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MASTER THESIS

A PRODUCT INVESTMENT DECISION-MAKING METHOD UNDER CARBON PRICING UNCERTAINTY

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Preface

I want to take a moment to express my appreciation to the individuals who have supported me throughout my journey in writing my master thesis in Industrial Engineering and Management, with a specialization in Production and Logistics Management.

To begin, I extend my gratitude to Vanderlande Industries for giving me the opportunity to conduct my thesis under their expert guidance. I am especially thankful to Martijn Fransen and Ber van Dijk, who both helped me in this journey. It started with a large search of what and where to conduct my thesis. I do believe that together we came to a great result and even though the start was not the smoothest I did always feel a sense of trust and respect within the entire process and also learned a lot during my time at Vanderlande. As the cherry on top of the cake I also created the opportunity to meet the CEO and COO, Remo, and Mart respectively, of Vanderlande to present the key findings of my thesis.

From an academic perspective, I am grateful for the privilege of collaborating with Patricia Rogetzer. She not only empowered me to function as an autonomous and independent researcher but also generously shared her expertise and insights whenever I required assistance. Lastly, I extend my thanks to Wouter van Heeswijk for joining our team early on in the process when his financial expertise was needed the most. His perspective added a valuable dimension to the work, and I have witnessed the substantial improvement of my thesis after each of our meetings, thanks to his constructive feedback and opportunity to reflect on my ideas and research directions.

In closing, I would like to express my gratitude to my family and friends for their support and genuine interest throughout this journey. Everyone entered my process in a different stage and I believe all the conversations and feedback resulted in the master thesis that I present today. A special thanks to Stef and my brother Mark for diligently proofreading parts of the document.

I hope that you find my thesis enjoyable to read.

Management summary

Problem context and research objective

Vanderlande Industries (VI) faces a critical challenge: the uncertainty surrounding future carbon pricing policies and their potential impact on VI's operations and products. This thesis researches how VI should navigate this uncertain future carbon pricing landscape. The objective is to develop a method for incorporating carbon pricing into VI's product investment decision-making. The research helps VI to monetize sustainability. The main deliverables of this study include a forecast to provide different carbon price paths and a Discounted Cash Flow (DCF) analysis tool, which supports with making product investment decisions. The DCF analysis tool operates under different carbon pricing scenarios, enabling VI to assess the financial implications of these different scenarios on investment decisions. These resources are designed to foster informed decision-making, enabling VI to thrive in an environmentally conscious, low-carbon future, while contributing to the broader field of sustainable business management.

Methodology

This thesis adopts a systematic approach that corresponds to the Design Science Research Methodology (DSRM) process model, which is a methodology that helps to guide the creation of an artefact, in this case the DCF tool. In the DCF tool we integrate different forecasted carbon price paths. Amongst others, the price paths are forecasted using the ARIMA model. We use Geometric Brownian Motion (GBM) and linear regression as benchmarks. The DCF analysis tool demonstrates cash flow of different product investments between which one wants to make a decision. Furthermore, we employ a case to validate and verify the DCF analysis tool created, using a Life Cycle Assessment (LCA) to assess both financial and environmental aspects of product investment alternatives. This step corresponds to the 'Demonstration' step of the DSRM. As the 'Evaluation' step an expert panel is utilized to validate and refine the methodology, ensuring its reliability and alignment with VI's objectives.

Results and Recommendations

We use the ARIMA model, GBM, and linear regression to forecast carbon price paths and based on these methods we conclude that the carbon price will increase until 2050. However, the degree to which it will increase depends much on the method chosen. For ARIMA the price reaches 1,776.84 Euros by 2050, for GBM the price reaches 86.29 Euros, and for linear regression the price is 175 Euros per ton of CO_2. In this research, we recommend using linear regression in the long term, which projects that the price will increase to 175 Euros per ton of CO_2 in 2050. We recommend linear regression due to the high level of uncertainty present when forecasting until 2050 and this method offers a stable price path based on the average trend in the previous years. VI itself looks at price developments for shorter horizons of two to three years generally, so we recommend using the ARIMA(2,2,2) model on the short-term (2-3 years) due to the performance indicators being the best, i.e. RMSE of 7.99 and MAPE of 0.079, which are both better than the benchmark methods, with GBM (RMSE: 9.16, and MAPE: 0.089) and linear regression (RMSE: 9.58, and MAPE: 0.094). We also recommend recomputing the price paths annually and inserting more recent prices.

