each cost factor for each year are subtracted from the costs in 2023, so we obtain change of the costs in comparison to 2023. These differences per method are aggregated for each year, so we obtain per year a total change in costs in comparison to 2023. This is done for each scenario, meaning we have a table with change in costs compared to 2023 for 7 scenarios and for 27 years, ranging from 2024 to 2050.

Due to data limitations on green sourcing and stranded assets, this research focuses on the first three ways of cost increases. Most companies report on sourcing green alternatives but not on the expenses of current and future greener materials. Some report on raw material quantities, but too many assumptions are needed to determine extra costs. To generalize results, we exclude this from our analysis and assume Scope 3 emissions are covered by CCS. Stranded assets are not clearly reported and mainly affect large energy companies, so we exclude this cost increase. We acknowledge these potential costs as quantifiable if data is available, suggesting companies can do this internally.

Cost Factor	Emissions	Cost Description	Quantification Method	Impact on Finances	Required Data
Carbon pricing	Scope 1	CO2 emission rights become more expensive.	Link Scope 1 emissions to projected carbon prices.	Annual expense in P&L statement reflecting the cost of emission rights.	Projected carbon prices, firm's Scope 1 emissions data.
Energy usage	Scope 2	Change of energy sourcing increases cost.	Model both future electricity and gas prices and usage and their impact on operational costs.	Higher operational costs in P&L statement due to increased energy sourcing prices.	Future electricity and gas price forecasts, firm's energy usage data.
Supply chain emissions	Scope 3	Greener sourcing strategies cost more.	Focus on costs of greener alternatives for purchased goods and services.	Increased costs in P&L statement for sustainable materials.	Cost data for conventional and greener materials, firm's procurement data.
Carbon capture and storage	Compensating all scopes	Investing in CSS technology.	Use cost and learning rates for various technologies to estimate expenses.	Annual expense in P&L statement for CCS per tonne of CO2.	Cost estimates for CSS technologies, firm's CO2 emissions data.
Stranded assets	Reducing all scopes	Write-offs of fossil fuel reserves that remain unused.	Estimate production share and apply global decline projections to establish yearly write-offs.	Write-offs in P&L statement, reducing net income and asset value on balance sheet.	Company's fossil fuel reserves data, global production decline projections.

Table 3.3: Methods of determining the added costs of the transition.

3.3 Ability to pass on costs

Next, we look at how a company can deal with cost increases. As shown in Figure 3.10, there are two options. Absorbing costs means that a business handles the cost increasing by using their own funds. Resulting in the costs increases becoming directly visible in the P&L statement. As cost increasing is directly accounted for, the additional costs will be reflected in measures as the Z-score already. Therefore, we want to focus in this research the other part, where we see how much of the costs a firm can pass on. To see how much of the extra costs can be handled by this side of the split creates a more complete overview of how much of the costs are actually visible on the P&L statement of a firm. Absorption of costs is not neglected, as all costs which are not passed on, will be absorbed by a firm, which becomes visible in the P&L statement. To assess the ability to pass on costs we follow Hontou et al. (2007) and distinguish three important factors: Demand elasticity, import penetration and the strength of the trade mark.

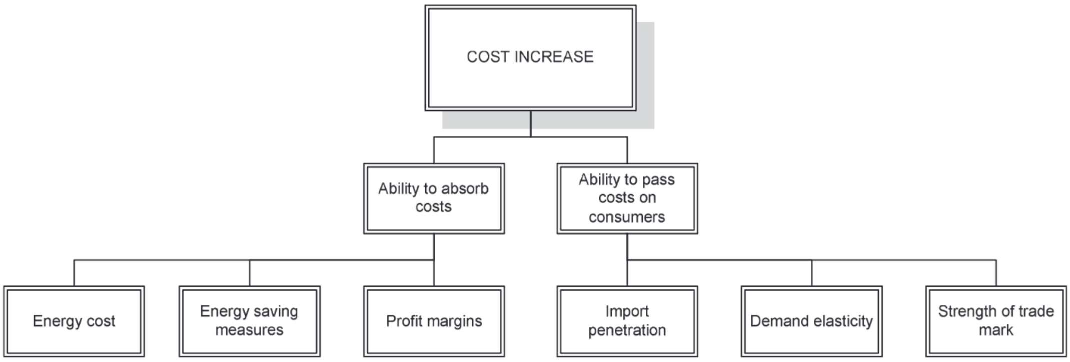

FIGURE 3.10: Sensitivity factors of a business of cost increase from Hontou et al. (2007).

Demand elasticity
Elasticity of demand can be measured in various ways, including price elasticity of demand (PED), cross-price elasticity of demand, and income elasticity of demand. This study focuses on PED to analyze companies at an individual level, assessing their ability to pass on transition-related costs to customers without altering other aspects of their business. We exclude cross-price elasticity because it requires detailed analysis of competitor and substitute effects within the same sector, adding unnecessary complexity to our model. Additionally, we do not consider income elasticity, as the research is centered on price changes due to the transition, assuming constant income levels. In this context, income and cross-price elasticities are not primary effects; price changes directly impact demand, making PED more relevant for evaluating financial implications for the company.

The PED measures the responsiveness of the quantity demanded of a product to changes in its price. A high elasticity indicates that consumers are very responsive to price changes, meaning a small price increase could lead to a significant drop in sales volume. Conversely, low elasticity suggests that consumers are less sensitive to price changes, allowing businesses to raise prices without a substantial impact on sales volumes. This concept is the focus of our interest. If a company can pass on increased transition-related costs without losing sales, the financial impact could remain limited. Due to price elasticity, changes in prices can significantly impact a company's revenue and profitability, and thus its Z-score. The PED is the percentage change in quantity demanded resulting from a given percentage change in price (Goolsbee et al., 2016). In mathematical terms, we obtain:

$$\text{PED} = \frac{\%\Delta Q_{\text{demanded}}}{\%\Delta P_{\text{rice}}} = \frac{\Delta Q_{\text{demanded}}/Q_{\text{demanded}}}{\Delta P_{\text{rice}}/P_{\text{rice}}}$$

There is an inverse relationship between price and quantity demanded. When prices decrease, demand typically increases. To focus on the strength of this relationship regardless of direction, we consider the absolute value of elasticity. If $|PED| > 1$, the demand is considered elastic, meaning sales volumes are highly sensitivity to price changes. If $0 < |PED| < 1$, the demand is considered inelastic, allowing firms to pass on costs with minimal sales volume impact. This study uses long-term elasticity, as it aligns with the research horizon extending to 2050. The elasticities we use are detailed in Chapter 4.

Import penetration
Import penetration refers to the extent to which foreign products compete with domestic products in a given market. High import penetration indicates a significant presence of imported goods, which increases competitive pressure on domestic businesses. This competition can limit a company's ability to pass on costs, as consumers may switch to cheaper imported alternatives if domestic prices rise. This effect can be significant, Bugamelli et al. (2015) show that a 0.1 percentage point higher Chinese import penetration restrains price growth by 0.17 percentage points per year in Italy. The import penetration ratio shows how much of the goods come from outside of the country/region. We look at the import penetration and see the EU as one, as it has the same climate regulation, which can cause outside competitors to have lower costs. This assumption allows us to remove EU import penetration from the equation of ability to pass on costs. The EU has implemented import tariffs on carbon intense products, in order to "put fair price on the carbon emitted during the production of carbon intensive goods that are entering the EU" (EC, 2023). The Carbon Border Adjustment Mechanism (CBAM), makes it impossible for companies to leave the EU and sell carbon intensive products for lower prices.

Brand strength
Brand strength, also known as the strength of a trademark, represents a brand's ability to influence consumer preferences and maintain customer loyalty. A robust brand can demand higher prices, retaining customer loyalty even when prices rise. This trait enables companies with strong brands to pass on additional costs to consumers more effectively. Brand strength is usually gauged through brand value rankings, customer loyalty indices, and market share stability. Understanding the influence of brand strength is significant for assessing a company's capacity to endure price increases without losing a considerable market share. This is shown by Krishnamurthi and Raj (1991), finding a difference in demand elasticity for loyal customers and non-loyal customers of -0.6 vs -2.6. Translating this into pricing strategies is complex, translation into elasticities of demand for an individual company even more so. Hence, we perform a sensitivity analysis on the PED and pricing strategies.

We argue that the assumption of consistent long-run demand elasticity is questionable. Demand elasticity is not only dependent on the good itself, but also on macro-economic conditions. Elasticities of the same products in a recession are different than in times of economic prosperity. New technologies can make a products less desirable in the future, increasing the elasticity of demand for such a product. We dive into this matter in Section 3.3.2 on how we come to different ranges of demand elasticities to per product type use for our sensitivity analysis.

3.3.1 Revenue changes from passing on costs

The entire amount of incremental costs per year per scenario, determined with the steps in Section 3.2, can modified to the extra marginal costs. This means we divide the extra costs by the amount of goods sold, to find the extra unit costs. Adding this extra cost per unit to the current sales price allows us to find the percentage change in price. Two things are important: (1) we do not use the inflated costs to determine the extra costs, (2) we use the 2023 average exchange rate of the US dollar to euros of 0.9248 to convert the extra costs in US dollars to euros (European Central Bank, 2024). We do this to compare the nominal prices of 2023 to the nominal price increases. We want to find the price impact of the transition and the relations to the demand elasticity and thus assume other factors, such as inflation and currency adjustments are constant. This is however only holding for the part where we make calculations using the demand elasticity. We do need to convert the costs from US dollars to euros, as the unit prices used for price increases are in euros as well. We need both prices to be in euros to find a percentage price increase. In Section 3.4, we explain how we adjust for inflation and currency projections, because from a credit risk perspective we do need to consider this. The current unit price is found by dividing net sales by the number of products sold. We need to be aware of different products and product groups, as each has a different PED. For instance, electricity demand differs for business and retail clients (Csereklyei, 2020). Details on each products are discussed in Chapter 4. We can multiply the price increment percentage by demand elasticity to get the new sales volume per product group. Subtract this from the 2023 revenue to see yearly revenue changes per scenario to obtain the extra revenue compared to 2023. We explore various pricing strategies, passing on either 100%, 80%, 60%, 40%, 20% or 0% of the costs. For example, using 60%, we determine the new price by multiplying the extra unit cost by 60%. This gives the percentage increase in sales price. These operations yield yearly revenue differences compared to 2023 per scenario. The sensitivity analysis assumes the PED from literature and the base NGFS scenario.

3.3.2 Sensitivity on price elasticities of demand

We conduct a sensitivity analysis on demand elasticity to assess the robustness of our demand projections. This analysis evaluates how the quantity demanded changes with price under different elasticity scenarios. We distinguish between two types of goods: elastic and inelastic. Elastic goods have $|PED| > 1$. For elastic goods, we examine a range up to $|PED| = 2$ in three equal steps, increasing elasticity in each step. For inelastic goods, where the elasticity is $0 < |PED| < 1$, we perform the sensitivity analysis in three equal steps, ranging from the base elasticity found in the literature up to $|PED| = 1$. We do not consider elasticities outside of these ranges as yearly price increases are unlikely to lead to lower elasticity, *ceteris paribus*. To clearly see the effects of changing elasticities, we use the Below 2°C NGFS scenario. This analysis provides a comprehensive evaluation of the financial implications of different elasticity scenarios, enhancing our understanding of the risks involved. The sensitivity analysis gives insight on the consequences on the revenue and see the effect of PED on default risk. We model price increments, the new sales volume and obtain the new revenue. We do a sensitivity analysis on different passing on percentages and on different price elasticities of demand.

3.4 Modifications

We cannot integrate the found new cost and revenues straight into the accounting ratios. We have to make adjustments and modifications first. In this section we describe what we do and the mathematics behind this. First, we convert the both type of cash flows to euros, which is the target currency in this research. Next, we adjust the cash flows for inflation to reflect their real value, accounting for the erosion of purchasing power. Finally, we determine the present value (PV) of these real, euro-denominated cash flows, establishing of their current worth. We use these to obtain a net result at the end of each year. All differences in costs and revenues are transition related, other parts of the business remain constant.

Currency conversion
For a meaningful analysis, all financial figures must be in the same currency, we use euros. The NGFS data is currently in 2010 US dollar, which we converted to 2023 US dollar using a CPI factor of 1.397 (Minneapolis, 2024). Since we focus on EU-based companies, we convert these amounts to euros. We estimate future exchange rates using the forward exchange rate, calculated with yield curves from the ECB and the Fed. The yield curve shows the interest rates on debt for various maturities, typically illustrating the relationship between interest rates (yield) and time to maturity for bonds of similar credit quality. We use a selection of all bonds, not just AAA, to align with the varied credit ratings of companies' loans. Specifically, we use the instantaneous forward rate derived from these yield curves to provide insights into expected future exchange rate movements based on interest rate differentials. The instantaneous forward rate at time t, derived from the yield curve, represents the future interest rate implied by the current term structure and is used for forward rate calculations. This rate is typically provided by central banks. Figures 3.11 and 3.12 show the instantaneous forward curves from the ECB and Fed, based on data from ECB (2024) and Federal Reserve (2024) as of 2024-05-24.

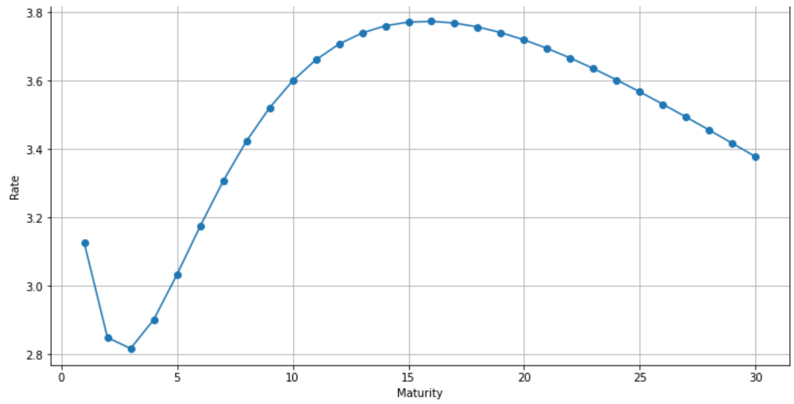

FIGURE 3.11: Instantaneous forward curve of euro from the ECB.

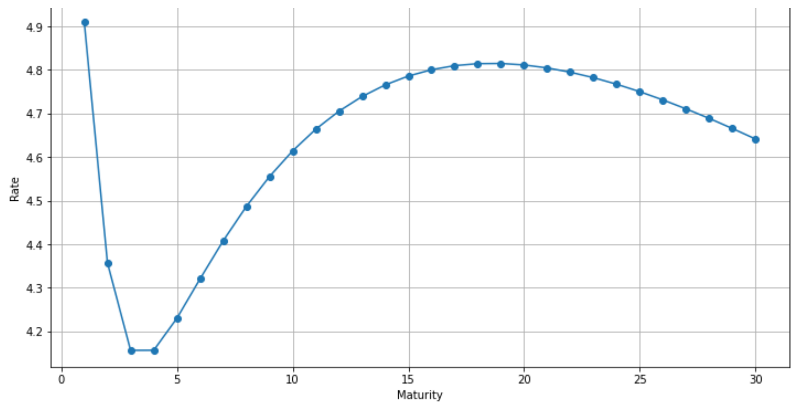

FIGURE 3.12: Instantaneous forward curve of US dollar from the Fed.

Both curves exhibit a similar shape, reflecting interest rate trends over various maturities. The initial dip followed by a rise and then a decline suggests changing perceptions of risk and return over time. Initially, the high rates could reflect immediate liquidity concerns, while the subsequent dip might indicate lower perceived risk in the short to medium term.

The rise in rates for longer maturities suggests increasing uncertainty or risk expectations as the time horizon extends. The decline at the last years suggest expected stability in the long run. The higher yields on the US dollar compared to the euro suggest that investors require more interest to hold US dollar-denominated assets, implying a higher perceived risk and an anticipated depreciation of the US dollar against the euro over time.

From these curves we can determine the forward exchange rate. We use the instantaneous exponential method, assuming continuously compounding rates. The forward exchange rate $F(t, T)$ reflects the expected future exchange rate between two currencies at a future date T, given the current exchange rate and the differential in interest rates between the two currencies. The formula for the forward exchange rate is given by:

$$F(T) = S(0) \cdot e^{(r_d - r_f)(T)}.$$

Where:

$S(0)$ is the spot exchange rate at time t, which is 1.084 euro/US dollar on 24/5/2024.

r_f is the instantaneous forward rate of the euro.

r_d is the instantaneous forward rate of the US dollar.

T is the maturity, ranging from 1 to 27 years.

The exponential term $e^{(r_f - r_d)(T)}$ adjusts the spot exchange rate by the interest rate differential over the period from t to T, accounting for expected changes in exchange rates due to differing interest rates. The forward exchange curve, plotted in Figure 3.13, shows the forward exchange rates over different maturities. We multiply each calculated cost increment by the corresponding maturity.

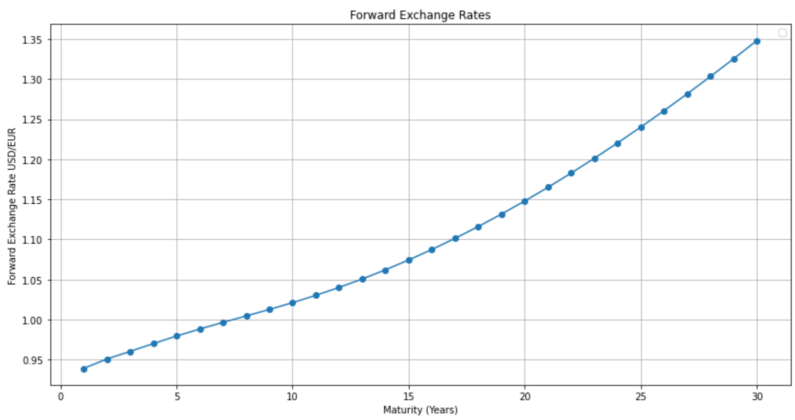

FIGURE 3.13: Forward exchange rate euro/US dollar

Inflation adjustment

Now all cash flows are in euros we take the next step: adjusting for inflation, as we need to reflect the true purchasing power of the business. This is essential to do, especially since we are modelling with a large time horizon. Since we have all cash flows in euros, we can adjust both tables with a 2% yearly inflation. Theoretically this is the goal of the ECB and thus also the long term projections of the inflation rate of the euro. We adjust for inflation, since we want the future costs and income to be worth the same as now. To make this work we adjust for inflation, which we need to do for every year. Mathematically this results for every maturity t, the year looked at minus the base year of 2023, in:

$$ICF_t = CF_t \times (1 + 0.02)^t,$$

where:

ICF_t is the cash flow at time t adjusted for inflation.

CF_t is the cash flow at time t.

0.02 is the expected annual inflation rate (2%).

t is the number of future years, ranging from 1 to 27.

Increasing both costs and revenue by 2% assumes that all inflation-related costs are passed through the supply chain—from suppliers to the company, and from the company to customers. This maintains profit margins despite inflation. Many industries can pass increased costs to customers without losing competitiveness. Aligning with the ECB's 2% inflation target ensures our model reflects realistic economic conditions. Thus, adjusting costs and revenues by 2% annually helps maintain the business's purchasing power. Note that these are not transition-related costs which are passed on.

Present value
We have determined the future incoming cash from the newly found revenue and the future outgoing cash from the extra costs. These amounts are measured per scenario per year, compared to the base year of 2023. We need to determine the PV of the future cash flows, to determine its current value. This is required for the 1 to 2 years horizon of the Z-score. Calculating the present value of future cash flows allows us to integrate these projections into current financial metrics. Discounting based on the principle that money has greater value now than it will in the future due to its potential earning capacity. When money is invested now, it is expected to earn returns over time. Future cash flows are discounted to their present value using the Weighted Average Cost of Capital (WACC). This number reflects the average rate that a company expects to pay to finance its business, for all sorts of sources of capital like common stock, preferred stock, bonds, and other forms of debt. This ensures that the valuation accounts for the overall cost of financing and the expected returns, providing a comprehensive measure for discounting future cash flows. For each scenario we discount both in- and outgoing cash depending on the year using the following formula:

$$PV_t = \frac{CF_t}{(1 + r)^t}.$$

Where:

PV is the present value of the cash flow of time t.

CF_t is the cash flow at time t.

r is the discount rate, the WACC of a firm.

t is the maturity, ranging from 1 to 27.

This formula is used for each year separately compared to 2023, as we have determined the annual extra costs and revenue. The maturities are the year we look at minus the base year 2023. After performing these calculations, we can subtract the extra costs from the extra revenue to obtain a net result. The net result is thus a subtracting of both PV's, if negative it means a loss, if positive profitability a profit. Note that this is solely the extra costs en revenue from transition related activities. In usual business this net result is added or subtracted from the profits made.

Weighted Average Cost of Capital
When analyzing companies, we must consider their capital structure. While we focus on profitability for credit risk assessment, discounting requires considering capital structure. Using the risk-free rate for discounting is unrealistic because companies cannot borrow at this rate. Instead, we use WACC, which accounts for the cost of equity and debt, weighted by their proportions in the company's capital structure. WACC is suitable for projects within a company's regular business model, as it reflects the average return a company must pay its security holders. We consider transition costs as part of the regular operations. Companies with substantial equity and minimal debt have lower investment risks, leading to lower required returns and financing costs, thus impacting profitability less compared to riskier businesses. We find the WACC of a business in the annual report of a company. We must ensure that these are real pre-tax discount rates. We use the real WACC because it accounts for future inflation and aligns with a long-term perspective. Since we adjust for inflation in our cost projections, it is crucial to consider inflation in discounting to maintain consistency. We need the pre-tax discount rate because our analysis is conducted on a pre-tax basis. In Chapter 4, we detail how we obtain and utilize a company's specified WACC.

3.5 Effects on accounting ratios

The net result from the previous sections is incorporated into the accounting ratios described in Chapter 2, based on the latest annual reports. These ratios are derived from five key accounting metrics: working capital, EBIT from the P&L statement and retained earnings, total assets, and total equity from the balance sheet. To maintain consistency, we follow a structured approach in updating each financial metric, ensuring that all calculations align with the overall conceptual framework. The metrics are updated as follows:

Profit & Loss statement metrics:
The adjustments to working capital and EBIT are straightforward, involving the addition of the net result for each year t. Here, 2023 represents $t = 0$:

- $\text{Working Capital}_t = \text{Working Capital}_{t=0} + \text{Net Result}_t$
- $\text{EBIT}_t = \text{EBIT}_{t=0} + \text{Net Result}_t$

Balance sheet metrics:
For balance sheet metrics, adjustments are cumulative. This means that for year t, these metrics include the net result from year t and the value of the metric from year $t-1$:

- $\text{Retained Earnings}_t = \text{Retained Earnings}_{t-1} + \text{Net Result}_t$
- $\text{Equity}_t = \text{Equity}_{t-1} + \text{Net Result}_t$
- $\text{Total Assets}_t = \text{Total Assets}_{t-1} + \text{Net Result}_t$

We do not consider how the liabilities change as we do not focus on how a company is financed. Based on the idea that companies grow as they make profits and shrink if they do not. We exclude newly attracted equity due to lack of strategic business information. This limits our ability to fully assess factors influencing growth or shrinkage, but focuses the research on transition effects. In reality, net results are added to retained earnings, and both sides of the balance sheet adjust throughout the year. Our approach, which assumes year-end adjustments, can be related to the Modigliani-Miller theorem, particularly Proposition I, which states that the value of a firm is independent of its capital structure under certain assumptions (Modigliani & Miller, 1958). This theoretical foundation supports our method of analyzing profitability through asset changes. Notably, one assumption of the Modigliani-Miller theorem is the pre-tax condition, which aligns with our pre-tax approach in this analysis. Other assumptions are more straightforward, such as efficient markets and information symmetry.