Based on a case, which compares two material decisions of a product, we conclude that including carbon pricing in business cases can contribute to the decision making between two product investments. The DCF tool is especially valuable to gain more insight into the CAPEX and OPEX of projects and see when investing in a more sustainable product is worthwhile and financially attractive. The case also provides valuable insights into whether to choose a crossmember made from aluminium or steel when looking at both financial and environmental aspects and monetizing those. We see that for every carbon price, the crossmember from steel is more financially attractive. When using the linear regression price path, we observe a lower NPV of 438.07 Euros for steel compared to 1,377.99 Euros for aluminum, highlighting steel's cost-effectiveness. Only when the discount factor falls below -0.5% does aluminum become more attractive. The entire method is also verified using an expert panel.

Conclusion

To conclude, by quantifying the financial and environmental implications using the DCF tool, this research offers valuable insights into how different carbon pricing policies may influence investment decisions between multiple alternatives. The combination of short-term forecasting using the ARIMA(2,2,2) model and long-term planning with the linear regression model empowers VI to make well-informed decisions that align with evolving industry standards and environmental responsibilities. The practical contribution of this research mainly lies in providing VI with the DCF tool that can help them to monetize carbon emissions and using this monetized insight it helps to make well-informed decisions. Moreover, this thesis also creates more awareness within VI regarding carbon pricing. This methodology stands as a pioneering approach in the literature, providing companies with the valuable insights necessary for informed decision-making, thus contributing significantly to both practical application and theory.

Keywords: carbon pricing, discounted cash flow (DCF) analysis, policy scenarios, ARIMA model, Geometric Brownian Motion (GBM), linear regression, product investment decisions, decision-making, monetizing carbon emissions, EU ETS.

Contents

List of Abbreviations

ACF	Autocorrelation Function
ACV	Autocovariance
ADF	Augmented Dickey-Fuller
AI	Artificial Intelligence
AIC	Akaike Information Criterion
AR	Autoregressive
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
BAU	Business-as-Usual
BIC	Bayesian Information Criterion
CAPEX	Capital Expenditure
CBAM	Carbon Border Adjustment Mechanism
CNN	Convolutional Neural Network
CO_2	Carbon Dioxide
CO_2e	Carbon Dioxide Equivalent
CSRD	Corporate Sustainability Reporting Directive
DCF	Discounted Cash Flow
DSRM	Design Science Research Methodology
ESG	Environmental, Social, and Governance
ETS	Emissions Trading System
EU	European Union
EUA	European Union Allowances
EUR	Euro
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
GBM	Geometric Brownian Motion
GHGs	Greenhouse Gases
GWP	Global Warming Potential
IRR	Internal Rate of Return
JB	Jarque-Bera
KPSS	Kwiatkowski-Phillips-Schmidt-Shin
LCA	Life Cycle Assessment
LSTM	Long Short-Term Memory
MA	Moving Average
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
ML	Machine Learning
MLP	Multi-Layer Perceptron
NFRD	Non-Financial Reporting Directive
NPV	Net Present Value
OPEX	Operational Expenditure
PACF	Partial Autocorrelation Function
RMSE	Root Mean Squared Error
rRMSE	Relative Root Mean Squared Error
R^2	R-squared
SFDR	Sustainable Finance Disclosure Regulation
VI	Vanderlande Industries
WACC	Weighted Average Cost of Capital
WTP	Willingness to Pay

List of Definitions

Carbon footprint	A carbon footprint is the measure of an activity, expressed in the total amount of greenhouse gases (GHGs) it emits – directly or indirectly. There are many GHGs, so we use the carbon dioxide equivalent (CO_2e) as the measure of the global warming potential. Global warming potential (GWP) is the heat absorbed by any greenhouse gas in the atmosphere, as a multiple of the heat that would be absorbed by the same mass of carbon dioxide (CO_2). For example, the GWP of methane is 21 times that of CO_2 therefore, 1 kg of methane is equals to 21 kg CO_2e.
Carbon pricing	Carbon pricing is an instrument that captures the external cost of greenhouse gas emissions […] and ties them to their sources through a price, usually in the form of a price on CO_2 (The World Bank, n.d.).
Product investment decisions	Product investment decisions refer to the strategic choices made by organizations to invest resources, capital, and time.
Sustainability	Sustainability is the ability to maintain or support a process continuously over time. Sustainability is often broken into three core concepts: economic, environmental, and social (Mollenkamp, 2023).

Reader's guide

Chapter 1: Introduction

This chapter provides an overview of the research problem and introduces the company, Vanderlande Industries (VI). The purpose of this chapter is to familiarize the reader with the context of the research problem that is being addressed.

Chapter 2: Problem Identification

The focus of this chapter is to identify and define the core problem faced by VI. It also illustrates the problem through visualization of its relationships and identifies the relevance and scope of the research. Additionally, this chapter outlines the research design, including the main research question and sub-questions.

Chapter 3: Current situation

This chapter analyses the current situation of VI and its customers to assess alignment and identify existing market conditions. This analysis provides a foundation for the research that follows.

Chapter 4: Literature review

The literature review chapter provides essential context for the reader to understand the key elements of the research problem. It also highlights the existing theories, approaches, and findings related to the research problem and how they are built upon in this study.

Chapter 5: Solution design

This chapter outlines the solution design used to conduct the research, including the steps taken to answer the research question. It explains the rationale behind the chosen research approach, data collection methods, and data analysis techniques.

Chapter 6: Diagnostic testing

The diagnostic testing chapter is important in modelling price series. Diagnostic tests are used to check whether the assumptions of the model are satisfied and to check the properties of the data set. Using these diagnostic tests an appropriate forecasting method is chosen.

Chapter 7: Forecast the EU ETS price

This chapter uses the historical EU ETS data to forecast the price path until 2050 using the forecasting method chosen from the results in Chapter 6. Additionally, two other methods are also used to compare the performance of the chosen method.

Chapter 8: Results and discussion

This chapter presents the results of the discounted cash flow analysis. The case, expert panel, and sensitivity analysis are also included in this chapter. The chapter ends with a discussion of the results.

Chapter 9: Conclusion, contributions, and future research

This chapter is subdivided into different parts. In the conclusion, we provide an answer to the main research question. It also discusses the implications of the findings and their significance for the field both practical and scientific. Additionally, recommendations are given to VI and for future research.

1 Introduction

This master thesis addresses the challenge of the impact of expected carbon pricing policies on investment decisions for Vanderlande Industries (VI). This chapter gives the context of the research that is conducted for the University of Twente and VI, including problem introduction and information on the company.

1.1 General problem introduction

In recent years, the issue of climate change and carbon emissions has become increasingly important for companies in all sectors (EEB, 2021). With the global community moving towards a more sustainable future, businesses are under increasing pressure to reduce their carbon footprint and find ways to accurately measure and manage their carbon emissions as well as create more low-carbon products (Scott, 2019; Lestari, Dania, Indriani, & Firdausyi, 2021). The challenge arises of how to make decisions to become more sustainable as a company. Quantifying the impact of decision-making, i.e. quantifying the carbon emissions for product A or product B, may help to guide trade-offs based on data (Haanaes & Olynec, 2022). Consider, for instance, the choice between two products - a conventional one (A) and a low-carbon alternative (B). Precisely quantifying the future cost differential between these options, particularly in the event of the imposition of a carbon pricing system, becomes pivotal. An example of how this can work is provided in Figure 1. Here the cost components are divided between capital expenditure (CAPEX) and carbon cost. The cost of purchase and the cost of its operations and maintenance are often separated on financial statements. The first term is also known as CAPEX, and the latter is part of operational expenditures (OPEX). In Figure 1 we see that the initial investment in the low-carbon alternative is higher, however, the projection of reduced future carbon costs can render it financially more attractive.