These updates allow us to see the direct impact of transition-related cost and revenue changes on a firm's financial health, reflected in the Altman Z-scores. Table 3.4 summarizes how metrics are updated with the net result. For each scenario, passing-on percentage, and year, we determine these metrics and use them to calculate the new Altman Z-score. This results in a three-dimensional dataset, with a Z-score per scenario, per year, and per percentage of costs passed on. This enables us to review the effects of passing on costs, differences per scenario, and changes in default risk over time. These computations can be done for different demand elasticities from literature, allowing us to compare their effects on the same company.

Measure	**Metric type**	**Action**	**Calculation Basis**
Working Capital	P&L statement	+ Net Result	Base Year
EBIT	P&L statement	+ Net Result	Base Year
Retained Earnings	Balance Sheet	+ Net Result	Previous Year
Book Value of Equity	Balance Sheet	+ Net Result	Previous Year
Total Assets	Balance Sheet	+ Net Result	Previous Year
Total Liabilities	Balance Sheet	Remains Constant	Base Year

Table 3.4: Updating formulas for accounting metrics.

3.6 Calculation example of the conceptual framework

We present a calculation example using a fictional company to illustrate how the conceptual framework operates. We focus on the steps following the determination of cost cash flows. Our goal is to calculate a Z-score by incorporating future cash flows of both costs and revenues. We use simplified numbers to establish the initial metrics for the Z-score. This example aims to illustrate the steps and sequence required to determine the Altman Z-score for a business over the years. Calculations are done up to 2030 using a single scenario, a fixed cost pass-through percentage, and one demand elasticity to maintain simplicity. Numbers are rounded to the nearest thousand US dollars or euros.

Step 1: Determine new revenue in 2030
Consider Company X, which produces bars of soap. Under a scenario aiming to limit global warming to below 2°C, the company will face annual cost increases due to the transition to a low-carbon economy. Assume the extra costs in 2030 compared to 2023 are €10,000,000 (or $10,813,148). Using the average 2023 exchange rate of 1.0813 euro/US dollar, we convert the extra costs from US dollars to euros by dividing the US dollar amount by the exchange rate. We use the average rate as we want to compare prices, for which we do not want to adjust for inflation and future currencies yet. We do use that for determining the present value. The total revenue of all bars of soap in 2023 is €100,000,000, with a sales volume of 100,000,000 pieces, making the sales price €1.00 per bar. Using a long-term demand elasticity of -0.75 and assuming a 60% cost pass-through to customers, we can determine the new revenue and the extra revenue compared to 2023.

New revenue calculation in thousands of units:

- Extra cost per unit: €10,000 / 100,000 bars = €0.10.
- Cost passed on to customers: 60%, resulting in a new price of €1.06 per bar.
- Price increase percentage: (1.06 - 1) / 1 = 6%.
- Percentage change in sales volume: 6% × -0.75 = -4.5%.
- New sales volume: 100,000 × (1 - 0.045) = 95,500 thousand bars.
- New revenue in 2030: 95,754 × €1.06 = €101,230.
- Extra revenue compared to 2023: €101,230 - €100,000 = €1,230.

	2030
Extra costs compared to 2023 (€ thousand)	10,000
Old price (€)	1.00
Extra cost per unit (€)	0.10
Cost passed on (€)	0.06
New price (€)	1.06
Percentage change new price	6%
Percentage change sales volume	-4.5%
New sales volume (thousand units)	95,500
New revenue (€ thousand)	101,230
Extra revenue compared to 2023 (€ thousand)	1,230

Table 3.5: Extra revenue for company X in 2030.

Step 2: Modify costs and revenue for PV calculations
We now adjust the new revenue and costs to determine the PV of the net result, taking into account a yearly inflation rate of 2%. This means we assume that inflation is passed on completely to the customer, as this represents measured price effects. We assume that this does not influence the PED. For accounting and credit risk purposes, we convert costs using the forward exchange rate of 1.05 euro/US dollar, reflecting the expected future value of costs and revenues more accurately. The extra costs in 2030 compared to 2023 are thus different than the 10 million mentioned before, as we use a different conversion rate. This rate reflects future costs better, while the old rate is better for comparing prices.

Cost conversion and modifications:

- Adjusted extra costs in € thousand (year 2030): \$10,813 / 1.05 = €10,298.
- Inflation adjustment (2% yearly): $1.02^7 = 1.15$.
- Inflated extra costs (€ thousand): €10,298 × 1.15 = €11,829.
- Inflated extra revenue (€ thousand): €1,230 × 1.15 = €1,412.

Year	2030
Extra costs compared to 2023 in US dollar (\$ thousand)	10,813.
Adjusted extra costs compared to 2023 (€ thousand)	10,298.
Extra revenue compared to 2023 (€ thousand)	1,230.
Inflated extra costs compared to 2023 (€ thousand)	11,829.
Inflated extra revenue compared to 2023 (€ thousand)	1,412.

TABLE 3.6: Modification to future extra costs and revenues for company X in 2030.

Step 3: Calculate present values
Next, we determine the present value of both the extra costs and the extra revenue in 2030, assuming a constant WACC of 4%.

Finding the present values:

- Discount rate (WACC): 4%.
- Discount factor for 2030: $1.04^7 = 1.32$.
- PV of extra costs in € thousand: €11,829 / 1.32 = €8,989.
- PV of extra revenue in € thousand: €1,412 / 1.32 = €1,073.
- Net result in € thousand: €1,073 - €8,989 = €-7,916.

	2030
Inflated extra costs compared to 2023 in euros(€ thousand)	11,829
Inflated extra revenue compared to 2023 in euros(€ thousand)	1,412
PV of extra costs compared to 2023 (€ thousand)	8,989
PV of extra revenue compared to 2023 (€ thousand)	1,073
Net result (€ thousand)	-7,916

TABLE 3.7: Present value calculations for company X in 2030.

Step 4: Determine PV of net results for 2024 to 2030
To integrate this result into financial metrics of the Z-score, we need the net results from 2024 to 2030.

Year	**2024**	**2025**	**2026**	**2027**	**2028**	**2029**	**2030**
Net result (€ thousand)	-8,894	-8,723	-8,555	-8,390	-8,229	-8,071	-7,916

TABLE 3.8: Present values of net results for company x from 2024 to 2030.

Step 5: Integrate results into financial metrics
Finally, we integrate the PV of net results into financial metrics for the Z-score. Note that the liabilities remain constant. Table 3.9 shows how the financial metrics are updated. We see the Z-score calculations per year, which slope down as most metrics are on the balance sheet. To verify, we confirm that the equality between assets and liabilities plus equity is maintained.

Final calculations for 2030:

- Working Capital: €10,000 + (€-7,916) = €2,084.
- EBIT: €15,000 + (€-7,916) = €7,084.
- Retained Earnings: $€50,000 - (€8,894 + €8,723 + €8,555 + €8,390 + €8,229 + €8,071 + €7,916) = € - 8,778$.
- Book Value of Equity: $€40,000 - (€8,894 + €8,723 + €8,555 + €8,390 + €8,229 + €8,071 + €7,916) = € - 18,778$.
- Total Assets: $€100,000 - (€8,894 + €8,723 + €8,555 + €8,390 + €8,229 + €8,071 + €7,916) = €41,221$.

Metric	**2023**	**2024**	**2025**	**2026**	**2027**	**2028**	**2029**	**2030**
Working Capital (€ thousand)	10,000	1,106	1,277	1,445	1,609	1,771	1,929	2,084
EBIT (€ thousand)	15,000	6,106	6,277	6,445	6,609	6,771	6,929	7,084
Retained Earnings (€ thousand)	50,000	41,106	32,383	23,828	15,438	7,209	-862	-8,778
Book Value of Equity (€ thousand)	40,000	31,106	22,383	13,828	5,438	-2,791	-10,862	-18,778
Total Assets (€ thousand)	100,000	91,106	82,383	73,828	65,438	57,209	49,138	41,222
Total Liabilities (€ thousand)	60,000	60,000	60,000	60,000	60,000	60,000	60,000	60,000
Altman Z-score	3.99	2.55	2.29	2.01	1.70	1.36	0.96	0.46

Table 3.9: Financial metrics for company X.

This calculation example shows how we use the extra costs for one year, compare these to 2023, and find new revenue using demand elasticity. The extra costs and revenue for that year are converted to euros, inflated by 2% per year, and discounted using the WACC. We obtain a net results by subtracting the present value of the extra costs from the present value of the extra revenue. This is a net result of solely transition related business income and expenses. This net result is integrated into the financial metrics of Company X, with yearly metrics of the P&L statement adjusted based on the base year 2023 and balance sheet metrics adjusted based on the previous year.

3.7 Overview of conceptual framework

We develop a conceptual framework that combines scenario analysis, cost modeling, revenue projections, and financial adjustments to assess the impact of the low-carbon transition on credit risk. We begin by describing the NGFS scenarios and models used for scenario analysis. We focus on carbon prices, energy usage and prices, and carbon capturing capacity to quantify transition costs. Next, we outline how these scenarios help identify new transition-related costs. To evaluate these costs from a credit risk perspective, we incorporate the concept of passing on costs using price elasticity of demand. By passing on incurred costs to customers, revenue increases, reducing losses from extra costs, and potentially leading to a higher Altman Z-score. We adjust costs and revenue for inflation and convert US dollars to euros to determine their present value using the WACC. These steps are crucial for calculating Altman Z-scores for each scenario. This process provides insights into default risk, aligning with the research question formulated in Section 1.3.

The conceptual framework is simplified with a calculation example that outlines the steps required to obtain an Altman Z-score per year. By adding yearly results to the metrics of the Z-score, we assess the impact of different pricing strategies and the effectiveness of passing on costs. This approach provides a realistic view of how additional costs influence default risk. We explain the process, step-by-step, showing how extra costs translate into an Altman Z-score for each year and scenario, including a sensitivity analysis on price elasticity of demand and pricing strategies. This forms the foundation for the following chapters, where we gather data and perform the modeling.

Chapter 4

Data Selection and Preparation

We gather data required for the conceptual framework developed in Chapter 3. We select relevant businesses and analyze their annual reports. The data include financial metrics for the Z-score, emissions, and emission targets. Additionally, we examine price elasticities of demand for the firms' products and financial ratios indicating their capital structure.

4.1 Business selection

The first step is defining selection criteria for the companies to assess. Keeping the scope of our research in mind, we want to find companies from different sectors most subject to transition risks. This gives insights in the difference between sectors. Various sectors have distinct production processes, resulting in varying levels and types of emissions. Moreover, each sector sells a different type of good and hence has different price elasticities of demand. We define different criteria such that we can select appropriate businesses for our research. The criteria were defined together with P&P, to ensure two things: 1) Relevance for both practical applications and insights and 2) feasibility. A company for our research should meet the following requirements: It should be Europe based, have clear business model, without many different revenue streams. A company should have good reporting history with clear strategic and environmental goals operating in a sector which is subject to transition risks.

Europe based
We focus on European businesses to ensure regulatory consistency, as they all comply with the same frameworks, allowing for comparable analyses. Since the transition is largely driven by policies, focusing on Europe-based companies allows for a more accurate assessment of policy impact. Furthermore, companies headquartered in Europe face similar macroeconomic conditions and market dynamics, making comparative analysis more straightforward and meaningful. Companies can have business operations in other regions of the world, as long as they are headquartered in Europe. Being able to make more robust comparisons contributes to the practical relevance of our research.

Clear business model
The company should have a clear business model without many different revenue streams to ensure that the primary focus of the business is easily identifiable. If companies sell many different goods, which are not really related it is complex to incorporate price elasticities of demand and determine the initial unit cost price. Hence, it should be clear

how the company creates revenue and incurs costs so that we can find unit cost prices and incorporate price elasticity analysis. Understanding the business model also allows us to potentially incorporate effects of the transition on the revenue. This criterion mostly contributes to feasibility of modeling.

Good reporting with clear targets for data availability
Finding clear data on emissions of a business is essential in our research. These data come usually from the businesses themselves. Hence, good reporting on environmental matters is an important requirement. Most likely this means that we use large listed companies, as these companies are the first required to report on these matters under the Non-Financial Reporting Directive (NFRD). Smaller and private companies follow later with these reporting, as regulation comes for them forces them to report in 2024, making it more difficult to find appropriate data (EBA, 2022). Besides environmental reporting, it is important that companies define clear sustainability strategies for the future. This enables us to project future emissions properly and make more robust assumptions on strategies on the implementation of carbon sequestration.

Operating in a vulnerable sector
As we perform our research from the perspective of a bank, we want to find the effects on the most vulnerable sectors, as these induce the highest risks for banks. Risk management insights are most valuable for these companies. Hence, finding companies based on the ECB report depicted in Figure 1.2, contributes to the practical relevance of our research. We want to find one company per sector and examine that company more in depth. We look into the following sectors: Agriculture, Mining, Electricity and Gas, Water Supply and Waste, Transport, and Manufacturing. Whilst the Accommodation and Food sector face considerable transition risks, we direct our research towards companies creating goods rather than services to focus on tangible production processes and supply chain impacts, which are more straightforward to quantify and model.

We note that these criteria lead to a lot of companies, which we cannot cover all. Hence, after finding companies meeting the set criteria, the final selection is made together with P&P. Companies operating in the Netherlands are preferred because their context is well-known, making the results easier to understand and more engaging. Additionally, we prefer companies with goods that have reliable literature on price elasticity.

4.1.1 Selected companies

We briefly describe the firms we selected to research. These firms are selected together with P&P and reflect the different sectors. We address each company, describing what their business model is and what goods they sell. We extend this analysis by describing how the company fits in the sector, as this is important for translating the results to competitors. The purpose of this section is to give some context on the companies selected.

Vattenfall - Electricity and Gas
Vattenfall is based in Sweden and operating primarily in the electricity and gas sector, with most of its operations in Sweden, Germany and The Netherlands. Vattenfall's business model revolves around the generation, distribution, and sale of electricity and gas, coming from both fossil and renewable sources. We use four different goods for our research: Gas, residential electricity, industrial electricity and heat measured in kilowatt-hour (kWh). As a major player in the European energy market, Vattenfall is regulated by EU

policies, which aligns with our research criteria. The company's sustainability reporting is well-developed, with clear targets we can use for emission projections, such as net zero in Scope 1 and 2 emissions in 2040 (Vattenfall, 2023). Looking at their emissions, Scope 1 emissions are significant due to power generation, whilst Scope 2 emissions are limited as they do not attract much external electricity from. Scope 3 emissions are generally speaking large for utility companies, especially due to the end consumers burning gas for instance. Vattenfall aims to achieve emission reduction by using renewable energy sources and no longer utilize fossil fuel processes.

Tata steel Netherlands - Manufacturing

Tata Steel Netherlands is part of the large Tata steel group and has significant operations in the Netherlands and some smaller business units in other parts of Europe, falling under EU jurisdiction. The main business is Tata Steel IJmuiden, where steel is produced and processed, making them a major player in the European steel industry. As a key entity in the manufacturing sector, Tata Steel faces transition risks due to regulatory pressures to reduce carbon emissions, which are significant in the steel manufacturing business. The company's sustainability reporting is detailed, addressing energy efficiency improvements and emission reductions. This particular sector faces significant challenges due to the energy intensive nature of the production process. We measure the goods sold in tonnes of steel produced, following Tata's approach (Tata Steel Nederland, 2023a). Tata Steel's emissions mainly result from chemical reactions in the production process (Scope 1) and the energy required for production (Scope 2). Tata captures flue gases and sends them to a neighboring power plant, which uses the gas to produce electricity for Tata's production process. Instead of sourcing energy from external gas extraction and combustion, Tata generates the gas and another company produces energy from it. Because of this construction they report most of their emissions in Scope 1 category, as they produce the gas used for electricity generation themselves. Reported Scope 2 is limited because of this, Scope 3 emission come mainly from purchasing the raw materials such as coal and ores (Tata Steel Nederland, 2023b). Tata developed a strategy where they fully focus on Direct Reduced Iron (DRI) technology. Using hydrogen for this process, they are able to produce carbon neutral steel. Tata steel commits to this technology rather than using CCS, however this technology does not reduce Scope 3 emissions. Hence our methodology of offsetting these emissions with CCS still holds.

Maersk - Transport

Maersk, headquartered in Denmark, operates in the transport sector. The company is involved in container shipping and logistics services, focusing on the sea transportation of goods. Maersk's primary services include shipping and logistics management, which facilitate global trade. As a significant player in the global transport sector, Maersk is relevant for understanding climate-related transition risks. The company has comprehensive sustainability reporting, emphasizing carbon emission reductions and logistics efficiency, targeting net zero in 2040 across the business. Even though the company does in fact not create goods or sells a physical product, we can use the price and elasticity for sea freight rates for our analysis. These rates are reported in price per forty foot equivalent (FFE) container unit, a standardized size sea container. This allows for comprehensive analysis, even though the company does not sell goods. We solely focus on the ocean operating segment of Maersk, which accounts for roughly 65% of the revenue in 2023 (A.P. Møller - Mærsk A/S, 2023a). This is possible due to the extensive reporting per segment. Maersk aims achieve decarbonisation by employing other fuels, like green methanol.

Vitens - Water Supply
Vitens is based in the Netherlands and operates in the water supply sector. The company's business model includes the extraction, purification, and distribution of drinking water to households and businesses. Providing drinking water, generates over 90% of the revenue (Vitens N.V., 2023). As the largest drinking water company in the Netherlands, Vitens is subject to EU regulations, making it suitable for our research. The company has robust sustainability reporting practices, focusing on water conservation and infrastructure resilience. Vitens is owned by Dutch local governments and as product we will use drinking water per m^3, obviously a necessary good. Most of the emissions come from electricity usage, for extracting, filtering and distribution of the water. Hence, changing the energy mix affects the emissions significantly. Scope 1 emissions are driven the release of methane from pumping up the water. Scope 3 emissions are predictably limited for this sector, as end users do not emit anything and entire value chain is limited. Vitens stands out from the other companies being owned by governmental entities. Vitens's target is to be climate neutral in 2050, as it aligns with the goals of the Dutch government. Its governmental ownership means that earning money might be less of a priority for the firm. Even though it is not likely that such a company will pass on all costs to its customers, it is interesting to see the effect if they did, giving the discussion on pricing of such as essential good as water more context.

FrieslandCampina - Agriculture
FrieslandCampina is headquartered in the Netherlands. The company operates as a dairy cooperative, focusing on the production, processing, and marketing of dairy products sourced from member farmers. FrieslandCampina's products include milk, cheese, butter, yogurt. As a major player in the global dairy production sector, FrieslandCampina faces transition risks, such as climate impacts on dairy farming and evolving sustainability standards. The company has comprehensive sustainability reporting, as it is a large global competitor. As product we will use an average dairy product in tonnes, a mixture of several dairy based products. Milk is the key ingredient for these products which they buy from their member diary farmers. These farms generate significant Scope 3 emissions. Production and transport lead to the Scope 1 and 2 emissions, which are considerably less for the non-farmers in the agricultural sector than Scope 3 emissions. As it is at the farms where significant amounts of GHG are emitted. A special note should be added on the structure of this company, as it is a cooperation of dairy farmers. Members hold bonds that earn interest and a proportions of the retained earnings is given to the members, hence there is a very direct link to the agricultural sector. A lower milk price means less money from members for their milk, but might lead to higher payouts of the retained earnings. Hence the milk price is a key component of the firm business model.

Boliden - Mining
Boliden is based in Sweden and operates in the mining sector. The company focuses on the extraction, processing, and refining of various non-ferrous metals. Boliden's business model includes operating mines and smelters, providing a range of metal products for industrial use. As a significant player in the European mining industry, Boliden is subject to EU regulations, making it a relevant subject for studying climate risks. They have two main streams of revenue, selling free metals and charging for treatment and refining of the metals. Most of the revenue comes from mining, treating and refining copper and zinc, hence we will use these two products for our analysis. Boliden is involved with all three

scopes, as they emit in their own operations, require significant electricity and source ores for their operations. They have set reductions goals for 2030, 42% reduction for Scope 1 and 2 emissions, a 30% reduction in Scope 3 emissions (Boliden, 2023). Boliden is part of the The International Council of Mining and Metals (ICMM), underwriting the net zero 2050 ambition. This makes Boliden a good representative for this sector.

4.2 Data collection

The required information for the companies can be found in annual reports and sustainability reports. In this section we describe what data from the annual reports we retrieve and argue why we choose for a specific metric. We begin with the metrics used for the Z-score, followed by our approach to interpreting emission reporting. Moreover, we outline how to obtain unit prices and describe how we determine potential revenue changes. This section functions as a stepping stone before finding the actual data per company, aiming to generalize the data collection process as much as possible.

Altman Z-score data
For the Altman Z-score, we extract several financial metrics from annual reports. Some metrics, like EBIT, are easily located, while others require more careful consideration. To capture recent performance while smoothing short-term fluctuations, we calculate EBIT as the average over the last three years. In cases where currency conversion is necessary, each year's figures are converted to euros using the year-end exchange rate, and the final EBIT is derived from averaging these converted values.

Balance sheet-related metrics, such as retained earnings, total assets, and book value of equity, are taken from the most recent consolidated balance sheet. This is because the consolidated balance sheet reflects the entire company's financial position, which is critical for assessing creditworthiness. Retained earnings include profits or losses accumulated up to 2023, the base year of our analysis. Using the consolidated figures ensures we capture the financial position of the parent company and its subsidiaries, especially since sustainability targets are set collectively.

For working capital, we adhere to Altman's definition, subtracting current liabilities from current assets. While some companies report working capital as a specific figure in their annual reports, these are often based on operating assets and liabilities, which differ from Altman's approach. Therefore, we use the current assets and liabilities reported in the consolidated balance sheet to ensure consistency with Altman's methodology, as outlined in Chapter 2.

Emissions
Companies report their exact Scope 1 and 2 GHG emissions in their annual reports, while Scope 3 emissions are estimated most of the times. These emissions are reported in CO2e, meaning other GHGs are translated to a CO2 value based on their global warming potential. The translation factors are standardized, allowing all GHGs to be combined easily into one number. For Scope 1 and 2 emissions, the exact total number is provided in tonnes of CO2e, sometimes split by parts of the production process they originate from. Some companies generate their own electricity, adding these emissions to Scope 1 rather than Scope 2. However, since we use electricity usage as a proxy for Scope 2, this does not affect our calculations. As Scope 1 and 2 are easier to measure and can be directly

impacted by the company, they are usually combined in their emission reduction goals. Large companies set strategic goals for percentage reductions compared to a base year. We use these targets the following way:

1. Identify base year emissions: Determine the emissions for the base year.
2. Determine target value and year: Establish the target emissions and the year by which they should be achieved.
3. Linear interpolation: Assume emissions decline linearly each year for computational simplicity.

This means we assume that emissions decline linearly each year for computational reasons. If a company has a net zero goal for, say, 2040, we assume emissions decline linearly until that year. If a company has set a target for emissions reduction by 2035 and also commits to a net zero goal by 2050, we interpolate twice: once between the current emissions and the 2035 goal, and again between the 2035 goal and net zero by 2050.

Scope 3 emissions are currently always estimated and split into several categories. Some companies also differentiate between upstream and downstream emissions. As these emissions cannot always be directly affected by the business itself, reducing them is more complex. Hence, companies set separate goals for their Scope 3 emissions. Our method for using these targets is similar to the other scopes. We use a base year, the emission goal, and target year for linear interpolation. We look at the annual reports of each company to determine whether they expect to achieve net zero with or without carbon capture, depending on their production processes. For example, steel manufacturing will always emit GHGs due to chemical reactions, so not all emissions can be removed. If a company mentions reduction targets that do not account for net zero despite having such a goal, we assume the remaining emissions are offset with carbon capture. We assume CCS implementation begins in 2030. From this point, we linearly interpolate its capacity from zero, reaching full deployment by the company's target net-zero year. 2030 is chosen as the starting year, as the first reduction targets, achieved through easier methods, should be met by then. Beyond 2030, further emission reductions will most likely require some sort of CCS.

We use electricity and gas usage as a proxy for Scope 2 emissions. We look at the current usage of electricity and gas of a firm from the annual reports. From here we change those numbers using expected percentage changes in the use of those energies. These changes are based on the NGFS scenarios, meaning we linearly interpolate over 5 years and calculate a yearly percentage change We project this on the current energy usage of a company, projecting future energy usage. The energy usage is in this case split up in gas and electricity usage, where gas usage decreases and electricity usage increases. The magnitude of these changes depends on the scenario.

Determining unit price

We need to determine per company, what goods we use for our demand elasticity input. We must find the revenue per product and volume of sales per product to find an average sales base price. These metrics can either be found directly in the report or need to be estimated. The goal is to find an estimate of the total revenue per product and of the total sales per product. We only look at the sales of the latest year to capture the most recent market dynamics faced by the company. If the revenues per product are given, we determine a ratio based on the revenue to split the total volume reported accordingly. If the sales volume per product is not given but only the total revenue, we split the revenue according to the sales volumes, as these are reported often in the same units. We select companies with straightforward business models, generating revenue from a few products and services. Even these companies have multiple revenue streams but we assume they remain constant, allowing us to exclude them from the analysis. We only look at the ability to pass on costs for the products that we select per company.

Sales adjustments
Even though our research looks at the costs side of the transition towards a low carbon economy, for some companies it is very relevant to look at the sales side as well. For instance, a utilities company will not only consume less fossil gas and use more electricity, it will also sell less fossil gas and more electricity. However this is not applicable to all products we analyze. Hence we only use revenue adjustments if the product is modelled in the NGFS scenarios. This way we remain consistent with the costs modelling. Additionally, if products are modeled by NGFS, they will likely be impacted by policies, either increasing or decreasing demand. We do not want to exclude these potential upsides or additional downsides from our transition analysis. We use percentage in or decrease of the use the product in the region and apply those yearly changes to the base year sales volumes. We incorporate these changes in sales before applying price elasticities of demand. If we do not use these percentage changes, we assume sales volume remains constant.

Weighted average cost of capital
To determine the present value of future cash flows, we need to discount these cash flows using a company's WACC before tax. We use a real WACC rather than a nominal WACC, meaning it is adjusted for inflation. The WACC can usually be found in annual reports or other official company documents and includes assumptions about the cost of equity and debt, market conditions, and the company's capital structure. Market conditions, such as current interest rates, inflation, and the overall economic climate, significantly impact the WACC. Low interest rates lower the cost of debt, reducing the WACC, while high inflation or economic uncertainty increases it. The risk-free rate and equity market premium also influence the cost of equity. These market conditions are typically assumed by the company based on current economic data, historical trends, and forecasts.

The advantage of using a company's reported WACC is that it already incorporates predictions about market conditions, such as inflation and interest rates, meaning we do not have to make these predictions ourselves. Additionally, the WACC is based on internal information regarding the company's performance expectations and strategic choices, which are not accessible to external analysts. However, there are some drawbacks. The primary issue is the mismatch in time horizons: while companies typically base their WACC on a 3 to 5-year horizon, our analysis may require a much longer horizon, such as 25 years. This discrepancy can lead to inaccuracies when applying the WACC over extended periods, as the assumptions underpinning the WACC may not hold true over time. Despite this, we can use the current WACC to discount future cash flows for an investment with a 25-year time horizon because the WACC represents the company's cost of capital at the present moment. Ideally, we would adjust the WACC over time to reflect changing market conditions and company-specific factors. However, this requires internal information from the company, which is not available to us.

In conclusion, using the current WACC and keeping it constant is an appropriate way to discount future cash flows. It includes market conditions and company-specific information, representing the cost of capital at the current time. However, it is important to acknowledge that this method assumes market conditions and company performance remains constant over the 25-year period. As such, while using the current WACC provides a practical solution, it also introduces potential risks and uncertainties into the valuation.

4.3 Vattenfall

We present the data from Vattenfall in the annual report of 2023 (Vattenfall, 2023). We discuss how we convert the data to our previously presented format.

Metrics
Table 4.1 presents the Z-score metrics in euros. The original values, in millions SEK, were converted to euros using the exchange rate on the balance sheet date for each year: 10.2503 (2021), 11.1218 (2022), and 11.096 (2023). The 2021 and 2022 rates were applied to average EBIT, while the 2023 rate was used for all other metrics. The average values in euros were then calculated. The Z-score of 1.89 suggests that Vattenfall is in the grey area of default risk.

Metrics	Values in m euros
Working Capital	4,380
Retained Earnings	10,833
EBIT	2,849
Equity	12,565
Total Assets	53,045
Total Liabilities	40,479
X1	0.08
X2	0.20
X3	0.05
X4	0.31
Z-score	1.89

TABLE 4.1: Financial metrics of Vattenfall.

Emissions
Tables 4.2 and 4.3 show the projected emissions of Vattenfall based on their net zero goals in 2040. Vattenfall used 2017 as a base year and wants to reduce Scope 1 and 2 emissions with 75% by 2030, this is a reduction of the both scopes combined. Scope 3 emissions should be reduced by 54% compared to 2017. The 2017 emissions are shown in Table 4.2. By 2040, Vattenfall aims to reduce 90% of emissions across all scopes and achieve net zero. We assume the remaining emissions are captured with CCS. We determine the capturing capacity required in 2040 and then linearly interpolated form the starting year 2030. From 2040 to 2050 we assume emissions and capturing capacity remain the same. The energy usage of Vattenfall was 6.6 Terawatt hours (TWh) of electricity and 28.4 TWh of gas, corresponding to 23.76 million GJ or 23.76 PJ and 84.24 million GJ or 84.24 PJ.

Variable	Unit	2017	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033	2034	2035	2036
Scope 1	Mt CO2e	23.7	7.9	7.604	7.307	7.011	6.714	6.418	6.121	5.825	5.4755	5.126	4.7765	4.427	4.078	3.728
Scope 2	Mt CO2e	0.2	0.2	0.179	0.157	0.136	0.114	0.093	0.071	0.05	0.047	0.044	0.041	0.038	0.035	0.032
Scope 3	Mt CO2e	24.3	15	14.454	13.908	13.362	12.816	12.27	11.724	11.178	10.3032	9.4284	8.5536	7.6788	6.804	5.9292
CCS	Mt CO2e	0	0	0	0	0	0	0	0	0	0.478	0.956	1.434	1.912	2.39	2.868

Table 4.2: Projected CO2e Emissions and CCS of Vattenfall in Mt CO2e (2017, 2023-2036).

Variable	Unit	2037	2038	2039	2040	2041	2042	2043	2044	2045	2046	2047	2048	2049	2050
Scope 1	Mt CO2e	3.379	3.029	2.680	2.33	2.33	2.33	2.33	2.33	2.33	2.33	2.33	2.33	2.33	2.33
Scope 2	Mt CO2e	0.029	0.026	0.023	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Scope 3	Mt CO2e	5.0544	4.1796	3.3048	2.43	2.43	2.43	2.43	2.43	2.43	2.43	2.43	2.43	2.43	2.43
CCS	Mt CO2e	3.346	3.824	4.302	4.78	4.78	4.78	4.78	4.78	4.78	4.78	4.78	4.78	4.78	4.78

Table 4.3: Projected CO2e Emissions and CCS of Vattenfall in Mt CO2e (2037-2050).

Sales per unit

Table 4.4 shows the four product types we use. The sales of electricity were 185,683 in SEK million, which we split up in 34.5% retail and 65.5% business sales. This is based on the sales volumes, as Vattenfall sold 27.6 TWh to retail customers and 52.4 TWh to industrial customers. We use the exchange rate of 11.096 euro/SEK form the annual report (Vattenfall, 2023). We show the unit price per KWh rather than per TWh, which is a 10^9 factor, as this is a commonly used unit. The additional costs are proportionately passed on to sales revenue as a percentage.

Source	Sales in m SEK	Revenue %	Revenue in m euros	Sales in TWh	Euro per KWh
Heat	22,920	0.0880	2,066	13.5	0.1530
Electricity retail	64,060	0.2461	5,773	57.96	0.0996
Electricity business	121,622	0.4672	10,961	110.04	0.0996
Gas	51,679	0.1985	4,657	44.5	0.1046

Table 4.4: Sales of Vattenfall.

Table 4.5 shows the original price elasticities of demand found from literature, quoted as PED. Next to that, the table shows the other price elasticities of demand we used for the PED. To determine these, we took the end point of -1 and split them up into three equally large steps, as explained in Subsection 3.3.2. This approach is followed for each firm. Together with the percentage of sales, we determined a weighted average of demand elasticity. This is not used for calculations as we use different one per product, but this number makes it easier for us to refer to a certain case. By multiplying the percentage of sales from Table 4.4 with the price elasticities of demand we obtain the average elasticities.

Product	Original PED	PED 1	PED 2	PED 3	Source
Heat	-0.683	-0.789	-0.894	-1	Trotta et al. (2022)
Electricity retail	-0.88	-0.92	-0.94	-1	Csereklyei (2020)
Electricity business	-0.545	-0.697	-0.848	-1	Csereklyei (2020)
Gas	-0.16	-0.44	-0.72	-1	Dilaver et al. (2014)

Table 4.5: Price elasticities of demand of heat, electricity and gas.

Sales adjustments
For Vattenfall we use the NGFS scenarios to adjust the revenue streams, as we assume that they will sell more electricity and less gas in the future. We use the percentage difference based on the NGFS scenarios for electricity and gas usage shown in Figures 3.4 and 3.6. Furthermore, we use the NGFS scenarios to also incorporate the future heat usage projections, and apply these projections in the same fashion. Figure A.6 shows the sales projections per scenario in TWh, without using price adjustments or elasticity. We do not differentiate between retail and industrial electricity, assuming this split remains consistent throughout the analysis. From the figure we see that electricity will indeed increase in sales, whereas heat and gas sales will decrease. We match these new sales with the current prices to obtain a revenue base without transition costs which we compare to.

WACC
Vattenfall utilizes a before tax WACC of 4.53% in the years 2024 to 2027. This WACC is real and not nominal and incorporates a long term perspectives, according to their annual report (Vattenfall, 2023). This makes it very suitable to directly use a our discount rate. A WACC of this size for a capital-intensive utility company is low but plausible, given the specific characteristics and market conditions of the utility sector. Investors' perception of utility companies as safe investments further lowers the required return on both debt and equity.

4.4 Data Tata steel

We present the data from Tata steel Netherlands in the annual report of 2022-2023, the most recent one. The report is split up in a financial report, (Tata Steel Nederland, 2023a) and a sustainability report (Tata Steel Nederland, 2023b). For information on the WACC we use the report of the Tata steel group as they report on these matters (Tata Steel Limited, 2023).

Metrics
Table 4.6 shows the different metrics in euros, as the main operations and the reporting are in this currency. The Z-score of 5.09 indicates a financially healthy company.

Metrics	**Values in m euros**
Working Capital	1,347
Retained Earnings	3,216
EBIT	0,387
Equity	3,622
Total Assets	6,134
Total Liabilities	2,512
X1	0.22
X2	0.52
X3	0.06
X4	1.44
Z-score	5.09

TABLE 4.6: Financial metrics of Tata.

Emissions
Tables 4.7 and 4.8 show the projected emissions of Tata Netherlands. Tata steel combines Scope 1 and 2 emissions as they use gas which is released from there operations for energy generation and consumption. Tata sets either unclear or conditional goals, so we need to make several assumptions. Tata wants to reduce Scope 1 and 2 emissions by 2030 with 35 to 40% by 2030 compared to 2019, when emissions where 12.9 Mt CO2e, we used the average 37.5% for our projection. They aim to produce carbon neutral in 2045 using Direct Reduced Iron (DRI) technology, which is only neutral if green hydrogen can be used. We estimate that in 2050, Tata will use 20% green hydrogen for productions and use 80% natural gas. This is in line with the projections of the European Hydrogen roadmap, saying 20% of European steel will be produced from using DRI technology with green hydrogen in 2050 (Fuel Cells and Hydrogen 2 Joint Undertaking, 2019). DRI technology with natural gas emits an average of 1.4 tonnes CO2e per tonne of steel, lower than the current method's 1.9 tonnes (Laguna et al., 2021). For Tata, we used the average steel sales in 2050 across all scenarios, which is 4.96 Mt (see Figure A.8 in Appendix A.1). To project grey steel production by 2050, we multiplied 4,96 Mt by 80% and then by 1.4, resulting in 5.55 Mt of Scope 1 and 2 emissions, used as the emissions in 2050. This is also used for interpolation to obtain the emissions for the other years. We assume Scope 3 emissions to be 10% compared to 2023 in 2050. Tata has yet to state a goal for Scope 3, hence we took the long-term target of 90% reduction by Science Based Targets initiative (2023). Tata refers to this framework for GHG protocols in their annual report (Tata Steel Limited, 2023). Even though Tata strategically puts its resources into the DRI technology and not into CCS, it is clear that for the steel sector CCS remains essential to achieve net zero in 2050 as green steel will not be completely feasible due to lack of hydrogen (Science Based Targets initiative, 2023). Hence we assume that the remaining emissions are captured with CCS in our model to achieve net zero in 2050. Tata does not report gas usage, but it does report coal usage.

Since the production process requires significantly more coal than gas, we substitute Tata's gas usage with coal. This is due to the chemical properties of coke, which are essential for the traditional steel-making process. Figures A.1 and A.2 in the Appendix A show the NGFS coal usage and prices used for the model. We note that rather than final energy, this data from the NGFS is primary energy, as no final energy data on coal was available. Primary energy is raw energy from natural resources, while final energy is the energy delivered to end-users after conversion. These prices thus include transport, taxes and such, primary coal prices do not. As input for our model, Tata used 7.61 PJ of electricity and 93.14 PJ of coal. The electricity usage is directly obtained form the annual report and covers both IJmuiden plant and other facilities in the EU. Tata reports 0.63 tonne coals consumption per tonne Crude steel made. Tata made 6.16 million tonnes of crude steel, resulting in 3.88 million tonnes of coal used. The caloric value of coking coal, a specific coal used in steel manufacturing, is 24,000 kJ/kg or 24 MJ/kg.(I. E. Agency, 2015). If we multiply these two, we obtain 93.12 PJ of coal used, as we cross out a factor 10^9 on both calculating from MJ to PJ and from kg to a million tonnes.

Variable	Unit	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033	2034	2035	2036
Scope 1	Mt CO2e	11.197	10.722	10.248	9.773	9.299	8.824	8.350	7.875	7.759	7.643	7.527	7.411	7.295	7.179
Scope 2	Mt CO2e	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Scope 3	Mt CO2e	3.815	3.674	3.532	3.391	3.250	3.109	2.967	2.826	2.723	2.620	2.516	2.413	2.310	2.207
CCS	Mt CO2e	0	0	0	0	0	0	0	0	0.316	0.632	0.948	1.264	1.579	1.895

TABLE 4.7: Projected CO2e Emissions and CCS of Tata in Mt CO2e (2023-2036).

Variable	Unit	2037	2038	2039	2040	2041	2042	2043	2044	2045	2046	2047	2048	2049	2050
Scope 1	Mt CO2e	7.063	6.947	6.831	6.714	6.599	6.483	6.367	6.251	6.135	6.019	5.903	5.787	5.671	5.555
Scope 2	Mt CO2e	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Scope 3	Mt CO2e	2.104	2.001	1.898	1.794	1.691	1.588	1.485	1.382	1.279	1.176	1.072	0.969	0.866	0.763
CCS	Mt CO2e	1.895	2.211	2.527	2.843	3.159	3.475	3.791	4.107	4.422	4.738	5.054	5.370	5.686	6.002

TABLE 4.8: Projected CO2e Emissions and CCS of Tata in Mt CO2e (2037-2050).

Sales per unit

Table 4.9 shows the crude steel that Tata produced in 2022-2023. The total revenue of Tata comes from delivering produced goods, which consist of a range of steel products. The basis of these products is crude steel, hence we use this as our product. We acknowledge these revenue streams include delivering processing the steel, which can be seen in the fact that the price in Table 4.9 is larger than the commodity price of steel of the year 2022-2023. We let only the increase production costs of steel affect the price of steel assuming *ceteris paribus*. We use a price per tonne of delivered steel.

Product	Total sales m tonnes	Revenue in m euros	Price per tonne in euros
Crude Steel	5.496	7,192	1,308.59

TABLE 4.9: Sales data of crude steel.

Table 4.10 shows the original price elasticities of demand found from Fernandez (2018). The elasticity for steel is -0.069, indicating that it is highly inelastic. Fernandez (2018) presents price elasticities of demand for several commodities, including steel across various regions. In the study data from 1980-2015 are used. The elasticity for Europe of -0.025 is insignificant, hence we use the elasticity for the world. As Tata Netherlands has clients all over the world, we can use this elasticity. For our sensitivity analysis we interpolate between -0.069 and -1 to obtain the other elasticities.

Product	Original PED	PED 1	PED 2	PED 3	Source
Crude steel	-0.069	-0.379	-0.690	-1	Fernandez (2018)

TABLE 4.10: Price elasticities of demand of steel.

Sales adjustments

For Tata we used the NGFS scenarios to adjust the revenue streams, as these scenarios project a decrease in sales of steel. We use the percentage difference based on the NGFS scenarios for steel to project future steel sales. Figure A.8 shows the sales projections per scenario, without using price adjustments or elasticities.

WACC

The WACC is 10.6% pre-tax, which includes expectations on macro-economic conditions and the steel market. To be precise, this is the pre-tax discount factor Tata Netherlands uses for internal valuation. They report a WACC based on the Tata groups and other steel manufacturers of 7.9% post-tax. Given this, a 10.6% pre-tax assumption is reasonable.

4.5 Maersk

This section presents the data from A.P. Møller - Mærsk A/S (2023b) and A.P. Møller - Mærsk A/S (2023c), the financial and sustainability reports of the transportation company Maersk. We focus on the ocean department of Maersk, detailing the decisions regarding the division of data from the group, to use it for the ocean department.

Metrics

Table 4.11 shows that Mearsk is a financially healthy organization. We use the EBIT from the past three years reported for the ocean segment. The other metrics are included on the consolidated balance sheet, but they are not reported separately for the ocean segment. The capital invested in the ocean segment and its proportion of the company's consolidated balance sheet is 59.2%. We multiply the values on the balance sheet to obtain the figures. The balance sheet is reported in US dollar, using the exchange rate from December 31, 2023. As the exact rate was unavailable, we used the average exchange rate of 0.9058 US dollar/euros from December 28, 2023, to January 2 (European Central Bank, 2024).

Metrics	Values in m euros
Working Capital	9,990
Retained Earnings	27,785
EBIT	14,581
Equity	29,538
Total Assets	44,020
Total Liabilities	14,482
X1	0.23
X2	0.63
X3	0.33
X4	2.04
Z-score	7.91

TABLE 4.11: Financial metrics of Maersk ocean.

Emissions

Tables 4.12 and 4.13 show the estimated emissions of the ocean segment of Maersk. 92% of Maersk's overall Scope 1 emissions come from burning fuel on the maritime vessels (A.P. Møller - Mærsk A/S, 2023c). The Maersk group aims to be net zero in 2040. We used this proportion of the group's Scope 1 emissions of 31.4 MT CO2e to find the ocean segments Scope 1 emissions, which is considerable with 31.4 Mt CO2e. The group itself has considerable less Scope 2 emissions, of 0.38 Mt CO2e. More than half of this of this comes from the terminal segment, hence we assume Scope 2 emissions of the ocean segment are zero. Maersk set a goal to reduce Scope 1 emissions by 35% in 2030 compared to 2022. In 2040 Scope 1 emissions should be reduced by 96%. We assume Scope 1 emissions to remain constant between 2040 and 2050. Scope 3 emissions are well reported by Maersk, aiming to reduce them by 22% by 2030 compared to 2022. This goal is to achieve a 90% reduction by 2040. We assume CCS starts in 2030 and captures all residual emissions in 2040, to achieve net zero targets. Maersk plans on utilizing GHG removal, supporting this assumption. We use three categories to find the total Scope 3 emissions for the ocean segment: upstream transportation and distribution, use of sold products and fuel and energy-related activities. All three of these emissions types are both significant and directly related to the ocean segment. As not all products sold come from maritime operations, we used 90% of these emissions. This results in 35.6 Mt of emissions, which is 79.3% of the total Scope 3 emissions of the group of 44.9 Mt CO2e.

The energy and gas consumption are negligible compared to the fuel usage of Maersk. Hence we use fuel consumption rather than gas and electricity usage. Figures A.3 and A.4 show the energy usage and prices projected by the NGFS we utilized. The consumption is specific for the maritime transport sector, prices were only available for the transport sector. In these scenarios the use of more efficient vessels and introduction of bio and green fuels is taken into account, reflecting the upcoming changes in the transport sector. This results in the fact that in a net-zero scenario Maersk will spend less money on fuel consumption compared to greyer scenarios. This makes sense if we take the investment costs of the new vessels using these new fuels into account. This is outside of our scope, but it should be mentioned that in more climate stringent scenarios, counterintuitively, costs decrease due to significantly lower consumption which is not countered by the height of the fuel prices. Maersk uses 115,404 GWh of both green and fossil fuels. This results in 415 million GJ of energy consumption in 2023.

Variable	Unit	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033	2034	2035	2036
Scope 1	Mt CO2e	31.4	29.857	28.314	26.771	25.229	23.686	22.143	20.6	18.666	16.732	14.798	12.864	10.93	8.996
Scope 2	Mt CO2e	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Scope 3	Mt CO2e	35.6	34.486	33.371	32.257	31.143	30.029	28.914	27.8	25.376	22.952	20.528	18.104	15.68	13.256
CCS	Mt CO2e	0	0	0	0	0	0	0	0	0.482	0.964	1.446	1.928	2.41	2.892

Table 4.12: Projected CO2e Emissions and CCS of Maersk in Mt CO2e (2023-2036).

Variable	Unit	2037	2038	2039	2040	2041	2042	2043	2044	2045	2046	2047	2048	2049	2050
Scope 1	Mt CO2e	7.062	5.128	3.194	1.26	1.26	1.26	1.26	1.26	1.26	1.26	1.26	1.26	1.26	1.26
Scope 2	Mt CO2e	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Scope 3	Mt CO2e	10.832	8.408	5.984	3.56	3.56	3.56	3.56	3.56	3.56	3.56	3.56	3.56	3.56	3.56
CCS	Mt CO2e	2.892	3.374	3.856	4.338	4.82	4.82	4.82	4.82	4.82	4.82	4.82	4.82	4.82	4.82

Table 4.13: Projected CO2e Emissions and CCS of Maersk in Mt CO2e (2037-2050).

Sales per unit

The sales of the Ocean department consist of freight revenue and revenue from hubs. The total sales volume is reported in FFE,, a standard container size used in the shipping industry. Table 4.14 summarizes the sales of Maersk ocean. We determined the price per loaded FFE by dividing the total revenue from freight by the volume of loaded FFE. We did not use the reported price per FFE, as this did not match the total revenue, suggesting other revenue streams from shipping are included in freight revenue. We use the same US dollar to euros conversion rate as before of 0.9058.

Product	Total sales in thousands	Revenue in m EUR	Price per loaded FFE in euros
Loaded FFE	11,904	25,743	2,162.62

Table 4.14: Sales data of loaded FFE.