Figure 1: Standard option A and the low-carbon alternative B with CAPEX and carbon cost.

The business landscape that companies are in is changing as well and brings much uncertainty on how governments will approach sustainability in the future. One of the main shifts can be observed in reporting directives and carbon pricing policies, making it imperative to investigate their potential impacts on companies. Carbon prices are specifically interesting to research as their potential impact in the future is large and the current carbon prices are increasing rapidly, which has a large impact on the cost of products (Trading Economics, 2023). Additionally, carbon pricing policies are rising worldwide as a measure to manage carbon emissions (The World Bank, Carbon Pricing Dashboard, 2023). There are different carbon pricing systems around the world: a carbon tax, Emissions Trading System (ETS), or a combination of the two. According to The World Bank (2021), a carbon tax is a fee imposed on the carbon content of fossil fuels, while an ETS system sets a cap on emissions and allows companies to trade emissions allowances (World Bank, 2021). Such policies reshape the conventional business landscape and introduce a significant degree of uncertainty. There is much uncertainty concerning carbon pricing. Examples of this uncertainty can be found in whether there will be carbon pricing for VI, the height of the carbon price, the industries they will apply to, and the year when to pay for them. Therefore, it is valuable to gain insight into the effect of these possible carbon pricing scenarios on companies. Additionally, it is valuable to gain insights into cash flows over time in case there is carbon pricing as an investment might earn itself back over time due to lower operational carbon costs. Therefore, the discounted cash flow tool is used which enables people to look at an investment from a more holistic scope including both the capital and operational expenditures.

1.2 About VI

VI is a global market leader in the design, manufacturing, and installation of innovative material handling solutions. An example of a material handling system can be found in an airport when a customer places their luggage on a scale. Hereafter, the luggage is moved by a material handling solution to end up in the designated aircraft. Founded in 1949, VI has grown to become one of the largest players in the automation industry, serving customers across a range of sectors, including airports, warehouses, and parcel sectors (Vanderlande, 2023a). VI has different types of customers, which can be categorized into four business segments, namely 'Airports', 'Amazon', 'Warehousing', and 'Parcel'. This study encompasses all of these business segments. With sustainability as a core value, VI is committed to reducing its environmental impact and contributing to a low-carbon future. VI has four missions regarding sustainability (Vanderlande, 2023c):

- To have a zero carbon footprint by 2040;
- To achieve circularity, to be a regenerative company by 2040;
- To do good business, meaning to conduct business in an ethical way and demand the same from suppliers;
- And to provide fulfilling experiences, meaning that people are put first and health, safety, fair treatment, and no discrimination are key elements that play a part in this mission.

VI produces all kinds of different products. An example of a product produced by VI that is used within this thesis' case is the Twinbelt module. Figure 2 shows the technical drawing of a Twin Belt with three crossmembers. This serves as an example as different types of Twin Belts can be present in a system, all having different numbers of crossmembers. A crossmember is an aluminium extrusion profile that connects and supports two sides of the Twin Belt module. The crossmember and technical drawings are provided in Chapter 8 when introducing the case.

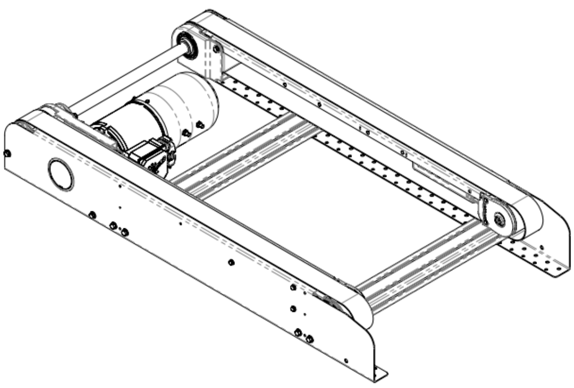

Figure 2: Example technical drawing of a Twin Belt with part number 001036-001-01602 with two crossmembers. Source: From internal documentation at VI.

1.3 VI and carbon emissions

In line with the first mission of VI, they want to reduce their carbon footprint. Section 1.1 sets out numerous elements in the legislative landscape that may also change in the future. This section discusses VI as a company and carbon emissions and legislation.