The PED of long distance sea shipping is difficult to determine, as it consists of many factors, starting with the products to be shipped. There are no studies which reflect the situation of Maersk perfectly, hence we have to choose the most suitable alternative. Several studies have examined the PED of short sea shipping or the cross elasticity of demand of waterways compared to trains or trucks. Merkel et al. (2022) provides a comprehensive overview of all types of price elasticities studied on transport. Notteboom (2010) provides elasticities for multiple freight transport distances in Northern Europe, using the amount of tonnes as dependent variable. This is more suitable for our research than using tonne-kilometers or mode of choice as depend variables. Furthermore, Notteboom (2010) examines the effect on competitiveness of using low sulphur fuel requirements in shipping. This is similar to why prices rise in our research: environmental choices. Notteboom (2010) shows a point price elasticity for the longest distance (>750 km) of -0.53, we use this as baseline elasticity. The sensitivity analysis on demand is crucial for Maersk as literature does not reach consensus on the PED for long term shipping, which ranges from values near zero to lower than -1 (Merkel et al., 2022). The price elasticities we use are presented in Table 4.15. The other elasticities are again found by using the approach outlined in Subsection 3.3.2, interpolating between -0,53 and -1.

Product	Original PED	PED 1	PED 2	PED 3	Source
Loaded FFE	-0.53	-0.687	-0.843	-1	Notteboom (2010)

TABLE 4.15: Price elasticities of demand of maritime freight transport.

Sales adjustments

The NGFS scenarios do not project future transport figures, hence we do not adjust the volume of loaded FFE per year. This means the sales volume is assumed constant during the analysis. It could be that in the future supply chains become shorter, so less long distance shipment is used. However, this is driven more by consumer choices than by policies. Hence different scenarios would not make a significant difference between the NGFS scenarios, as these are primarily policy and technology based.

WACC

Maersk ocean specifically used a pre-tax discount rate of 9.8% from an impairment test. We use this rate because Maersk does not present their WACC, and it includes business expectations on growth rates and macroeconomic conditions. Calculating a WACC from the balance sheet does not include these factors. Using the rate for an impairment test is justified as it reflects the specific risks and cost of capital for the ocean segment.

4.6 Vitens

We present the data we use for our analysis from Vitens N.V. (2023), the latest annual report of Vitens. Vitens is not part of a group or segment, so we can use most figures from the annual report directly for our analysis. Even though Vitens is a private company, the shareholders are Dutch governmental entities, municipalities and provinces. This means that it is a risk averse and conservative company compared to others.

Metrics

Table 4.16 shows that Vitens has a low Z-score of 0.79, meaning they are already at default risk. What stands out is the negative working capital of the company, as current liabilities are higher than current assets. Vitens reports in euros.

Metrics	**Values in m euros**
Working Capital	-203
Retained Earnings	543
EBIT	46
Equity	677
Total Assets	2,237
Total Liabilities	1,559
X1	-0.09
X2	0.24
X3	0.02
X4	0.43
Z-score	0.79

TABLE 4.16: Financial metrics of Vitens.

Emissions

Vitens is a relatively small company only operating in the Netherlands. This can be seen in the company's emissions, which are reported in kilotonnes rather than megatonnes. Most emissions come from the electricity used by Vitens, Scope 2. The water extraction process releases methane, resulting in most of the Scope 1 emissions. Vitens's goal is to produce a total of 100kt of CO2e by 2030. They align their goals with the Dutch government, so we assume carbon neutrality by 2050. We use the current emissions ratio to determine the emissions in 2030. Scope 1 and 3 emissions are assumed to be constant as this is the nature of their production process. We reduce the Scope 2 emissions using linear interpolation, as we assume 100% green electricity by 2050. We start CCS in 2030, and linearly interpolated this to using the assumption of carbon neutrality in 2050. Vitens aims to implement a type of methane capturing technology, hence the use of CCS technologies is a valid assumption.

Vitens used 168 GWh of energy in 2023, almost all coming from electricity, as no gas is used in the production process. Gas is merely used for heating the buildings (Vitens, 2021). For simplicity we assume 100% of this energy consumption is electricity.

Variable	**Unit**	**2023**	**2024**	**2025**	**2026**	**2027**	**2028**	**2029**	**2030**	**2031**	**2032**	**2033**	**2034**	**2035**	**2036**
Scope 1	kt CO2e	39	37.8571	36.7143	35.5714	34.4286	33.2857	32.1429	31	31	31	31	31	31	31
Scope 2	kt CO2e	72	70	68	66	64	62	60	58	55.1	52.2	49.3	46.4	43.5	40.6
Scope 3	kt CO2e	13	12.5714	12.1429	11.7143	11.2857	10.8571	10.4286	10	10	10	10	10	10	10
CCS	kt CO2e	0	0	0	0	0	0	0	0	2.05	4.1	6.15	8.2	10.25	12.3

TABLE 4.17: Projected CO2e Emissions and CCS of Vitens in kt CO2e (2023-2036)

Variable	**Unit**	**2037**	**2038**	**2039**	**2040**	**2041**	**2042**	**2043**	**2044**	**2045**	**2046**	**2047**	**2048**	**2049**	**2050**
Scope 1	kt CO2e	31	31	31	31	31	31	31	31	31	31	31	31	31	31
Scope 2	kt CO2e	37.7	34.8	31.9	29	26.1	23.2	20.3	17.4	14.5	11.6	8.7	5.8	2.9	0
Scope 3	kt CO2e	10	10	10	10	10	10	10	10	10	10	10	10	10	10
CCS	kt CO2e	14.35	16.4	18.45	20.5	22.55	24.6	26.65	28.7	30.75	32.8	34.85	36.9	38.95	41

TABLE 4.18: Projected CO2e Emissions and CCS of Vitens in kt CO2e (2037-2050)

Sales per unit

The total revenue coming from selling drinking water and the sales volume, averages out on €1.25 per m^3. Table 4.19 shows the sales and revenue of Vitens.

Product	Sales in m euros	Sales in million m^3	Price in euro per m^3
Drinking water	426.3	340.6	1.25

TABLE 4.19: Sales data of drinking water.

Table 4.20 shows the price elasticities of demand we used for the sensitivity analysis. We use the study by Schleich and Hillenbrand (2019), showing a PED for drinking water of -0.17. They describe that in Germany, sharing similarities with the Netherlands on infrastructure, the PED varies between increasing and decreasing prices. We use the estimate of price elasticity for increasing prices, as this fits into the scope of our research. The value of -0.17 is similar to other the results of other studies on price elasticities of drinking water in Europe, in the range of (-0.15,-0.25) (Martinez-Espiñeira, 2002), (Schleich & Hillenbrand, 2009).

Product	Original PED	PED 1	PED 2	PED 3	Source
Drinking water	-0.17	-0.447	-0.723	-1	Schleich and Hillenbrand (2019)

TABLE 4.20: Price elasticities of demand of drinking water.

Sales adjustments
The NGFS scenarios do not project future drinking water figures which makes sense as we do not expect large changes in water consumption coming from transition policies. Therefore, the sales for Vitens remain constant, shown in Table 4.19.

WACC
Vitens has the goal to achieve a WACC of 2.95% set by the The Dutch Drinking Water Act, but achieved 2.92% in 2023 (Vitens N.V., 2023). According to the Dutch authority on competitive markets, the pre- and post-tax WACC are equal for drinking water companies, with a target rate of 2.95% for both (Harris et al., 2021). We use the achieved WACC, as this is the most realistic one. The WACC is very low, but this can be explained by the fact that it is owned by the government. Government-owned companies typically have a lower WACC due to lower perceived risk, access to cheaper debt, and the stability provided by implicit government backing.

4.7 FrieslandCampina

We present the data we use for our analysis from Royal FrieslandCampina N.V. (2023), the latest annual report of FrieslandCampina. The company is owned by a cooperative of dairy farmers. We can use most figures from the annual report directly for our analysis. The company has four segments, Food & Beverage, Specialised Nutrition, Ingredients and Trading. We focus on Food and Beverage and ingredients as these cover more than 80% of total revenue and both consist of selling dairy products involving a production process. Trading does not involve a production process and specialised nutrition is a high end segment, with luxury goods which does not fit into the sales per unit analysis. Meaning we assume those two departments to remain constant in our analysis. We do not adjust the financial metrics for the company as the revenue streams of the two segments are substantial.

Metrics

Table 4.21 shows the financial metrics of FrieslandCampina and the Z-score of 1.30. What stands out is the negative working capital of the company, as current liabilities are higher than current assets, lowering the Z-score. FrieslandCampina reports in euros so there is no need for currency conversion.

Metrics	Values in m euros
Working Capital	-28
Retained Earnings	1,125
EBIT	293,667
Equity	3,670
Total Assets	9,119
Total Liabilities	5,449
X1	-0.003
X2	0.12
X3	0.03
X4	0.67
Z-score	1.30

TABLE 4.21: Financial metrics of FrieslandCampina.

Emissions

FrieslandCampina reports their emissions in kilotonnes. The company has set clear goals for 2030 as well as a net zero ambition in 2050. Furthermore, they acknowledge the need for CCS to compensate for residual emissions coming from dairy farmers. The company reports exact goals for 2030 for Scope 1 and 2 emissions, which can be seen in Table 4.22. In their annual report, the FrieslandCampina states that Scopes 1 and 2 can be zero in 2050, which is the goal. Malliaroudaki et al. (2023) show that sustainable dairy manufacturing can reduce carbon emissions up to 90.2%. We assume this is the potential of reduction possible in the business model, and that FrieslandCampina will achieve this. The study only focuses on the manufacturing itself, hence we apply this study for Scope 1 and 2 emissions. What stands out is the Scope 3 emissions of the company, mainly due to members of the cooperation who have the emissions of the dairy milk production, which account for roughly 60% of the Scope 3 emissions. This is mainly caused by the methane emitted by cows. As the company states it wants to achieve the SBTi (2024) targets, we assume a 90% reduction of their emission in 2050. Their annual report states Scope 3 emissions are 17,436 CO2e in 2023. They use the year 2020 as a base year for their reduction goals. Hence we use that as well, which accounts for 25Mt CO2e (Royal FrieslandCampina N.V., 2020), corresponding to 2.5Mt or 2500 kt CO2e in 2050. FrieslandCampina used 2934 TJ of electricity and 8557 TJ of gas in 2023, which we convert to GJ by a division with factor 10^3.

Variable	Unit	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033	2034	2035	2036
Scope 1	kt CO2e	639	581	524	466	409	351	294	236	225	213	201	189	177	166
Scope 2	kt CO2e	313	285	257	228	200	172	144	116	110	104	98	93	87	81
Scope 3	kt CO2e	17436	16513	15590	14667	13744	12821	11898	10974	10551	10127	9703	9280	8856	8432
CCS	kt CO2e	0	0	0	0	0	0	0	0	125	250	375	500	625	750

TABLE 4.22: Projected CO2e Emissions and CCS of FrieslandCampina in kt CO2e (2023-2036).

Variable	Unit	2037	2038	2039	2040	2041	2042	2043	2044	2045	2046	2047	2048	2049	2050
Scope 1	kt CO2e	154	142	130	118	106	95	83	71	59	47	35	24	12	0
Scope 2	kt CO2e	75	69	64	58	52	46	41	35	29	23	17	12	6	0
Scope 3	kt CO2e	8008	7585	7161	6737	6313	5890	5466	5042	4619	4195	3771	3347	2924	2500
CCS	kt CO2e	875	1000	1125	1250	1375	1500	1625	1750	1875	2000	2125	2250	2375	2500

TABLE 4.23: Projected CO2e Emissions and CCS of FrieslandCampina in kt CO2e (2037-2050).

Sales per unit

Calculating sales per unit for FrieslandCampina requires an extra step due to the variety of milk-based products they sell. We used one unit of dairy product, measured in tonnes, and applied the product distribution from the Dutch Dairy Organization (NZO, 2024). Although this split only represents the Dutch industry and not the European one, it is relevant since FrieslandCampina sources most of its milk from the Netherlands. Using these percentages and the average prices per tonne reported by FrieslandCampina, we calculated a weighted average price of €2,595.38 per tonne dairy product. Milk prices, based on a 5-year average, are lower than those of more processed goods. Table A.1 in Appendix A.1 provides an overview of these prices. While this method involves some estimation, it is appropriate given that all products are milk-based, and we have a demand elasticity for dairy products. We then used the reported revenue for the Food & Beverage and Ingredients segments and the unit price to calculate sales in tonnes. Table 4.24 shows the sales data of FrieslandCampina we use for the analysis.

Product	Sales in m euros	Sales in tonnes	Price in euro per tonne
Dairy products aggregated	10,553	4,066,071	2595.38

TABLE 4.24: Sales data of FrieslandCampina.

Table 4.25 shows the PEDs we use for the sensitivity analysis. We use two literature reviews who observed all studies on PED for dairy products. Andreyeva et al. (2010) looked at the US, using 26 studies for different foods. For milk, this results in a mean value of -0.59. Bouamra-Mechemache et al. (2008) looked at studies in Europe, the PED for all dairy products came output at an average of -0.57, using 5 studies. We use the value of -0.57 as this is a European study, where more than half of the revenue of FrieslandCampina is generated.

Product	Original PED	PED 1	PED 2	PED 3	Source
Dairy products	-0.57	-0.713	-0.857	-1	Bouamra-Mechemache et al. (2008)

TABLE 4.25: Price elasticities of demand of dairy products.

Sales adjustments

The NGFS scenarios do not provide projections for future milk consumption figures. Hence we use the sales from Table 4.24 as our base for the analysis of FrieslandCampina.

WACC

FrieslandCampina does not report a WACC, however it does report a pre-tax discount rate for an impairment test. For the same reasons explained by for Maersk we use this rate of 9% for the WACC. This rate is explicitly mentioned for the two segments we use for our analysis and hence applicable for our analysis.

4.8 Boliden

We analyze the mining and smelting company Boliden using data from their annual and sustainability report (Boliden, 2023). This report provides useful data that can be applied directly with minimal adjustments. Our focus is on two key products, copper and zinc, which together account for 56% of Boliden's mining revenue in 2023, this was 61% in 2022. Boliden highlights copper and zinc as their most significant products in terms of revenue generation. Consequently, we assume that the sales and prices of other metals in their portfolio will remain constant. Although gold ranks third in revenue, it is excluded from our analysis due to its lower production volume and higher price, making it less suitable for the comparison than the other two metals.

Metrics
Table 4.26 shows the different metrics in euros. The numbers are originally presented in millions SEK. It is converted from SEK to euros by using the following conversion rate: is 11.096 euro/SEK. We use the same rate as we used for Vattenfall, to remain consistent. Boliden is a financial healthy company with a solid Z-score of 4.58.

Metrics	Values in m euros
Working Capital	1,324
Retained Earnings	4,361
EBIT	1,079
Equity	5,085
Total Assets	9,189
Total Liabilities	4,104
X1	0.14
X2	0.48
X3	0.11
X4	1.24
Z-score	4.58

Table 4.26: Financial metrics of Boliden.

Emissions
Boliden commits to the SBTi (2024) , so we assume that CCS is a part of their net zero strategy. They report clear emissions and targets for Scope 1 and 2. Scope 3 is not yet reported in the year 2023, hence we use the reported value for 2021, which also serves a base year. The Scope 1,2 and 3 emissions in the base year where respectively 625 kt, 375 kt and 2814 kt. By 2030 they want to reduce 42% of Scope 1 and 2 emissions and 30% of Scope 3 emissions. We assume a 90% emission reduction in 2050 for Scope 1 and 2. This figure based on a report from the International Copper Association (ICA) (2023), who states that there is a potential to reduce Scope 1 and 2 by 85% to 95% in the sector. Boliden is part of this association. As Boliden wants to become net zero, we assume they will put their best efforts in, reaching the potential and thus achieving a 90% reduction. For Scope 3 emissions we also use the 90% reduction compared to the base year from the SBTi (2024).

66% of the energy consumption is electricity, where coal and coke is 8%. We do not include diesel as we assume this is solely for transportation purposes. Oil is also a substantial energy source, however the NGFS does not report on specific (industrial) oil energy use, hence we exclude this from our energy consumption analysis. In 2023 Boliden acquired 15,778 thousand GJ of electricity and 1,946 thousand GJ of coal and coke. For coal and coke we use the same NGFS usage and price data as we used for Tata, shown in Figures A.1 and A.2 in Appendix A.1.

Variable	Unit	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033	2034	2035	2036	2037
Scope 1	kt CO2e	639	581.49	523.98	466.47	408.96	351.45	293.94	236.43	229.2978	222.1656	215.0334	207.9012	200.769	193.6368	186.5046
Scope 2	kt CO2e	313	284.83	256.66	228.49	200.32	172.15	143.98	115.81	116.6737	117.5374	118.4011	119.2648	120.1285	120.9922	121.8559
Scope 3	kt CO2e	17436	16512.91714	15589.83429	14666.75143	13743.66857	12820.58571	11897.50286	10974.42	10550.699	10126.978	9703.257	9279.536	8855.815	8432.094	8008.373
CCS	kt CO2e	0	0	0	0	0	0	0	0	136.3435	272.687	409.0305	545.374	681.7175	818.061	954.4045

Table 4.27: Projected CO2e Emissions and CCS of Boliden in kt CO2e (2023-2037).

Variable	Unit	2038	2039	2040	2041	2042	2043	2044	2045	2046	2047	2048	2049	2050
Scope 1	kt CO2e	179.3724	172.2402	165.108	157.9758	150.8436	143.7114	136.5792	129.447	122.3148	115.1826	108.0504	100.9182	93.786
Scope 2	kt CO2e	122.7196	123.5833	124.447	125.3107	126.1744	127.0381	127.9018	128.7655	129.6292	130.4929	131.3566	132.2203	133.084
Scope 3	kt CO2e	7584.652	7160.931	6737.21	6313.489	5889.768	5466.047	5042.326	4618.605	4194.884	3771.163	3347.442	2923.721	2500
CCS	kt CO2e	1090.748	1227.0915	1363.435	1499.7785	1636.122	1772.4655	1908.809	2045.1525	2181.496	2317.8395	2454.183	2590.5265	2726.87

Table 4.28: Projected CO2e Emissions and CCS of Boliden in kt CO2e (2038-2050).

Sales per unit

Table 4.29 shows the sales, revenue and unit prices for copper and zinc. The price per product is given by Boliden, these are the planning or so called long term prices. The do not reflect the actual prices achieved, but are used mostly for internal projections. These estimates are comparable with the markets prices for refined non-ferrous metal on the London Metal Exchange, hence we use these (London Metal Exchange, 2023). The prices are given in US dollar, but Boliden states its own conversion to euros of 1.10 euro/US dollar, hence we divide by this. The annual report provides the production in kilotonnes, which is used to calculate revenue by multiplying the unit prices by the units sold. We split the extra costs per product based on percentage of revenue, meaning 85% is for the copper sales and 15% for the zinc sales.

Product	Total sales in m euros	Sales in tonnes	Price in euro per tonne
Copper	3,248	458,000	7090.91
Zinc	573	225,000	2545.45

Table 4.29: Sales of Boliden.

Table 4.30 shows the original and other values used for the PED. Fernandez (2018) provides the long-run elasticities for both copper and zinc. We use the world based data, as Europe based data did not result in significant results. For the world based data, the elasticity of copper is found with a p-value of 0.114, making it also not significant. But we still use it, as this is the best estimate. This was found with the same methodology as the other metals used in this study. The demand for the metals is very inelastic, which makes sense as these are crucial elements for the energy transition. Copper is one of the best conductors of electricity. It is widely used in electrical wiring, power generation, and transmission. Zinc is used in various applications, such as batteries, solar panel technology and corrosion protection.

Product	Original PED	PED 1	PED 2	PED 3	Source
Copper	-0.042	-0.361	-0.681	-1	Fernandez (2018)
Zinc	-0.068	-0.379	-0.689	-1	Fernandez (2018)

TABLE 4.30: Price elasticities of demand of copper and zinc.

Sales adjustments
Copper and zinc and many other non-ferrous metal play a crucial role in the energy transition. Therefore, the NGFS has projected future sales of these metals. Figure A.5 shows the projected sales of these metals. We use the percentage changes and apply these in the current sales. We use the same method as we did for Vattenfall and Tata.

WACC
Boliden reports a reel pre-tax WACC of 10%, which we use as well. The nominal WACC is 12%, but we want to use the one corrected for inflation, as we do this as well. This 10% is used for longer time horizons.

4.9 Concluding remarks on data selection and preparation

In this chapter we have picked out six companies which we want to research in this study. The companies operate in sectors vulnerable to transition risk. We collected data from the following companies:

- Vattenfall in the Utilities sector
- Tata Steel in the Manufacturing sector
- Maersk in the Transport sector
- Vitens in the Water Supply sector
- FrieslandCampina in the Agricultural sector
- Boliden in the Mining sector

We demonstrated how we collect data from the annual and sustainability reports of these companies for our analysis. We outlined a general methodology, including assumptions, to derive financial metrics, current and future emissions, and price elasticities of demand. Additionally, we detailed our approach for determining unit prices and potential sales adjustments. The section concludes with a brief explanation of the capital structure, focusing on the WACC as discount rate. For each company, we explained the specific modifications made to the data from the reports to ensure consistent and coherent use in our analysis. Furthermore, we justified our assumptions regarding emission goals, the division of balance sheets, and the determination of unit prices for products.

Chapter 5

Model Application and Evaluation

We present the results of our analysis. We review the net results and Z-scores per company. Sensitivity analyses help to reflect on how price elasticity of demand and passing-on costs affect the default risk. Additionally, we provide the credit ratings and associated PD that correspond to the Z-score to enhance interpretability. Next, we review the generalized results on transition risk and we describe the effect of pricing strategies and elasticities on default risk. We conclude by outlining the difference between the companies representing their sector. This section aims to answer the research question: *What is the effect of the low-carbon transition on the probability of default of a business?*

We use figures to provide a clear and comprehensive overview of the results. The base scenario uses the original PED from the previous chapter, the Below 2°C scenario, and assumes 60% of the costs are passed on to consumers. In competitive markets, it's unlikely companies can pass on 100% or even 80% of extra costs. The results are shown until 2050. We discussed mapping the Z-score to credit ratings and PDs. While this mapping helps interpret results, it involves assumptions and range-based mappings that reduce accuracy. Therefore, we primarily present Z-scores, but we also include credit ratings and PDs for the general results to aid interpretation, especially for managers without detailed financial knowledge. In the sensitivity analysis, we focus on Z-scores. We use one-year default rates since we calculate the Z-score annually based on the expected financial metrics for each year. For each company, we examine the reasoning behind the results, considering the industry they operate in and assessing whether the outcomes are consistent with sector-specific factors.

5.1 Vattenfall

5.1.1 General effect of the transition for Vattenfall

We present the net results in Figure 5.1 and the Altman Z-scores in Figure 5.2. In all scenarios, Vattenfall faces default risk. The net results show rising CCS costs until 2030, stabilizing or decreasing by 2040. Passing on 60% of these costs does not prevent default risk. Vattenfall's initial Z-score of 1.89 is already in the grey zone, indicating weak financial health. The Net-Zero 2050 scenario has the largest impact due to high carbon prices. The Z-score declines significantly, especially around 2040, as CCS costs stabilize or decrease. In the best case the Z-score drops with 1.89 to 0.13. In the Below 2°C the Z-score drops with 143% to -0.82 .

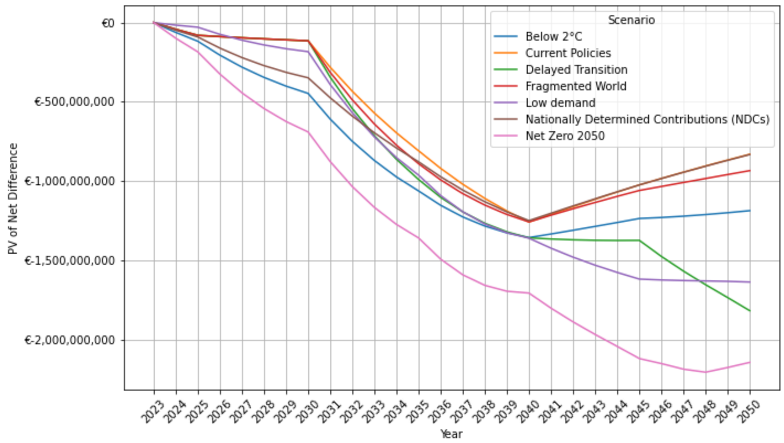

FIGURE 5.1: PV of net result of Vattenfall till 2050, passing on 60% of the costs.