For VI one of the main incentives to become more sustainable is due to the fact that large customers are demanding more sustainability from their suppliers. However, these customers can be seen as the front runners in this aspect, and thus not all VI's customers have this same maturity in terms of early adaptors. Knowing that there are different maturity levels of customers is valuable as it can help guide business decisions and see where the added value is when it comes to sustainability. Even if only a limited amount of customers are currently demanding and asking for sustainability in a tender process, it is important for VI and its customers to proactively address sustainability issues and incorporate sustainable practices into their operations due to the following reasons:

- **Sustainability is becoming increasingly important**: While there may currently be a limited number of VI's customers demanding sustainability, the importance of sustainability is growing. Many governments, international organizations, and consumers are prioritizing sustainability, and this trend is likely to continue. Companies that are proactive in addressing sustainability will be better positioned to meet the evolving demands of customers and other stakeholders (Lestari, Dania, Indriani, & Firdausyi, 2021; Zhivkova, 2022).
- **Sustainability may be subject to changing legislation:** Possible legislative consequences may be in place in the future, and much speculation is there. Even some larger industries are already subject to laws and regulations in the past years, i.e. the power and heat generation and production of iron and steel (Parry, Black, & Zhunussova, 2022; Pietzcker, Osorio, & Rodrigues, 2021; Delgado-Téllez, Ferdinandusse, & Nerlich, 2022). Another large change that can be observed is the introduction of the Corporate Sustainable Reporting Directive (CSRD), which obligates companies to report on sustainability (Vries, 2023).
- **Sustainability can provide a competitive advantage**: Incorporating sustainability into operations can provide a competitive advantage in the market (Parida & Wincent, 2019). Companies that can demonstrate a commitment to sustainability and a track record of sustainable practices may be more attractive to customers and other stakeholders, which can lead to increased business opportunities and revenue. In the market, it is also noticed that customers are also pursuing sustainability and want to know what VI's plans are regarding sustainable solutions (Vanderlande, 2022; Lestari, Dania, Indriani, & Firdausyi, 2021; Zhivkova, 2022). Based on internal information it can be observed that most customers are currently incorporating sustainability in their strategy, and this will affect the future business of VI. Examples can be seen at LEGO, Nike, Heathrow Airport, and Amazon (LEGO, 2023; Heathrow Airport, 2023; Amazon, 2021; Nike, 2023).
- **Sustainability can reduce costs**: Sustainable practices can often lead to cost savings. For example, reducing energy consumption and waste can result in lower operational costs, while using sustainable materials can reduce procurement costs over time (Makridou, 2021). By adopting sustainable practices, companies can reduce their costs and improve their bottom line.
- **Sustainability is the right thing to do**: Finally, it is important to recognize that sustainability is simply the right thing to do morally. Businesses are responsible to minimize their impact on the environment and to act in a socially responsible manner. By taking sustainability seriously, companies can demonstrate their commitment to these values and to making a positive impact on the world.

In this thesis, our emphasis centers on carbon pricing as both a mechanism to monetize carbon emissions and a means to align with potential shifts in legislation like taxes. Carbon pricing may affect the product investment decisions of VI as there is a financial incentive to decarbonize as a company. It can also impact their ability to sell more sustainable products.

To illustrate the impact that carbon pricing will have on VI we computed the impact of different carbon prices to provide insights. To provide a tangible sense of how carbon pricing can affect project costs, we consider VI's annual expenditure on raw materials, which amounts to approximately 40 million Euros. When looking at the amount of carbon created in the production process of these materials, VI computed that there are around 48,676 tons of Carbon Dioxide (CO_2) in raw materials. For different carbon prices, we compute the possible carbon cost that can be added to these raw material prices. This can have a large impact on the total cost as can be seen in Table 1. It shows the relevance of this research as the cost of VI can increase by a few percent until more than double in price.