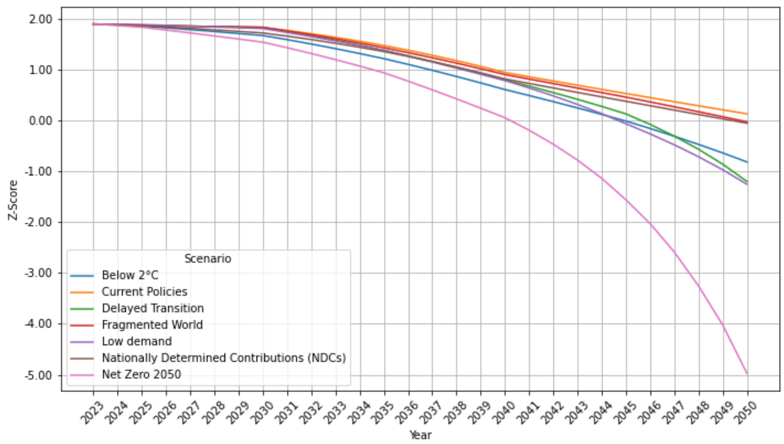

FIGURE 5.2: Altman Z-score of Vattenfall till 2050, passing on 60% of the costs.

Credit rating for Vattenfall

The credit rating for Vattenfall indicates high probabilities of default, which should be interpreted with caution. This holds for all firms. Our analysis focuses solely on the option of passing on additional costs to mitigate default risk. We do not explore other measures such as cost-cutting, new business strategies, or attracting new resources to reduce default risk. This topic is further discussed in Section 6.2. The credit rating of Vattenfall differs between the scenarios, as can be seen in Figure 5.3. In the Net Zero 2050 scenario, the company defaults. In other scenarios, the credit rating, which starts at BB in 2023, drops to CCC-, CCC, or CCC+, each carrying a significant PD of 25.98%. This means the PD increases by over 25% across the remaining scenarios compared to 2023. The PDs rise in a stepwise pattern, staying within the same range for several years before increasing. This pattern is consistent across all scenarios, with greener scenarios seeing a later increase, while others maintain the same rating in the final years. For Vattenfall, the transition adds both short- and long-term default risk, with the PD increasing by 0.43% in all scenarios before 2026.

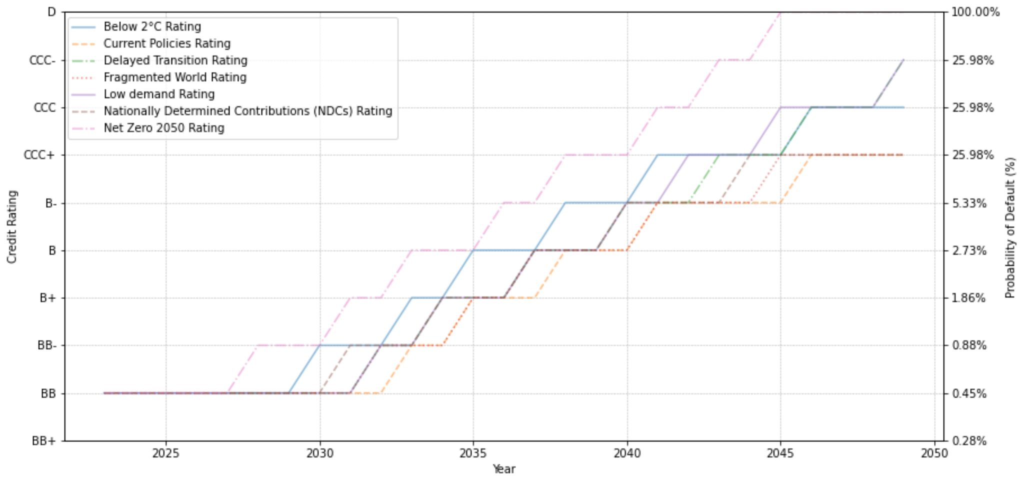

FIGURE 5.3: Credit ratings and one year probabilities of default for Vattenfall.

Vattenfall's financial difficulties are mainly due to its heavy use of gas, which makes the company vulnerable to rising carbon prices and the costs of meeting climate goals, especially in the Net-Zero 2050 scenario, so it makes sense that the greener scenarios result in lower Z-scores. High costs can lead to lower energy usage, indicated by the PED of -0.563, making it more difficult for Vattenfall to pass on the costs. This is reflected in the declining credit rating and other financial measures, showing the challenges the company faces in adapting to stricter climate regulations.

5.1.2 Effect of pricing strategies for Vattenfall

We observe in Figure 5.4 that the passing on costs mitigates the losses for Vattenfall. The effect of between passing on seems to be quite the same, which indicates that the effects of passing on costs is scales linear, which makes sense a we have a constant PED. The Z-score difference between passing on all costs and passing on nothing is 2.19. We see that the effect on Z-score increases as less costs are passed on. The percentage difference in 2050 Z-score between 60% of costs-passed-on and 100% of costs-passed-on is 92%, whereas the difference between 60% of costs-passed-on and 20% of costs-passed-on is 149%.

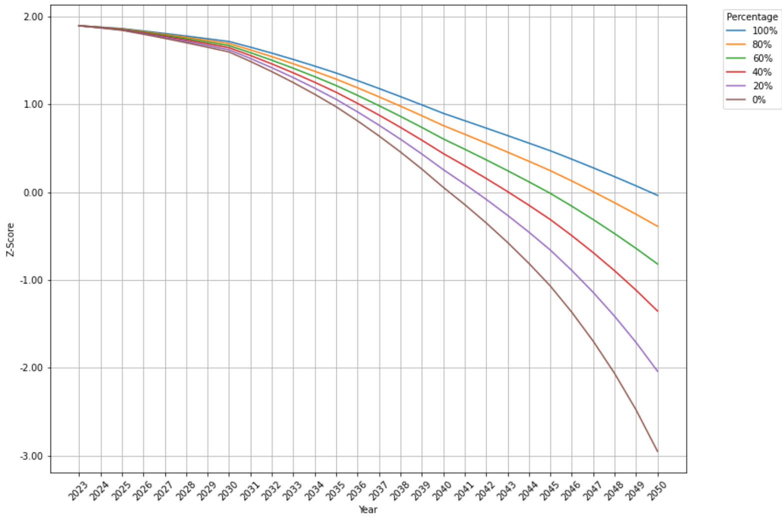

FIGURE 5.4: Altman Z-score of Vattenfall till 2050 for the Below 2°C scenario per pricing strategy.

5.1.3 Effect of price elasticity of demand for Vattenfall

We see that the effects of PED scale increasingly for Vattenfall. A lower PED means more costs can be passed on, losing less revenue. This means the default risk decreases as PED decreases. Figure A.7 in Appendix A.1 shows the net results of Vattenfall used for the Altman Z-score calculations. The first step reduces the Altman Z-score with 0.69, then 1.48 and then 2.68 for the most elastic demand. We see that the effect on the Z-score increases for a uniform step in elasticity. More elastic demands leads to higher the sensitivity to the price elasticity of demand.

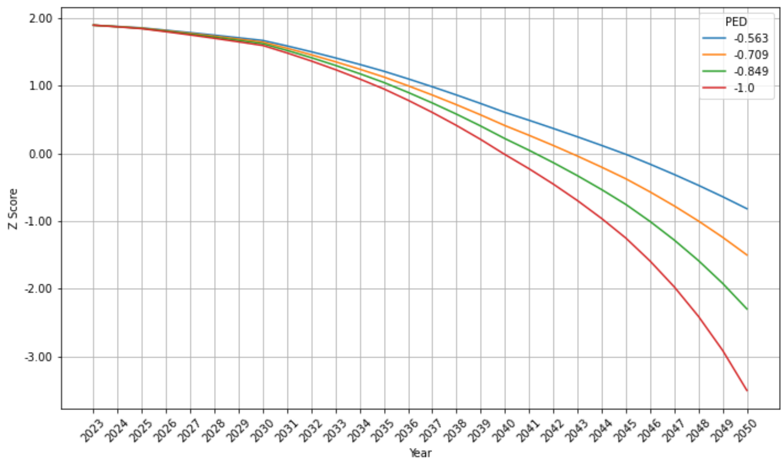

FIGURE 5.5: Altman Z-score of Vattenfall till 2050 for the Below 2°C scenario per price elasticity of demand.

5.2 Tata Steel

5.2.1 General effect of the transition for Tata steel

Figure 5.6 shows the net results over time used for the Altman Z-scores in Figure 5.7. The Net Zero 2050 scenario puts Tata at significant default risk fairly early, similar to the low demand scenario. All scenarios incur extra costs that cannot be fully covered with 60% passing on. Extra costs come in waves with heavy carbon pricing, but this effect diminishes in later years as emission reductions outweigh carbon price increases. CCS starts in 2030, causing losses to gradually decrease, but the Z-scores continue to slope downwards due to cumulative losses. Tata steel stays above a Z-score of 3.00 in three out of seven scenarios, avoiding default risk. In the other four scenarios, Tata faces significant default risk. We see that the default risk of Tata is sensitive to the type of scenario.

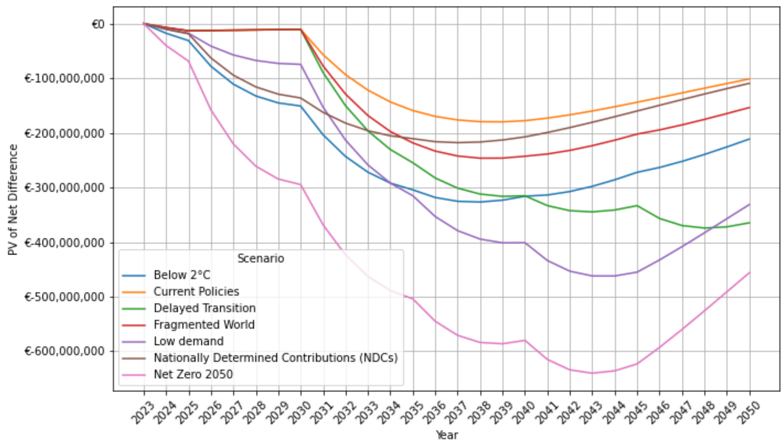

FIGURE 5.6: PV of net result of Tata till 2050, passing on 60% of the costs.

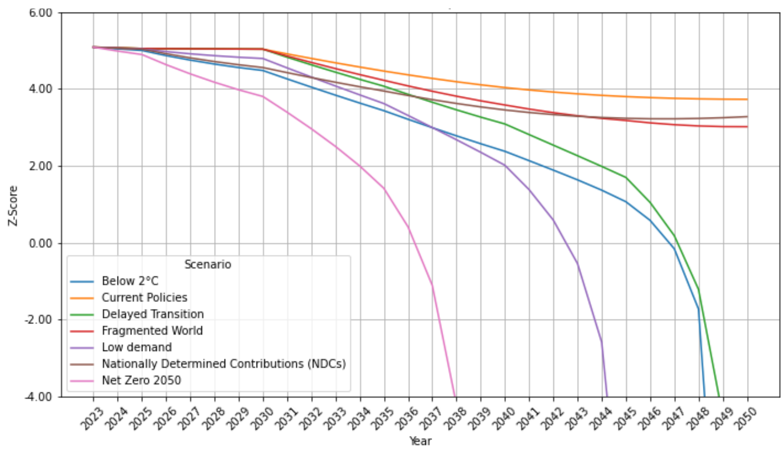

FIGURE 5.7: Altman Z-score of Tata till 2050, passing on 60% of the costs.

Credit rating for Tata

The effects on the credit rating and PD of Tata are very significant in some scenarios. Though it is clear that Tata cannot survive the transition by merely passing on costs, these figures exclude some factors. For instance, Tata Netherlands could receive support from the Dutch government to become more environmentally friendly (Blom & Wijers, 2023). Next to that, our analysis does not look into our strategies to mitigate default risk. Tata is financially healthy in 2023. Figure 5.8 shows PD increases significantly during the transition, with notable differences between scenarios. In Hot House World scenarios, the NDC and Current Policies scenario, one-year PD rises to a maximum of 0.45%. In other scenarios, PD increases to 25% or defaults in the Net Zero 2050 and Low Demand scenarios. Different patterns emerge: the delayed transition remains low and builds up in steps, increasing after 2035 and even more after 2045. The Hot House World and Fragmented World scenarios follow similar step patterns. Low Demand and Below 2°C are similar until 2039, after which Below 2°C increases less rapidly. The Net Zero 2050 line is the steepest, defaulting by 2036. Other scenarios show significant PD increases only after 2030 or 2035 in Hot House World scenarios. The short-term additional default risk is significant only for the Net Zero 2050 scenario.

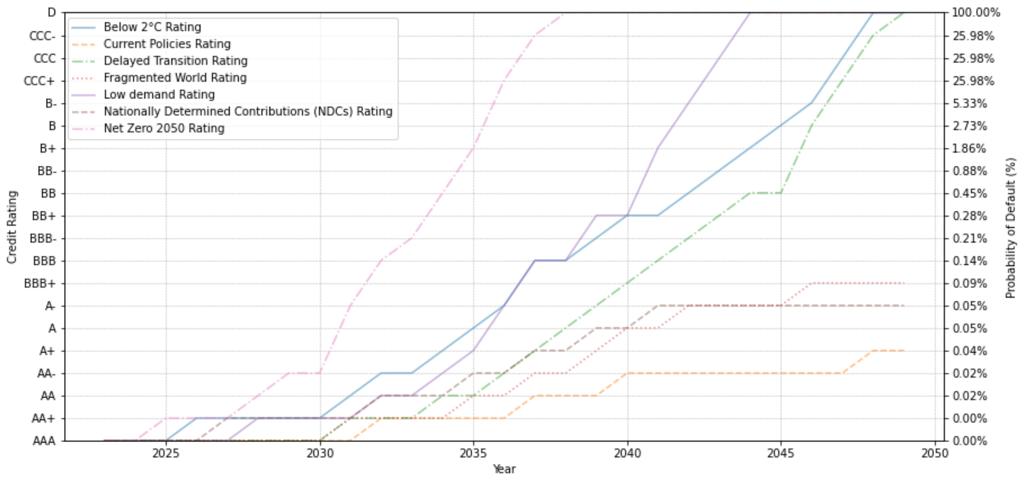

FIGURE 5.8: Credit ratings and one year probabilities of default for Tata.

Tata Steel's significant exposure to the transition towards a low-carbon economy is largely due to its reliance on energy-intensive steel production processes, particularly the use of coal in traditional blast furnaces. Steelmaking is one of the most carbon-intensive industries, and Tata Steel's operations are heavily impacted by rising carbon prices and the costs of decarbonization. This explains the results in the scenarios with significant carbon pricing. The company's financial vulnerability makes sense in this context, given the challenges of transforming such a core industrial process. While Tata has been financially stable in the past, the shift towards cleaner production methods requires substantial investments and operational changes. Without additional support from for instance governments the company's financial health will likely come under increasing pressure.

5.2.2 Effect of pricing strategies for Tata

Figure 5.9 shows that it matters significantly whether Tata passes on costs or not. If Tata would be able to pass on 100% of the costs, then there is little default risk. This risk increases significantly as the ability to pass on costs increases. From 60% to 0% passing on the default risk is significant. We observe the effects of the very low elasticity of steel, as passing on 100% of the costs keeps Tata in the safe zone with an Altman Z-score above 4.00. Passing 80% mitigates the default risk effectively as well.

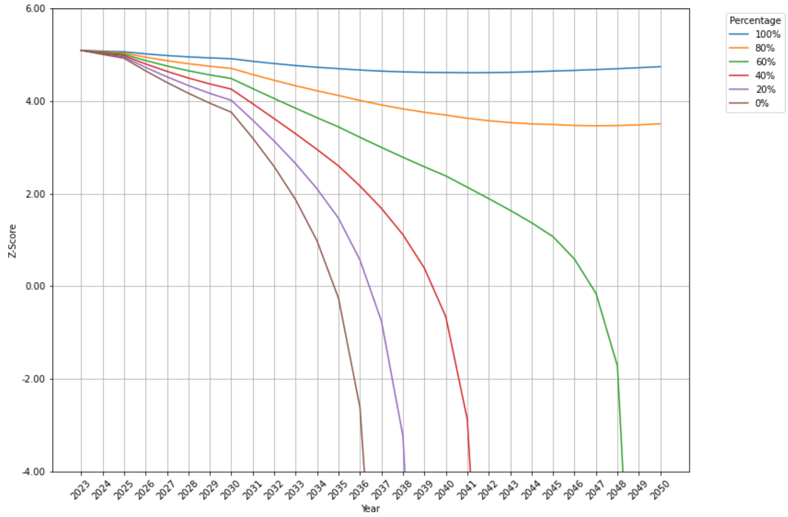

FIGURE 5.9: Altman Z-score of Tata till 2050 for the Below 2°C scenario per pricing strategy.

5.2.3 Effect of price elasticity of demand for Tata

We see in Figure 5.10 that the effect of PED is considerable for Tata. However, for each PED the company goes into default. Inelastic demand helps to postpone default with over 8 years. Due to the cumulative character of the Z-score, the company will eventually default in our analysis, no matter the PED.

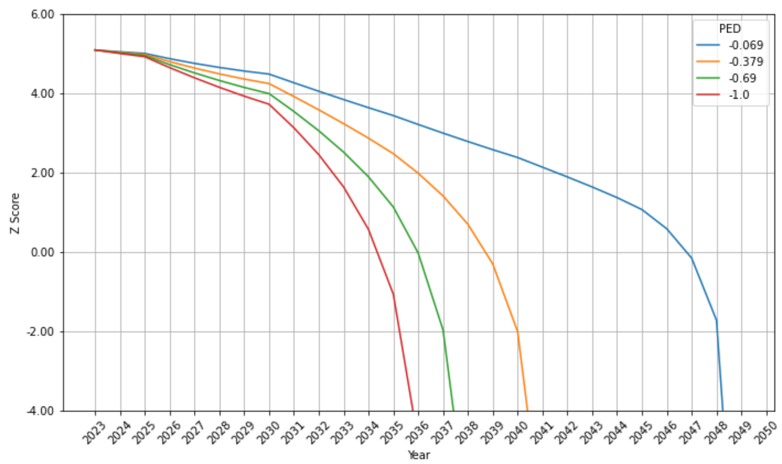

FIGURE 5.10: Altman Z-score of Tata till 2050 for the Below 2°C scenario per price elasticity of demand.

5.3 Maersk

5.3.1 General effect of the transition for Maersk

The effects of the transition on the default risk are little for Maersk ocean. In Figure 5.11 we see that the costs increase from carbon pricing, as Maersk emits substantially in the beginning. We see the minima in the net results between 2030 and 2040 for all scenarios. The effects, although significant in terms of losses, do not lead to Z-scores under the 7.60, which can be seen in Figure 5.12. Meaning there is no default risk for Maersk. The Current Policies scenario gives the lowest Z-score as the Low demand scenario gives the highest. Most likely due to the extensive energy consumption of maritime freight transport in that scenario. Figure A.3 in Appendix A.1 shows the energy consumption per scenario. The lower energy consumption in some scenarios resulted in negative extra costs compared to 2023. We used the same methodology to determine new prices, resulting in lower prices in this scenario. The competitive and global nature of the freight market makes it difficult for any company, even a large one like Maersk, to set prices alone. Since energy effects impact all competitors, the assumption of lowering prices is justified.

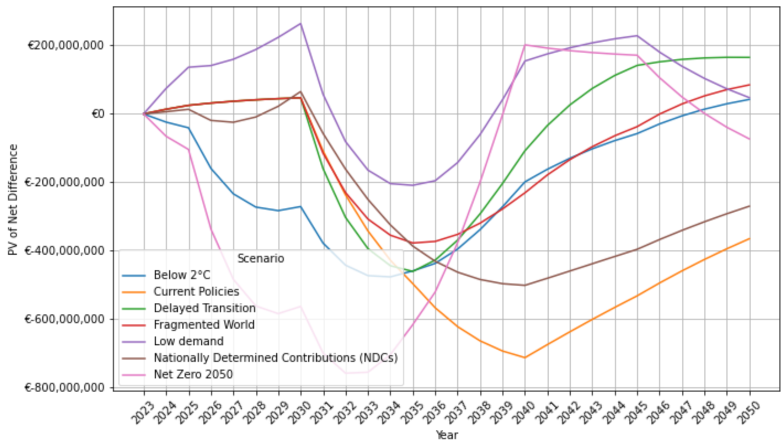

FIGURE 5.11: PV of net result of Maersk till 2050, passing on 60% of the costs.

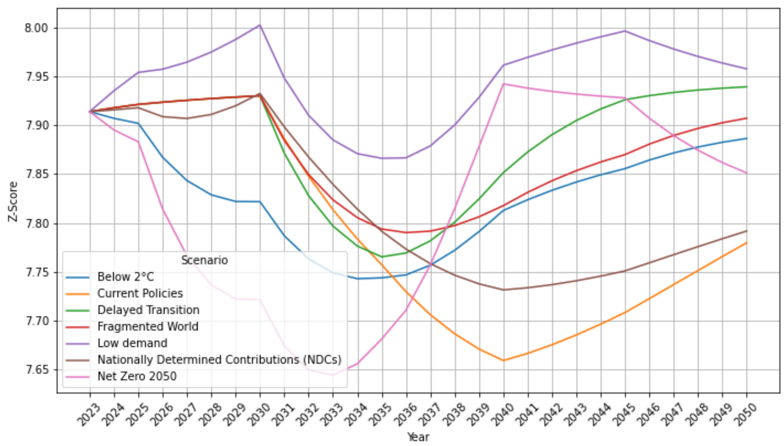

FIGURE 5.12: Altman Z-score of Maersk till 2050, passing on 60% of the costs.

We observe that both figures have similar shapes. While the Z-score incorporates cumulative effects over the years, it still closely resembles the net result. This similarity arises partly from the high weights given to EBIT and working capital in the Z-score formula. The other part can be explained by the size of the balance sheet. Despite the cumulative nature of some balance sheet metrics, their impact is smaller due to the large size of the balance sheet, allowing EBIT and working capital to have a more pronounced effect.

Credit rating for Maersk

For Maersk, the credit rating remained AAA+, and the PD stayed at 0% across all scenarios. While the transition does affect Maersk's financial performance by lowering the Z-score, the impact on PD is minimal, with no significant default risks emerging as long as 60% of costs are passed on. This stability suggests that Maersk is not required to explore alternative strategies under the assumption that investment costs, such as new vessels, are not factored in.

Maersk, as a global leader in shipping, operates in an energy-intensive sector, making it vulnerable to carbon pricing. However, its large strong balance sheet enable it to absorb these on costs on the balance sheet without threatening its financial health. The projected use of alternative fuels, which become cheaper in greener scenarios, further reduce long-term risks associated with the transition. Additionally, the critical role of freight shipping in global trade allows it to pass on a portion of these increased costs to customers, helping it maintain financial stability even in a challenging regulatory environment.

5.3.2 Effect of pricing strategies for Maersk

Figures 5.13 shows that while passing on costs mitigates their impact, the effect is minimal. The Z-scores follow a similar trajectory, but strategies with fewer costs-passed-on have steeper declines. Interestingly, when Z-scores rise due to low losses or profits, passing on fewer costs boosts revenue, likely because prices aren't reduced as significantly in these scenarios.