These insights show the impact of carbon pricing on decision-making. Given the dynamic nature of carbon pricing and the underlying principles of sustainability, it is key to adopt a holistic perspective when evaluating the financial implications of various product alternatives throughout their lifecycle. For instance, consider two product options: one with higher carbon emissions in its materials but fully recyclable, and the other with fewer carbon emissions during production but without recycling potential. This distinction significantly influences the cash flows that must be taken into account. In such cases, an initial higher carbon price investment may be required for the recyclable material, while this carbon price can be earned back entirely at the end of the lifecycle, assuming a 0% discount factor, while this is not the case for the lower-emission material. Therefore, it becomes crucial to consider the entire lifespan of a product and the associated cash flows. To facilitate comprehensive financial evaluations and informed product investment decisions, Discounted Cash Flow (DCF) analysis emerges as a widely recognized method. Therefore, this thesis creates a DCF analysis tool as final deliverable.

Table 1: The impact of different hypothetical carbon prices on the additional expenditure called total carbon costs in raw materials and their ratio of total carbon cost to total current expenditure in raw materials.

Carbon price (Euros per ton CO_2)	**Total carbon cost (Euros)**	**Ratio carbon cost/total current expenditure (%)**
0	0	0%
50	2,433,800	6%
100	4,867,600	12%
150	7,301,400	18%
200	9,735,200	24%
250	12,169,000	30%
300	14,602,800	37%
500	24,338,000	61%
1000	48,676,000	122%

VI is a complex organization with operations in multiple countries and jurisdictions, making it challenging to measure and manage its exact carbon footprint. This also makes it more complex to see to which laws and regulations they must comply with as this may change per site. Even though the organization is complex it is still seen as valuable to gain insights into the environmental impact as those that measure and manage their environmental impact tend to outperform their competitors financially (Eccles & Serafeim, 2013). Therefore, this thesis develops a tool that provides VI with a clear and transparent measure to calculate the cost of its carbon emissions in projects under different carbon pricing scenarios. By doing so we can help with the decision-making process and to start including carbon emissions in business cases for VI and its customers and stakeholders. We do this by making a forecast of different scenarios of the price of CO_2 and using the forecasted price as a minimal expected additional cost of a product. In this way, VI and its customers are enabled to make more informed decisions about buying different products (Rudnik, Hnydiuk-Stefan, Kucinska-Landwójtowicz, & Mach, 2022).

In summary, even if only a limited number of VI's customers are currently demanding sustainability actively, and no legislation is in place for VI yet, it is important for VI to proactively address sustainability issues. Addressing this is especially important as there may be legislative changes in the future and due to the fact that it is one of the main missions of the company. Especially due to the fact that possible changes and the introduction of carbon pricing will have a major impact on VI.

1.4 Outline

This thesis aims to help with the monetization of carbon dioxide emissions and by doing so making it possible to start including carbon emissions in a business case and decision-making. In order to achieve this objective the Design Science Research Methodology (DSRM) is used (Peffers, Tuunanen, Rothenberger, & Chatterjee, 2007).

DSRM is a research process that includes six steps and it serves as a basis for the research method of this study. Figure 3 shows the outline of the DSRM from left to right, which starts by identifying the problem. Hereafter, it continues by defining the objectives of the solution. The following step is the design and development of an artifact. In terms of this research, the artifact is the discounted cash flow analysis tool that is created. Once this artifact is developed it is applied in practice to demonstrate it and evaluate how effective and efficient the artifact is using a case. Then an iterative approach starts in which we go back to the design and development phase to make adjustments. Lastly, the results are communicated to the main audience of the research.