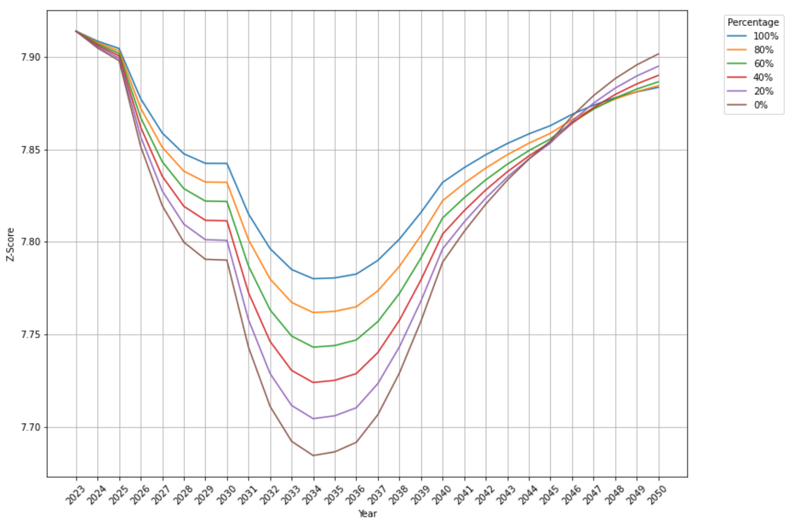

FIGURE 5.13: Altman Z-score of Maersk till 2050 for the Below 2°C scenario per pricing strategy.

5.3.3 Effect of price elasticity of demand for Maersk

Figure 5.14 shows that the effect for the PED is similar to the effect of different pricing strategies. A lower PED mitigates losses but restricts profits. So once profits are made and prices are lowered a bit, the revenue is boosted the most if PED is elastic.

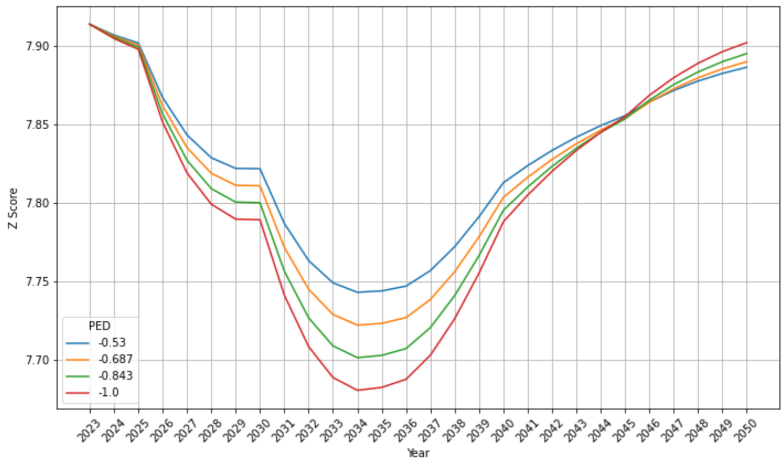

FIGURE 5.14: Altman Z-score of Maersk till 2050 for the Below 2°C scenario per price elasticity of demand.

5.4 Vitens

5.4.1 General effect of the transition for Vitens

Figure 5.16 illustrates that all scenarios result in a lower Z-score, ranging from a 0.40 reduction in the current policies scenario to a 1.26 reduction in the worst scenario. The Net Zero 2050 scenario shows a steep decline in the net results starting from 2030. The two most stringent climate scenarios exhibit a slower decrease from 2045, whereas the Delayed Transition scenario becomes steeper. This trend suggests that electricity usage significantly impacts the company's financials, with the Delayed Transition scenario becoming more costly from 2045, while other scenarios become less expensive.

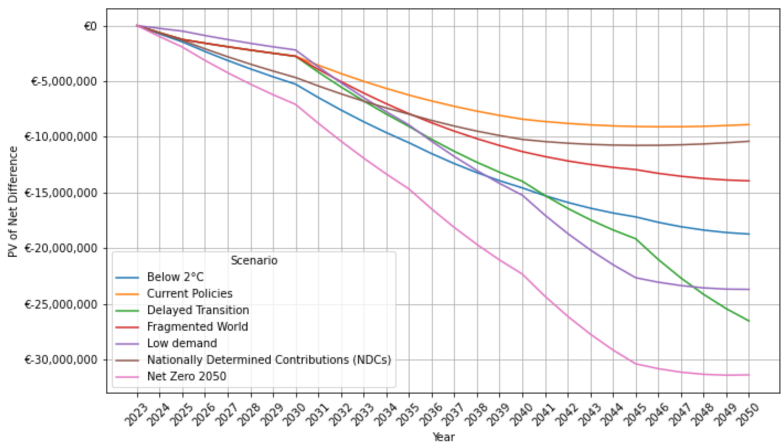

FIGURE 5.15: PV of net result of Vitens till 2050, passing on 60% of the costs.

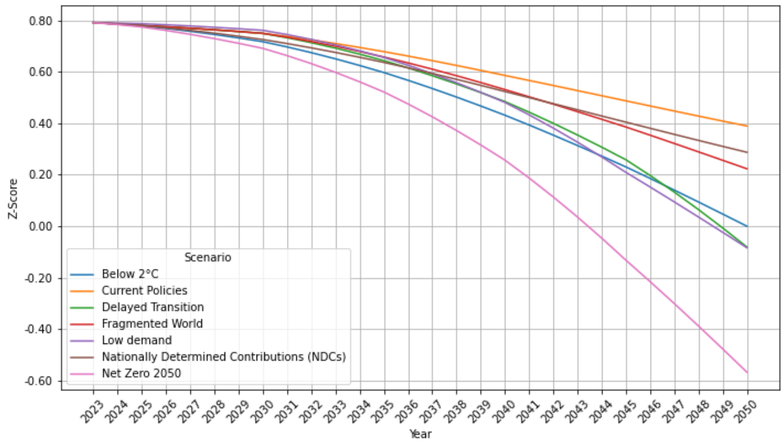

FIGURE 5.16: Altman Z-score of Vitens till 2050, passing on 60% of the costs.

Credit rating for Vitens

The credit rating for Vitens stays stable till after 2035 for every scenario. Figures 5.17 shows that in all scenarios but one the credit rating drops one step from B- to CCC+. This step does mean a great step in PD, as this is a 20% increase of PD for all scenarios because of the transition for Vitens. The increase in PD yet only occurs after the year 2035, meaning the extra default risk is limited on the short-term.

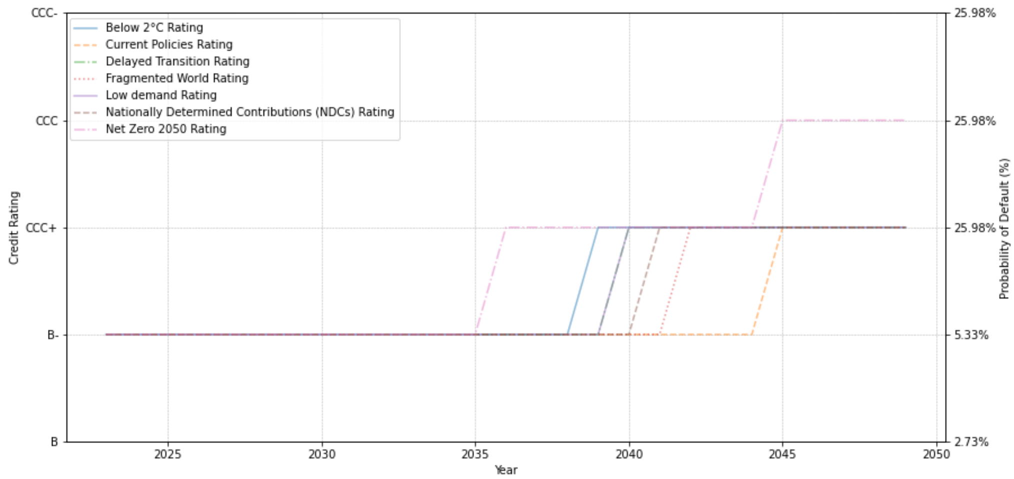

FIGURE 5.17: Credit ratings and one year probabilities of default for Vitens.

Vitens is owned by governments, where making a profit is not the top priority, partly explaining its already weak financial position. The results are consistent with the company's heavy dependence on electricity for its water treatment and distribution, making it especially susceptible to increasing energy costs during the transition. Therefore, under stricter climate scenarios, increased electricity prices lead to a significant decline in financial performance starting from 2030. Vitens' operations, being energy-intensive, face significant costs increases that are difficult to offset, despite its low PED.

5.4.2 Effect of pricing strategies for Vitens

Figure 5.18 shows that for Vitens, passing on costs can effectively mitigate default risk. Although it is unlikely that Vitens will pass on all costs, the difference in the Z-score between not passing on any costs and passing on all costs is 1.73. The Z-score lines slope more steeply downward with fewer costs-passed-on, which makes sense. At 100% costs passed-on, the Z-score almost remains level in the final years. The difference in Z-score between passing all costs and 80% of the costs is 0.28. This increases per step up to 0.42 in the last step of 20%.

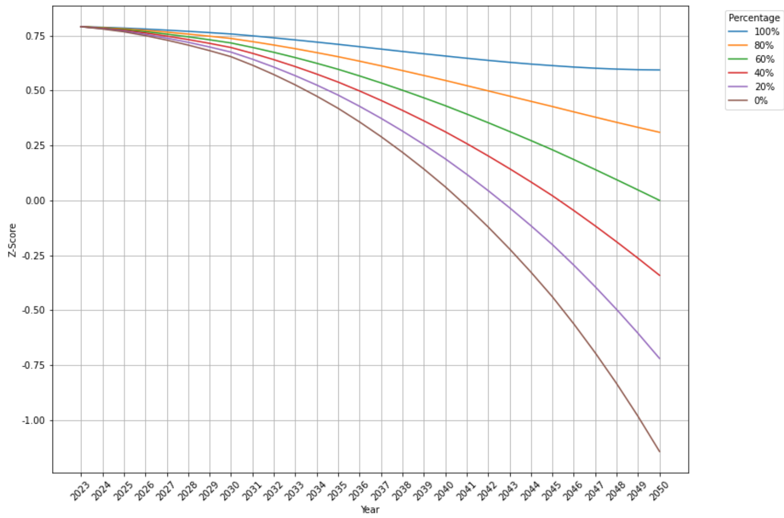

FIGURE 5.18: Altman Z-score of Vitens till 2050 for the Below 2°C scenario per pricing strategy.

5.4.3 Effect of price elasticity of demand for Vitens

Figure 5.19 shows that the default risk of Vitens is sensitive to the PED. The gap between the Z-score lines increase as the PED becomes more elastic. The first step results in a 0.37 reduction of the Z-score, 0.41 in the second step, and a 0.46 reduction in the third step. The original PED does not result in default, maintaining a Z-score above 0. For the lowest PED, it comes very close to default with a Z-score of -1.25.

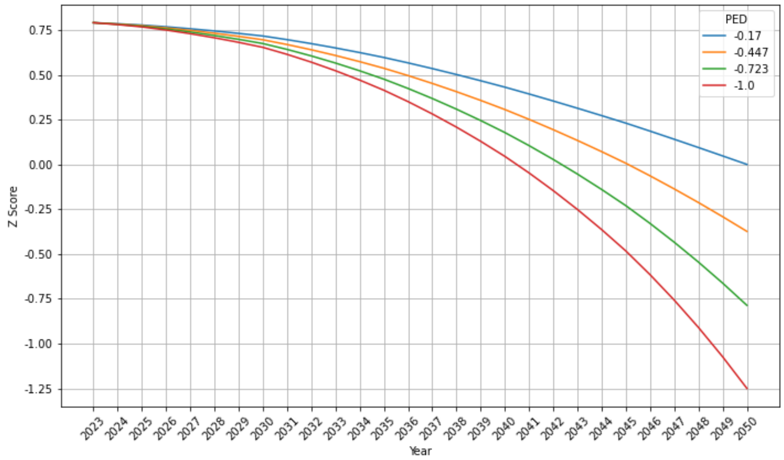

FIGURE 5.19: Altman Z-score of Vitens till 2050 for the Below 2°C scenario per price elasticity of demand.

5.5 FrieslandCampina

5.5.1 General effect of the transition for FrieslandCampina

Figure 5.21 illustrates that Scope 3 emissions, captured in the model by using ccs, significantly impact FrieslandCampina's results. From 2030, there is a noticeable steep decline in net results, which aligns with the high proportion of Scope 3 emissions. This is inherent to the agricultural sector, primarily from land-based sources. Both figures indicate minimal differences, illustrated by the narrow ranges, between the various scenarios since the costs of CCS do not vary significantly across them. Additionally, the dip around the year 2041 reflects a period where losses slightly decrease, attributed to the declining costs of CCSa s global capacity expands. The increased use of CCS in the final years does not lead to larger losses, as this is offset by the reduced price of ccs. The Z-score drops between 1.88 and 2.24 for all scenarios, which is a small range.

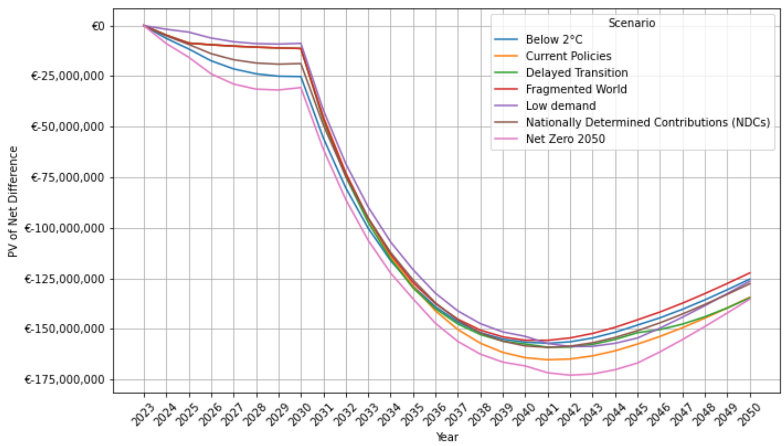

FIGURE 5.20: PV of net result of FrieslandCampina till 2050, passing on 60% of the costs.

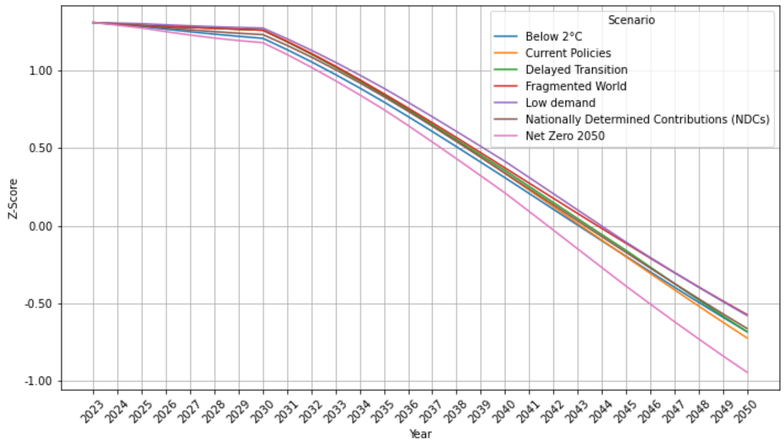

FIGURE 5.21: Altman Z-score of FrieslandCampina till 2050, passing on 60% of the costs.

Credit rating for FrieslandCampina

FrieslandCampina faces a significant default risk increase due to the transition, with PD rising over 23% in all scenarios. This leads to a consistent CCC credit rating for all scenarios but Net Zero 2050. This scenario leads to a credit rating of CCC-. The low-carbon transition will cause financial troubles regardless of the scenario, largely due to substantial Scope 3 emissions. FrieslandCampina cannot stay out of default risk by merely passing on costs to the customer, they must introduce other strategies. There is time for that as the PD does not increase until after 2030, indicating limited short-term default risk.

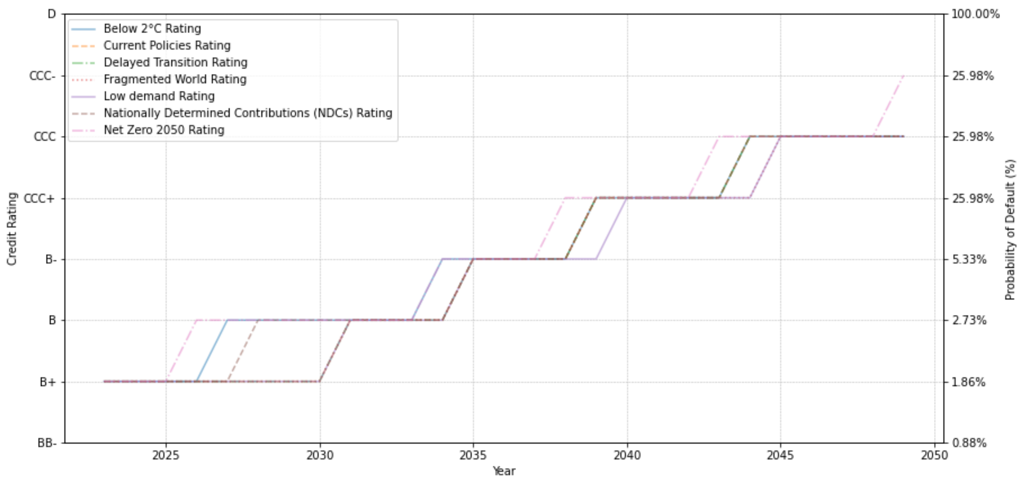

FIGURE 5.22: Credit ratings and one year probabilities of default for FrieslandCampina.

FrieslandCampina operates in the agricultural sector, which faces significant challenges during the low-carbon transition due to its reliance on dairy farming, a major source of Scope 3 emissions. Dutch farmers, deeply tied to dairy production, struggle to shift to more sustainable practices or alternative products. The high emissions from land use and livestock make reducing the environmental impact difficult without major changes. For FrieslandCampina, these emissions lead to financial strain, with costly carbon pricing and mitigation strategies like CCS. The decline in financial performance from 2030 reflects the burden of addressing these emissions, while farmers' difficulty in moving away from dairy intensifies the long-term risks for the company.

5.5.2 Effect of pricing strategies for FrieslandCampina

Figure 5.23 shows the influence of different pricing strategies for FrieslandCampina. As we can see, the difference between 100% and 80% is smaller than between the lowest to prices. The first step results in a difference of 0.234 and the last step in a result of 0.392. Passing on 100% results in the company being two credit ratings higher than passing on none. For all strategies the company has a low Z-score indicating significant default risk.

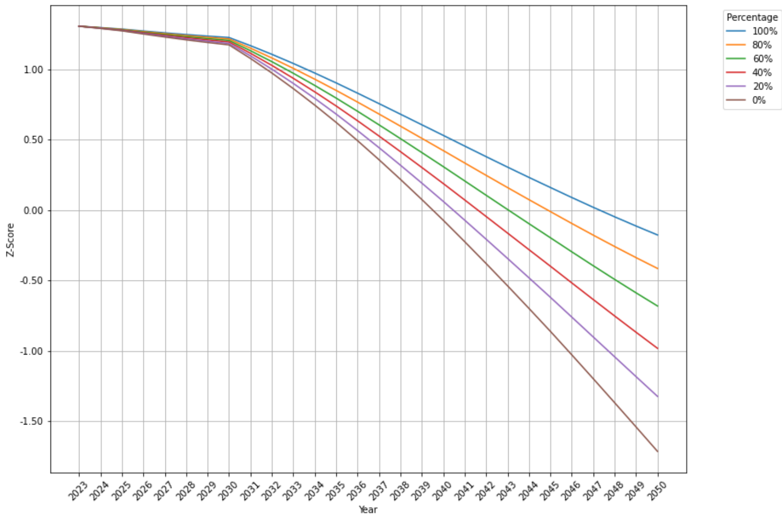

FIGURE 5.23: Altman Z-score of FrieslandCampina till 2050 for the Below 2°C scenario per pricing strategy.

5.5.3 Effect of price elasticity of demand for FrieslandCampina

The effect of the price elasticity is shown in Figure 5.24. In 2050 the Z-score is -0.68 for the regular price elasticity and decreases in a Z-score of -1.9 for a price elasticity of -1. The first step is 0.35, then 0.39 then 0.42, which makes sense as the lines declines steeper. Thus the default risk is sensitive to PED and becomes more sensitive as PED lowers Figure. A.12 in Appendix A.1 shows the net results used for the calculations of the Z-scores.

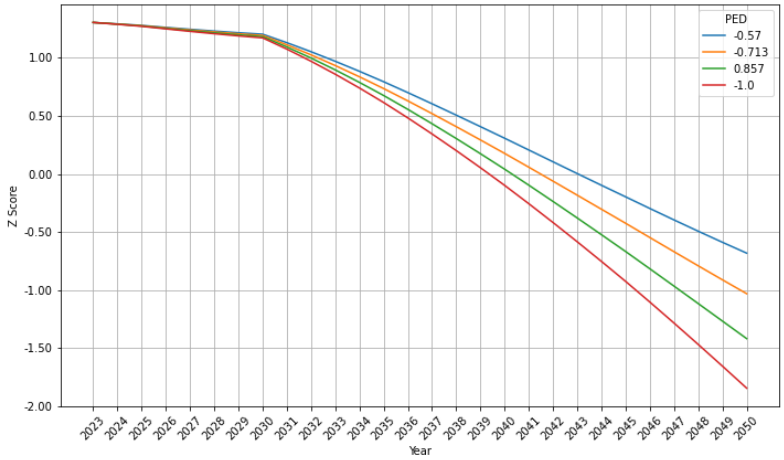

FIGURE 5.24: Altman Z-score of FrieslandCampina till 2050 for the Below 2°C scenario per price elasticity of demand.

5.6 Boliden

5.6.1 General effect of the transition for Boliden

Figure 5.26 illustrates that Boliden's revenue initially grows with additional sales but begins to decline after 2030 due to CCS costs. The Net Zero 2050 scenario has the highest Z-score, driven by inexpensive CCS and significant Scope 3 emissions for Boliden. Increased sales boost revenue, making current policies the least favorable scenario. Sales of non-ferrous metals increase in all scenarios, especially under current policies and NDC. We base new revenue projections on these scenarios, adjusting for sales volumes and prices. The positive revenue differences are smaller since sales would rise even without added costs. Low demand elasticities allow costs to be passed on to customers, making extra costs and rising demand profitable. Our approach uses adjusted sales volumes as the base year, leading to Z-score declines across all scenarios, from 0.02 to 0.07 over 27 years. However, these drops are minimal, and Boliden does not face additional default risk due to the transition.

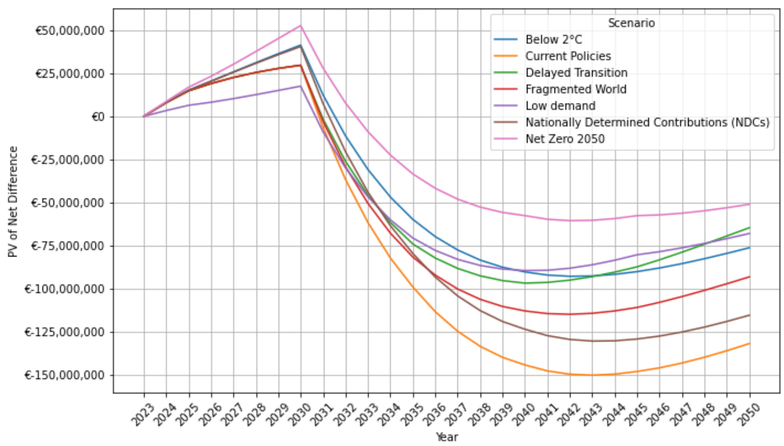

FIGURE 5.25: PV of net result of Boliden till 2050, passing on 60% of the costs.

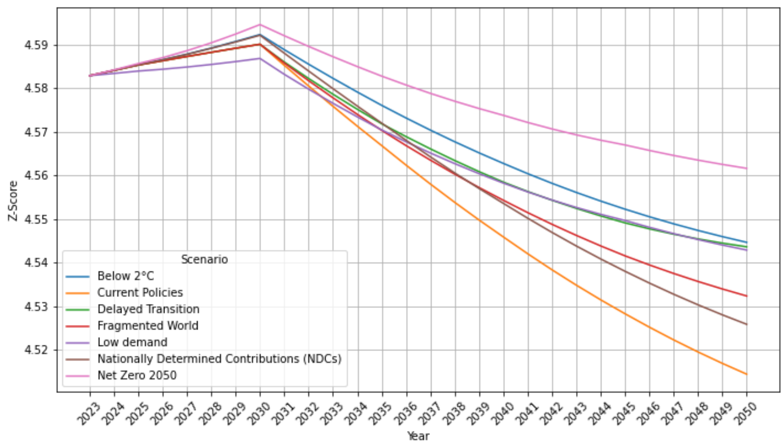

FIGURE 5.26: Altman Z-score of Boliden till 2050, passing on 60% of the costs.

Credit rating for Boliden

Boliden is a financially healthy company with a small PD of 0.02% in 2023. The credit rating of AA+ remains the same for all scenarios, as the Z-score stays above 4.50. The low carbon transition does not change the PD for Boliden. Due to the low PED of their products and their role in the transition. Boliden does not face significant default risks if the costs are passed on for 60%. Hence, Boliden is not forced to look into other strategies under our assumption to not take investment costs into account. These new investments might be necessary to keep up with production, required for the increased demand due to the transition.

The results for Boliden make sense because the company plays a key role in the metals industry, which is essential for the energy transition. As demand for metals needed in renewable energy grows, Boliden is in a strong position to benefit. The company's solid financial situation, increase in demand and low PED of the metals help it manage the rising costs of decarbonization. Given the importance of metals in the transition, it makes sense that Boliden remains financially stable even as climate policies become stricter.

5.6.2 Effect of pricing strategies for Boliden

Figure 5.27 shows the impact of the pricing strategies. As the PED is low, passing on extra costs is very effective for Boliden. We note that the metal market can be competitive in terms of prices, however it is likely all companies in this sector will face the same challenges and costs. Hence unilateral price increases are unlikely, but as a sector, incurring the same costs, this is more likely. In 2050, passing on 100% of the costs results in a 4.58 Z-score. The reduction in Z-score per 20% less passing remains constant with 0.02, this gap increases in negligible amounts.

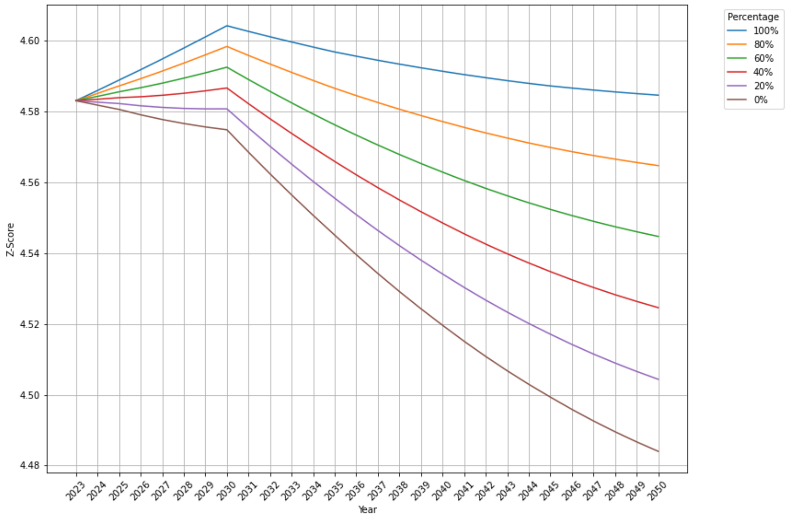

FIGURE 5.27: Altman Z-score of Boliden till 2050 for the Below 2°C scenario per pricing strategy.

5.6.3 Effect of price elasticity of demand for Boliden

In Figure 5.28 we see that the price elasticity has a strong effect on the transition. If Boliden would face a price elasticity of -1, the Z-drops from 4.58 to 4.48 instead of 4.54. The gaps between the lines at 2050 are very similar, increasing in negligible amounts.

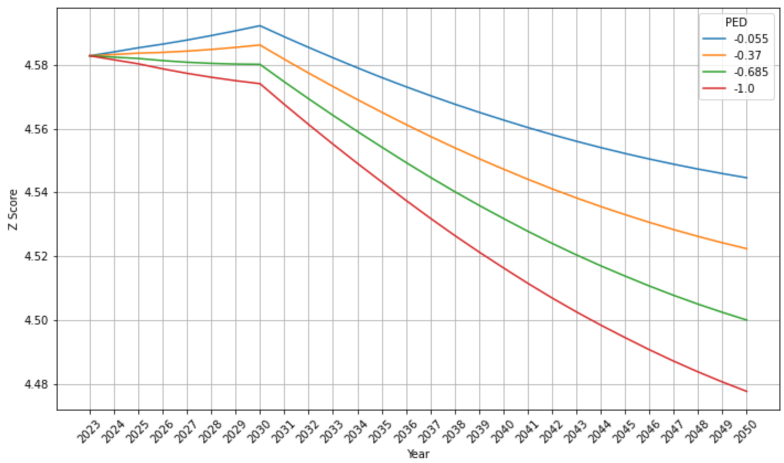

FIGURE 5.28: Altman Z-score of Boliden till 2050 for the Below 2°C scenario per price elasticity of demand.

5.7 General results

In this section we zoom out, not looking into the the companies individually anymore but extrapolate general results from these individual findings. First we look at what the effects of the transition is on the PD of a business. Next, we look into the effects of pricing strategy to see if this variable gives significant effects in general. We extend the analysis by discussing the effects of price elasticity on the transition default risk of companies. We conclude this section by discussing the cross-sectoral differences, looking a what characteristics of a sector cause what effects on the default risk. In here we look at different type of emissions per sector, as well as how scenarios work out better for some sectors than others.

5.7.1 The effect of the low-carbon transition on the probability of default of a company

The low-carbon transition can increase the PD of firms. Companies with high direct and indirect emissions, like Vattenfall and Tata Steel, face the greatest financial challenges, while those that can effectively reduce their carbon footprint and pass on costs, like Maersk, are better positioned to maintain financial stability. The transition's financial impact underscores the importance for businesses to adopt strategic measures to mitigate emissions and manage the associated costs to reduce their default risk. As for most companies merely passing costs on to customers does not prevent default. For each company specific the effects are the following:

- Vattenfall experiences a significant drop in credit rating from BB in 2023 to CCC or CCC- in most scenarios, with the PD increasing by over 25% by 2050. Vattenfall cannot merely pass on costs to customers to prevent default.
- Tata Steel faces a sharp rise in PD, reaching up to 25% in scenarios like Net Zero 2050 and Lower Demand, indicating severe financial strain in greener scenarios. Tata requires other strategies to accomplish the transition to the low-carbon economy successfully.
- Maersk maintains a stable credit rating of AAA+ and a PD of 0% across all scenarios, demonstrating resilience due to effective cost pass-on strategies and the use of alternative fuels, which lower emissions-related costs in greener scenarios.
- Vitens remains relatively stable until significant carbon costs emerge after 2035. Its credit rating drops one step from B- to CCC+, resulting in a 20% increase in PD. The company cannot rely on passing on costs to prevent default risk. This highlights the need for alternative strategies.
- FrieslandCampina sees a consistent increase in default risk across all scenarios due to high Scope 3 emissions from agricultural activities. The company's credit rating drops to CCC-, with a PD increase of over 23% by 2050. The firm needs to incorporate other strategies to mitigate the default risk coming from the transition.
- Boliden initially benefits from increased sales but later faces financial strain from CCS costs. Despite this, Boliden's credit rating remains constant, demonstrating the importance of their products role in the transition and its low PED in mitigating financial risks associated with emissions.

5.7.2 Effects of pricing strategy

The figures displaying different pricing strategies reveal that default risk is heavily dependent on a company's ability to pass on costs. For companies facing a high default risk in the standard setting of passing on 60%, such as Tata Steel and Vattenfall, the effects are substantial. These companies experience very low Z-scores in scenarios where no costs are passed on. For companies like Boliden, Vitens, and FrieslandCampina, the Z-score difference between passing on all costs and passing on none ranges from 1 to 1.5, which is considerable. Vitens, in particular, can mitigate a lot of its default risk due to the low elasticity of its product. The effects for Maersk should not be neglected. However, the transition effect on the PD is minimal, just as the effect of the pricing strategy is also minimal, only 0.20 in Z-score. Overall, it is important to consider the ability to pass on costs, as the outcomes in credit risk assessment differ greatly along the various pricing strategies for all types of vulnerability. The higher the transition risk in the standard settings, the more important the pricing effect becomes. This effect is fairly predictable as the scaling effect is clear for most companies, which is useful information for a company and the bank to use for their internal projections.

5.7.3 Effects of price elasticity

The ability to pass on costs for the pricing strategy cannot be seen apart from the PED. Companies such as Tata Steel and Boliden, which produce very inelastic products, can mitigate the effects of the low-carbon transition significantly by passing on costs. The increase in revenue by raising prices without losing much sales can be key in their transition risk management strategy. However, the credit ratings of these companies are also sensitive to the price elasticity of their products. Due to the interactive nature between price elasticity and pricing strategy, we observe similar sensitivities to both. If the extra transition costs become larger, the sensitivity to PED increases. We notice a consistent pattern where changes in price elasticity have predictable impacts on financial outcomes. This predictability allows for calculations of precise effects on Z-scores and PDs, which can be used to forecast different scenarios and strategies.

5.7.4 Difference across sectors

Table 5.1 summarizes key transition risk characteristics across various sectors and companies. The table covers several dimensions: first, how companies handle their key emissions, then their sensitivity to different scenarios. Grey scenarios include Current Policies, NDCs from the Hot House World quadrant, and Fragmented World from the Too-Little, Too-Late quadrant. Green scenarios cover Net Zero 2050, Below 2°C, and Low Demand from the Orderly quadrant. Delayed Transition from the Disorderly quadrant falls between green and grey scenarios. Lastly, we evaluate the effectiveness of passing on costs to mitigate default risk, considering the sensitivity to pricing strategies and the PED.

Sector	Key emissions	Scenario sensitivity	Effectiveness of passing-on-costs strategies
Utilities: Vattenfall	Scope 1, 2	**Moderate**: significant default risk in all scenarios. More risk in green scenarios.	Passing on costs alone cannot mitigate default risk effectively, requiring alternative strategies. Passing on 100% does not prevent default either. More elastic demand significantly increases default risk.
Manufacturing: Tata Steel	Scope 1, 2, 3	**High**: low default risk in grey scenarios. High default risk in greener scenarios.	Passing on costs alone cannot mitigate default risk effectively, requiring alternative strategies. Passing on 100% or 80% does prevent default, due to low PED. More elastic demand significantly increases default risk.
Transport: Maersk	Scope 1,3	**Moderate**: diverse trajectories but small impact. Some scenarios show slight default risk reduction. Grey scenarios have highest risk increase, but risk remains limited.	Passing on costs mitigates default risk effectively. However, the gap between passing on all costs and none is relatively small, indicating minimal transition risk from the start.
Water Supply: Vitens	Scope 1, 2	**Moderate**: significant default risk in all scenarios. More risk in green scenarios.	Passing on costs alone cannot mitigate default risk effectively, requiring alternative strategies. Passing on 100% does mitigate default risk, due to low PED. More elastic demand significantly increases default risk
Agriculture: Friesland Campina	Scope 3	**Low**: almost the same Z-score in all scenarios due large Scope 3 emissions.	Passing on costs alone cannot mitigate default risk effectively, requiring alternative strategies. Passing on 100% does not prevent default either. More elastic demand significantly increases default risk
Mining: Boliden	Scope 1, 2, 3	**Low**: all scenarios follow same trajectory. No default risk in all scenarios with very little difference in Z-score.	Passing on costs mitigates default risk effectively. Passing on 100% decreases default risk. More elastic demand increases default risk, but the risk is still very limited.

TABLE 5.1: Transition risk characteristics across different sectors.

The type of emissions most significant to a company plays a critical role in shaping its default risk profile. Companies with substantial Scope 1 and 2 emissions, like Tata Steel and Vattenfall, are heavily impacted by carbon pricing, especially in greener scenarios, where default risk is notably high. However, for companies like Boliden, with a mix of Scope 1, 2, and 3 emissions, passing on costs can effectively mitigate default risk, particularly due to lower PED and stable demand across scenarios. In contrast, companies with significant Scope 3 emissions, such as FrieslandCampina, face persistent challenges in reducing default risk, as their emissions are more difficult to mitigate and consistent across scenarios. This leaves them vulnerable, even when attempting to pass on costs. The maritime sector, represented by Maersk, demonstrates that switching to alternative fuels can reduce emissions and mitigate default risks effectively. For Maersk, the difference between passing on all or none of the costs is small, indicating a relatively low transition risk even from solely a cost perspective. Ultimately, the financial impacts of the low-carbon transition vary widely across sectors, emphasizing the importance of sector-specific strategies for managing transition risks. Companies with more elastic demand or a heavy reliance on Scope 1 emissions will need to adopt alternative strategies beyond simply passing on costs to navigate the transition effectively.

Chapter 6

Conclusion and Discussion

6.1 Conclusion

This work investigated the effects of the transition to a low-carbon economy on the default risk of businesses, focusing on the increasing importance of transition risk for banks under upcoming European regulations like the CSRD and the Pillar 3 regulations of the EBA. These regulations require large companies and banks to report on ESG risks, with mandatory climate risk frameworks beginning in 2024. Climate risk consists of transition- and physical risk. Transition risk, driven by policies, technological advancements, and changing consumer behavior, poses in general a greater challenge to quantify than physical risks. This study aimed to deepen the understanding of how transition risk varies across sectors and businesses, particularly in relation to the probability of default (PD). To address this, we focused on the following research question:

> *How can we assess the impact of the low-carbon transition on the probability of default of a business?*

A key innovation in this work is the integration of price elasticity of demand (PED) into the analysis of credit risk. We developed a unified framework that incorporates PED, the low-carbon transition, and credit risk to assess how companies handle the costs associated with carbon pricing, energy consumption, and carbon capture and storage (CCS) technologies. The framework includes a comprehensive view of emissions, covering all three scopes—Scope 1, Scope 2, and Scope 3—which is a challenging but emerging trend in this field, allowing for a more complete assessment of transition risk and its financial impacts. We applied seven NGFS scenarios to model future price changes, consumption patterns, and capacities, highlighting the importance of policies in driving transition risk. These factors were used to project the additional costs businesses may face up to 2050.

In contrast to many transition risk studies, this work included an analysis of firms' ability to pass on the additional costs they face by utilizing PED. This innovative angle allows us to examine not only the costs but also the potential revenue impacts of the transition. This offers both theoretical and practical insights into credit risk modeling. Incorporating revenue implications enhances current transition modeling practices as we do not limit models to cover solely the costs perspective of the transition. This exploratory work provides initial magnitudes for transition effects and pricing strategies, showing the necessity for the development of more accurate and robust financial models that can better assess the financial impacts of the low-carbon transition. To illustrate the magnitude of default risk we use the Altman Z-score. The results show whether a company can fully pass on these costs to mitigate default risk or if alternative strategies are needed to reduce this risk. Additionally, we assessed the sensitivity of each firm's default risk to PED and pricing strategies. The projected PDs are based on the firms' ability to pass on costs and should be interpreted cautiously, as other strategic factors were not included.

The framework was applied to six companies from various sectors identified by the ECB as vulnerable to transition risk:

- Vattenfall in the energy sector
- Tata Steel in the manufacturing sector
- Maersk in the transport sector
- Vitens in the water supply sector
- FrieslandCampina in the agricultural sector
- Boliden in the mining sector

For each company, we gathered data on emissions, energy consumption, and financial performance. The key products were identified, and their price elasticities of demand were used to model future revenues. Financial statements were reviewed to calculate each company's current Z-score. Adjustments were made based on NGFS data and specific market conditions where applicable. Z-scores for each firm were projected under different combinations of NGFS scenarios, pricing strategies, and PED levels, which were then mapped to credit ratings and PDs for easier interpretation. Based on the results obtained from following this approach, we draw the following conclusions.

6.1.1 General conclusions

- The transition towards a low-carbon economy imposes significant financial challenges. This results in reduced profitability and increased default risk, raising credit risks for banks. The impact varies across sectors, based on the investigation of six companies representing these sectors. These companies have different types and magnitudes of emissions, and they sell products with varying elasticities, all of which influence the results. Tables 6.1 summarizes the key findings for each company in the base scenario, passing on 60% in the Below 2°C scenario. We conclude that some firms need not pursue additional risk mitigation strategies, while others must find alternatives to passing costs to customers.

- Passing on costs can mitigate default risk, but the extent depends on the company. The ability to pass on costs depends on the PED of the products sold by the firms. For Tata Steel, only passing on a large portion of costs could substantially reduce default risk, which may be unrealistic due to its limited pricing power. Maersk and Boliden do not face transition risks, but passing on costs does give a higher Z-score. Other companies, such as Vitens, Vattenfall and FrieslandCampina, would still face substantial financial strain even with substantial cost pass-on strategies in place. In scenarios where product demand becomes more elastic, default risk increases for all companies, though the extent of this increase varies.

- The type of emissions most relevant to a company affects how sensitive its default risk is to different scenarios. Companies with high Scope 1 emissions, like Tata Steel and Boliden, are highly sensitive to carbon pricing and scenario changes, as carbon pricing fluctuates significantly across different policies. In contrast, companies with significant Scope 3 emissions, such as FrieslandCampina, face consistently high risks across all scenarios.

Company	2023			2050		
	Z-score	**Credit Rating**	**PD (%)**	**Z-score**	**Credit Rating**	**PD (%)**
Vattenfall	1.89	BB	0.45	-0.82	CCC	25.98
Tata Steel	5.00	AAA	0.00	<-1.5	D	100
Maersk	7.92	AAA+	0.00	7.89	AAA+	0.00
Vitens	0.80	B-	5.33	0	CCC+	25.98
Friesland Campina	1.30	B+	1.68	-0.68	CCC	25.98
Boliden	4.58	AA+	0.00	4.54	AA+	0.00

TABLE 6.1: Z-scores, Credit Ratings, and PDs for 2023 and 2050, passing on 60% in the Below 2°C scenario.

These results are likely more conservative than real-life outcomes, meaning the actual PDs would likely be lower. This is because we focused solely on passing on costs as a mitigation strategy and used the Z-score. In reality, companies may use additional strategies, leading to different and likely lower PDs. Interpret these results with caution.

6.1.2 Key insights

Based on the conclusions, we derived key insights aimed at enhancing the understanding of transition risk modeling and assessment. In general, banks should introduce and customize transition risk models taking into account each company's specific profile. This includes considering factors like emissions type, cost pass-on ability, and PED to accurately evaluate credit risks and make informed financial decisions. The following key insights are derived from this approach:

- **Cost pass-on ability is essential:** Companies' ability to pass on costs plays a significant role in reducing default risk. Firms that can effectively pass on costs show lower financial strain. The concept of PED in this ability is essential, more elastic demand worsens the effectiveness of passing on costs as a mitigation strategy. This factor should be introduced in credit risk frameworks to asses the risks more accurately.
- **Emissions profiles shape outcomes:** Scope 1 emissions lead to greater variability in credit risk depending on policy scenarios, while large Scope 3 emitters experience more consistent risks. Understanding a company's emissions profile is essential for assessing long-term credit risk.

6.2 Discussion

This section reflects on the assumptions and methodological choices made in the analysis. We discuss the consequences of these choices on the outcomes. We conclude with a brief reflection on the plausibility of the results.

2050 Net Zero targets: We applied companies' Net Zero 2050 targets across all scenarios, even in those not focused on net zero. This lowered the emissions in our model significantly for all scenarios. However, the model still reflects realistic cost variations, as carbon prices are adjusted accordingly in the grey scenarios. Although this approach may not capture higher emissions in some scenarios, it simplifies comparisons and aligns with the expectation that companies will likely stick to their Net Zero commitments due to the high costs of deviating from this path.

Handling future sales: NGFS scenarios adjust future sales predictions to reflect realistic market conditions. For sectors without NGFS data, we assume sales remain constant. We compare future and current revenues using today's prices for these adjusted volumes. Companies without adjusted sales volumes may show larger revenue differences, as we compare with the 2023 sales volume and not with volumes projected for a future year. This can lead to higher Z-scores compared to firms with modeled demand increases, causing minor differences between companies. Despite this, using NGFS data provides realistic insights into the differences between companies actively contributing to the low-carbon transition, like Boliden and Vattenfall, and those that are not, like FrieslandCampina.

Focus on the cost pass-on strategy: This analysis focused solely on passing costs to customers as a loss-mitigation strategy. Other approaches, such as cost-cutting or raising new equity, were not considered to avoid unnecessary complexity. As a result, the projected default rates should be interpreted with caution, recognizing that these alternative financial strategies were not included. In reality, the PDs are likely to be much lower, notice that a 25% PD is very high. Losses would not accumulate year after year in the same way as in our approach, since strategic decisions would be made earlier to mitigate losses. This accumulation factor negatively impacts the Z-score significantly. However, this focus allowed us to assess whether companies should consider other approaches for managing the low-carbon transition. Additionally, this strategy can be analyzed without needing detailed firm-specific strategic data, helping to address data limitation.

Focus on profitability: This research focused on company profitability by analyzing yearly cost increases passed on to customers but did not account for larger investments. We excluded significant one-time investments, such as greener technologies beyond CCS, renewable energy infrastructure, and energy efficiency upgrades. For instance, we did not cover Maersk acquiring new vessels, which can run on new greener fuels. These investments are typically written off over several years, affecting yearly profitability, but some should eventually repay themselves over time. However, we excluded them because determining the specific investments for companies without inside information is not feasible.

Company data limitations: Data limitations from annual and sustainability reports restricted the analysis, requiring assumptions about unit prices and revenues. Companies with clearer data, such as Vattenfall and Maersk, allowed for more accurate inputs compared to companies like FrieslandCampina, where we used complex market assumptions.

Furthermore, we could not include market competitiveness due to lack of reliable data on pricing power. Including these factors may have introduced uncertainties in the results, particularly for companies with less transparent data.

Additionally, we faced data limitations for assessing Scope 3 mitigation strategies, such as procurement rates. To address this, we assumed that CCS would cover all Scope 3 emissions. However, in reality, reducing Scope 3 emissions involves other investments and business strategies related to the emissions of both suppliers and customers, CCS is only one of these.

Reflection on obtained results

We discussed the assumptions which influenced the order of magnitude of the results. Now, we discuss whether the different trajectories of the results make sense. The results align with each company's emission profile and the climate scenarios analyzed. Companies with high Scope 1 emissions, like Vattenfall and Tata Steel, face significant financial strain in stringent scenarios like Net Zero 2050, where carbon pricing is high, but experience less pressure in weaker climate action scenarios from the Hot House World quadrant. Vitens, reliant on electricity for its operations, sees financial stress as energy costs rise under stricter climate policies, which is consistent with its heavy energy dependence. Similarly, FrieslandCampina, with its high Scope 3 emissions, faces financial difficulties in scenarios focused on reducing agricultural emissions, reflecting the challenges of decarbonizing its supply chain. Boliden, a key supplier of metals for the energy transition, benefits from rising demand in these scenarios, resulting in more stable financial outcomes compared to companies with higher emission profiles. Maersk benefits from green fuels, with reasonable extra costs absorbed by its size, especially since new vessel investments were excluded from the analysis. Overall, the results reflect the plausible impact of the transition on each company, with higher risks for those with high emissions and more stable outcomes for those contributing to the transition.

To conclude, this analysis provides useful insights but relies on key assumptions, such as focusing on cost pass-through strategies and excluding one-time investments in greener technologies, which may affect profitability. Varying data quality also introduced limitations, requiring assumptions that could impact accuracy. Therefore, the projected default rates should be interpreted cautiously, recognizing that companies have other cost reduction strategies which were not considered. However, the trajectories and sensitivities of the results are consistent with the emission profiles of the different firms.

6.3 Contribution and recommendations

6.3.1 Contribution to practice and theory

Theoretically, this study is one of the first to examine how transition risk interacts with a company's ability to pass on costs. While others have used price elasticity, we specifically analyze how different elasticities and pricing strategies impact default risk. Our new framework incorporates all three emission scopes, climate targets, and company-specific traits, enabling credit risk assessment at the individual company level—unlike most portfolio-based studies. This approach, along with our elasticity sensitivity analysis, provides new methodologies int the field of transition risk modelling.

Practically, our findings stress the importance of integrating cost pass-on ability, based on PED insights, into credit risk models of banks. Companies with significant Scope 3 emissions are less scenario-sensitive, while large Scope 1 emitters are more affected by varying carbon prices. These insights help banks better assess and manage transition-related credit risks based on company characteristics.

6.3.2 Further research

We finalize our thesis by outlining several interesting topics for future research. These recommendations vary in context and size, some are detailed to this research, whilst others should be seen in the broader context of transition risk.

- **Incorporating PED into advanced credit risk models:** This study utilized the Altman Z-score, a simplified credit risk measure. However, banks typically require more advanced models, such as Internal Ratings-Based (IRB) models. Future research should explore integrating PED into these models to yield more accurate PD assessments. This would create models suitable for practical applications.
- **Exploring additional elasticities:** While we focused on PED, future studies could investigate other elasticities such as income elasticity and cross-price elasticity. These could provide further insights into cost pass-on abilities. Additionally, exploring green product elasticities would be valuable. If consumers are willing to pay higher prices for environmentally-friendly products, it could serve as a strategy to reduce default risk. Understanding how these elasticities interact could significantly enhance both credit risk models for banks and transition strategies for firms.
- **Include investments in models:** Future research should explore whether companies can pass on the financing costs for green investments and include these into the models. While sustainable investments often require high upfront costs and have long payback periods, they can reduce future emissions-related expenses and transition risks, ultimately paying off in the long run. Understanding this trade-off between immediate financial burden and long-term cost savings would provide a more comprehensive view of transition risk and credit risk assessments during the low-carbon transition.
- **Robustness checks:** Future research should include robustness checks on factors like the Weighted Average Cost of Capital (WACC), splitting net results between assets and liabilities, and improved inflation modeling. These checks would help understand how discount rates, capital structure, and inflation fluctuations impact the outcomes.

We propose two examples to illustrate how advanced credit risk models can incorporate new elasticity measures:

1. Investigation of cross-price elasticity's role in the Vasicek model, commonly used in IRB models, to understand how the correlation between two companies affects credit risk. The interaction between substitute or complementary goods can influence credit risk correlations within a portfolio.
2. Integrating green price elasticity into the Merton model. Research could investigate whether demand for greener products is more inelastic and how this could impact credit risk.

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Appendix A

Additional Figures

A.1 NGFS Scenarios

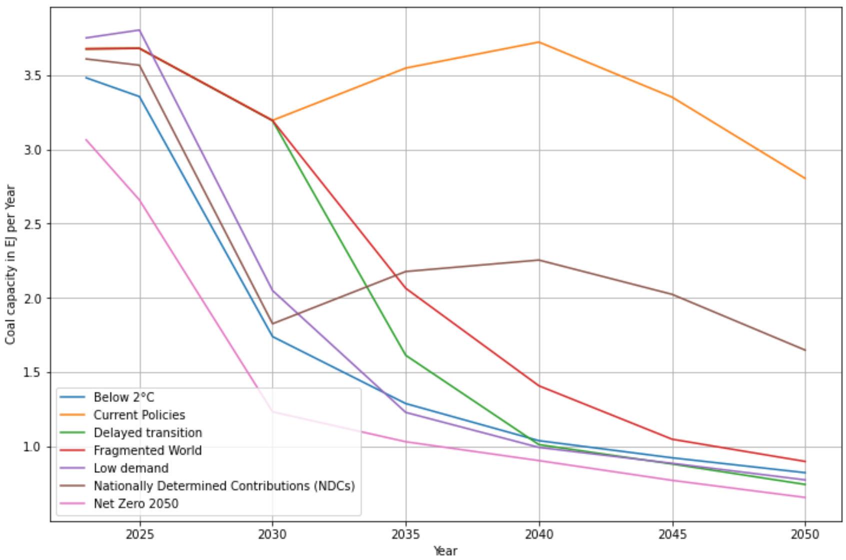

FIGURE A.1: Coals usage in EJ per year for EU-15 countries from NGFS (2023), mentioned in 4.4.

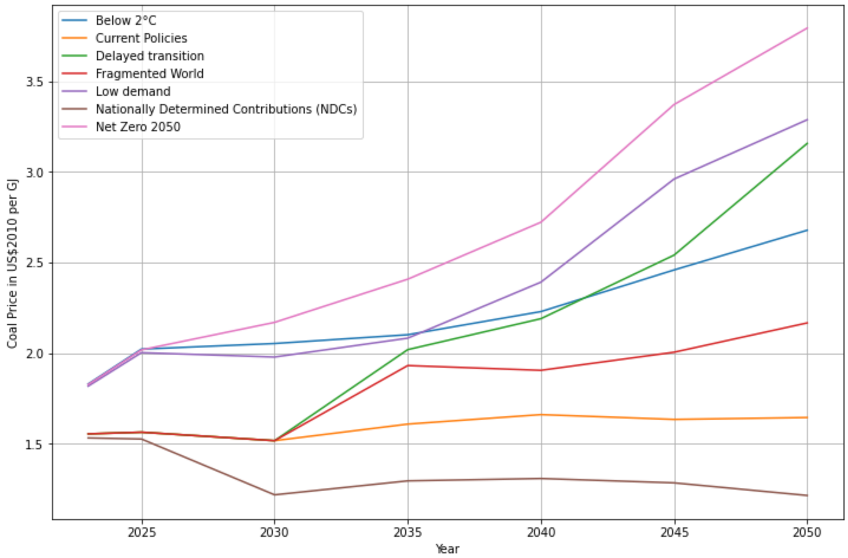

FIGURE A.2: Coals prices in US$2010 per GJ for EU-15 countries from NGFS (2023), mentioned in 4.4.

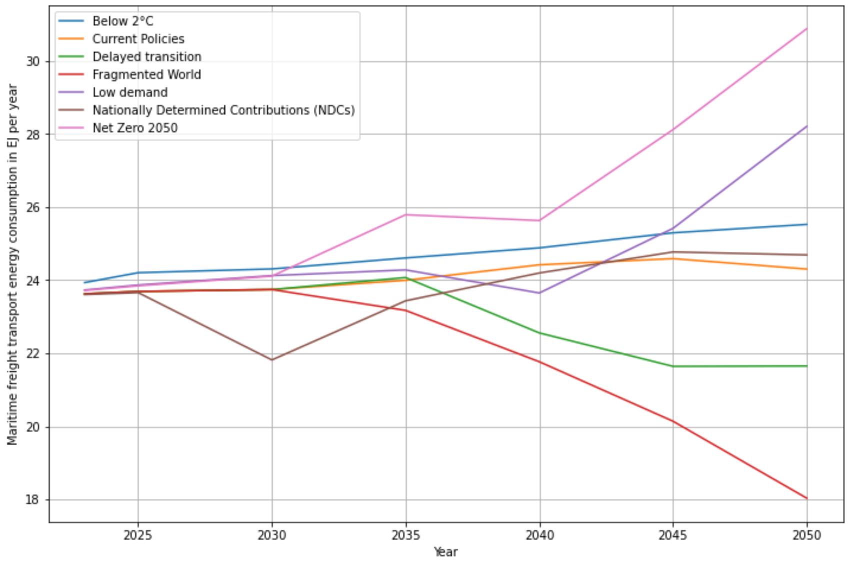

FIGURE A.3: Maritime freight transport energy consumption in EJ per year for EU-15 countries from NGFS (2023), mentioned in 4.5.

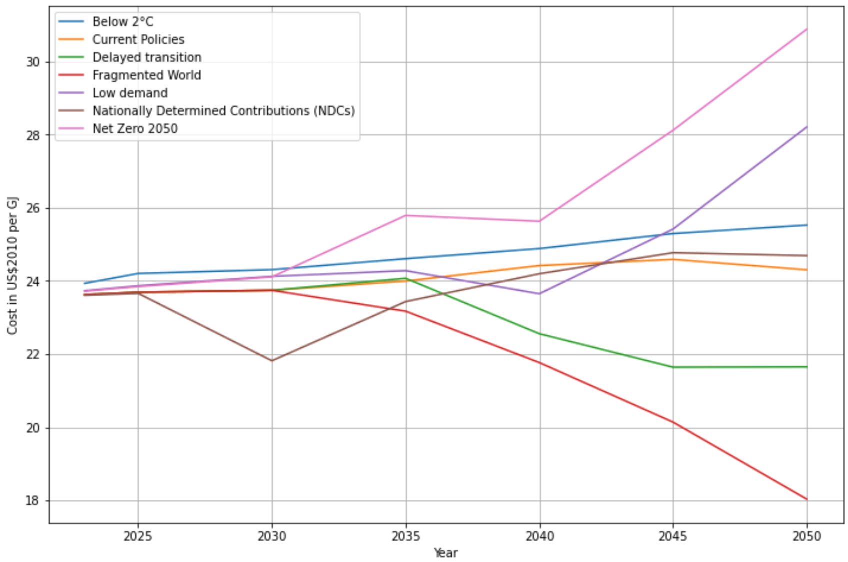

FIGURE A.4: Transport fuel prices in US$2010 per GJ for EU-15 countries from NGFS (2023), mentioned in 4.5 and 5.3.

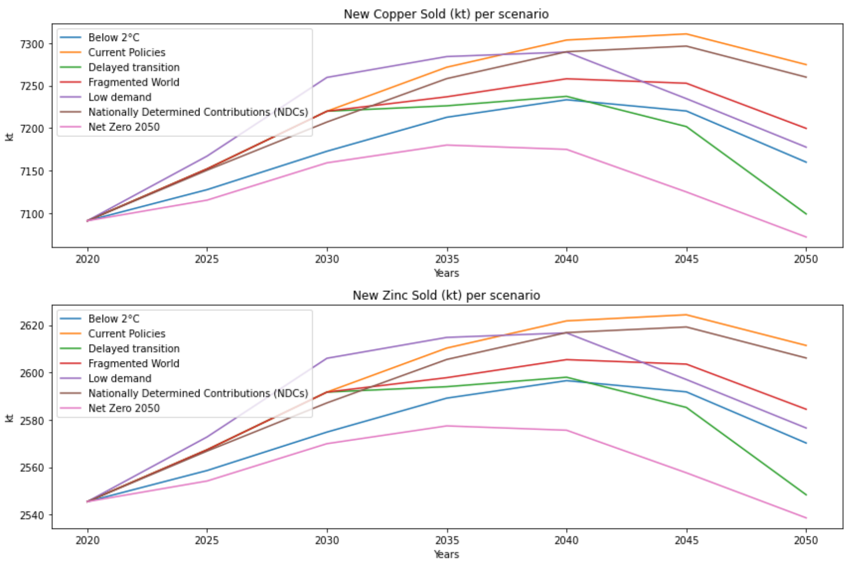

FIGURE A.5: Non-ferrous metals production in MT per year for EU-15 countries from NGFS (2023), mentioned in 4.8 and 5.6.

A.2 Additional Figures Vattenfall

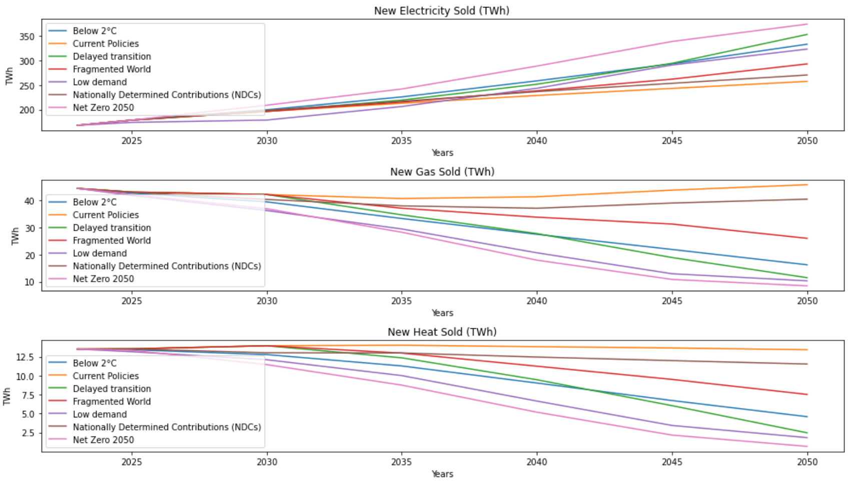

FIGURE A.6: New sales of Vattenfall per scenario in TWh, mentioned in 4.3.

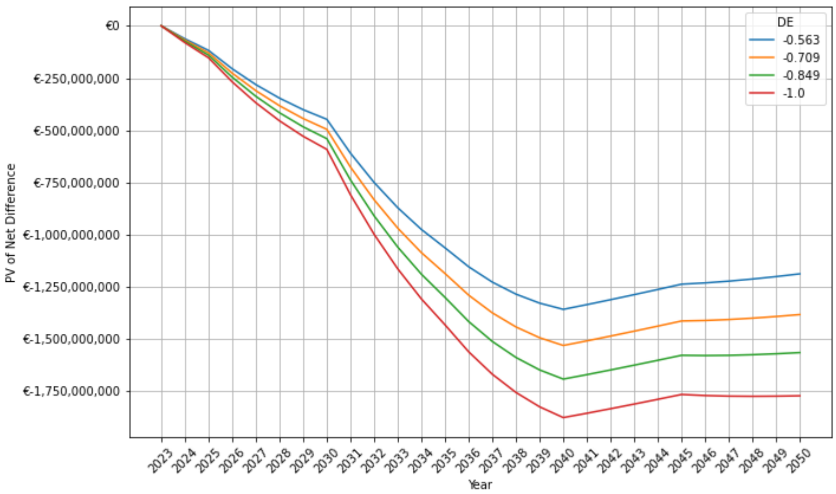

FIGURE A.7: Net results of Vattenfall with different demand elasticities.

A.3 Additional Figures Tata Steel

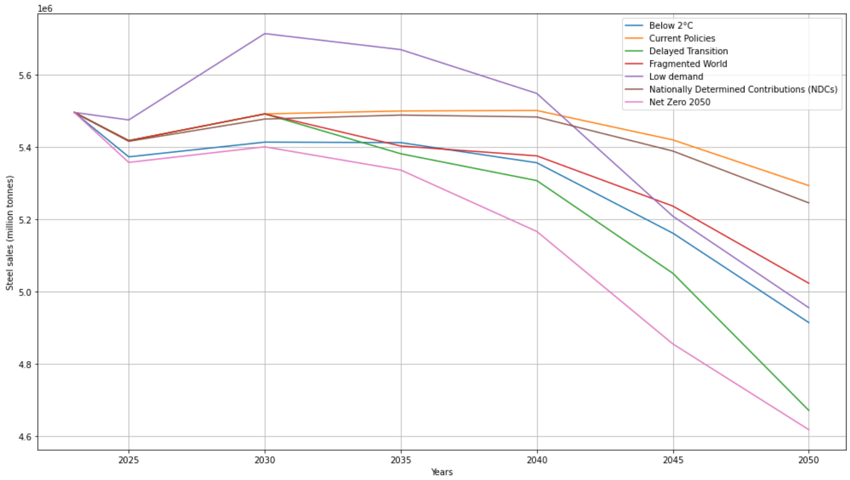

FIGURE A.8: New sales of Tata steel in million tonnes, mentioned in 4.4.

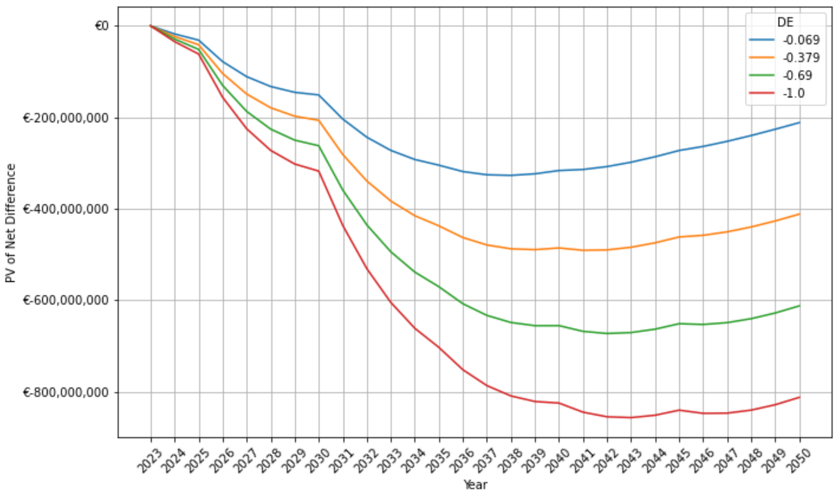

FIGURE A.9: Net results of Tata steel with different demand elasticities.

A.4 Additional Figures Maersk

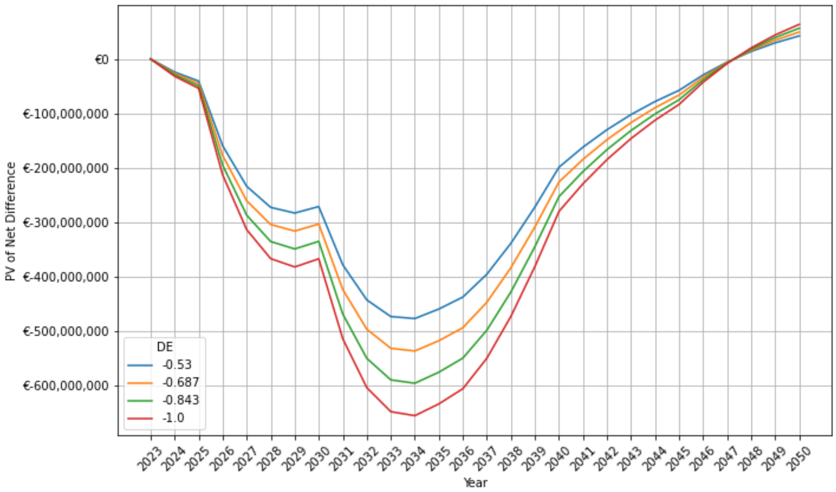

FIGURE A.10: Net results of Maersk with different demand elasticities.

A.5 Additional Figures Vitens

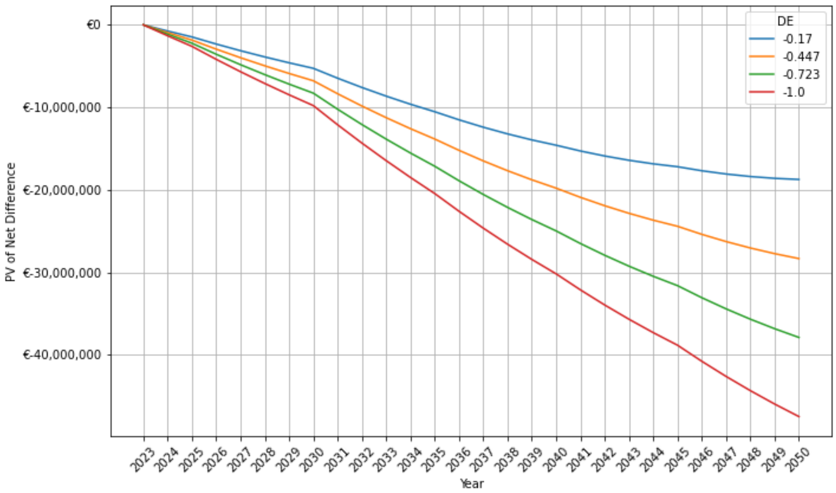

FIGURE A.11: Net results of Vitens with different demand elasticities.

A.6 FrieslandCampina

Product	Percentage of sales	Price per tonne	Weighted price per tonne
Milk	0.2	456.7	91.34
Butter	0.02	4763	95.26
Powder	0.14	2922	409.08
Whey	0.16	680	108.8
Cheese	0.55	3438	1890.9

TABLE A.1: Weighted average price of dairy products per tonne, mentioned in 4.7.

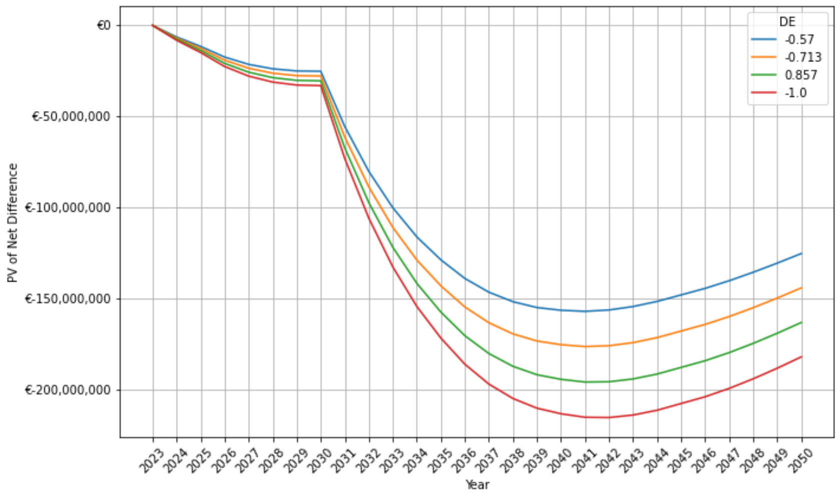

FIGURE A.12: Net results of FrieslandCampina with different demand elasticities.

A.7 Additional Figures Boliden

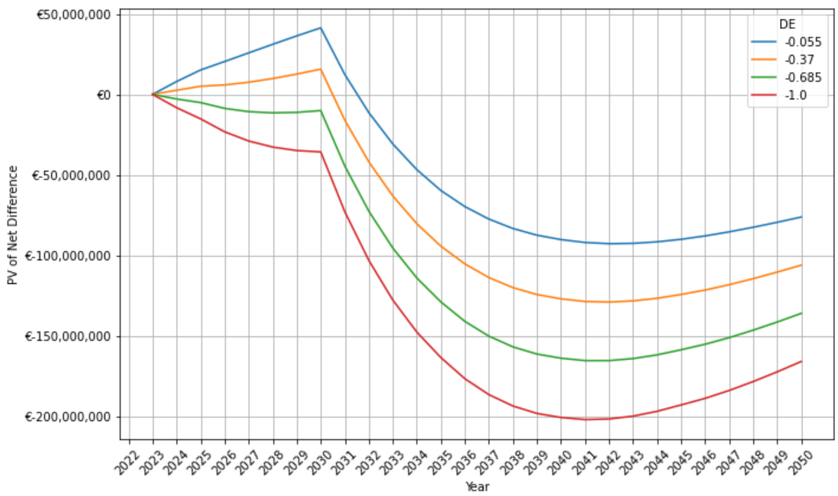

FIGURE A.13: Net results of Boliden with different demand elasticities.