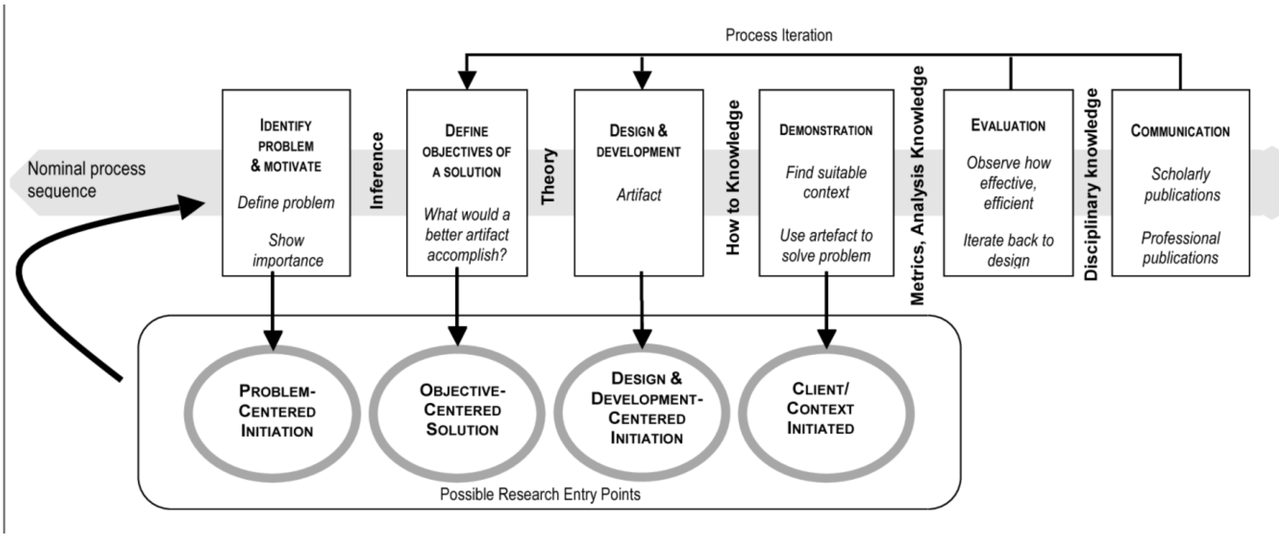

Figure 3: Design Science Research Methodology (DSRM) process model (Peffers, Tuunanen, Rothenberger, & Chatterjee, 2007).

In this last paragraph, we summarize how the DSRM process aligns with the outline of this thesis. The design and development of the artifact aligns with creating a discounted cash flow analysis template and carbon price forecast in this thesis. Using this carbon price forecast as an input, the thesis develops a tool that integrates data on VI's energy consumption, emissions, and business operations to estimate the expected cost of carbon for a product of VI. In order to develop the artifact a literature review is conducted to create more knowledge on the topic and to find the best forecasting method for this thesis as well as the basis for the discounted cash flow analysis. Additionally, we also analyse the current situation to make sure it integrates well with the current methods used at VI as well as the fact that it solves the problem VI is facing. Once this method is developed it is applied in practice on the case to demonstrate and solve a product investment decision and incorporate carbon pricing in this decision-making process. This case also validates and verifies the approach created. After applying the method to a business problem, its quality is evaluated using an expert panel, which is also part of the validation and verification.

2 Problem identification

In this chapter, we start by identifying the research problem, which is the first step of the Design Science Research Methodology (DSRM). This involves examining both the current situation and the desired future state, following the method outlined by Heerkens & Van Winden (2017). We also explain the scope of the research and the reasons driving it, which constitutes the second step of the DSRM. Finally, we outline the sub-questions that help answer the main research question.

2.1 Problem cluster

In this section, we show the problem cluster and determine what the core problem is of this thesis. We do so by showing an existing problem overview from the literature and our findings at VI and these combined result in the problem cluster. First, we introduce the concept of a problem cluster.

To identify the core problem we use a problem cluster. A core problem is a problem that has no influencable underlying cause. In a problem cluster, we distinguish core problems, knowledge problems, and action problems. The core problem can (partly) solve the presented main problem of VI (Heerkens & van Winden, 2017). The core problem is being analysed to determine the current and desired state. From this analysis, we derive the main research question. The action problem is defined as the discrepancy between the norm (the level at which the situation should be) and the reality (the level at which the situation currently is). Figure 4 displays an overview of general barriers to reducing emissions in a supply chain, these were also taken into consideration when creating the problem cluster. The concept of scope 3 emissions is explained in Chapter 3. Figure 5 shows the problem cluster which is based on unstructured interviews with the employees of VI. This is also verified within the company through these interviews and expert panels to assure completeness.

Figure 4: Several barriers regarding the reduction of emissions in a supply chain (World Economic Forum, 2021).

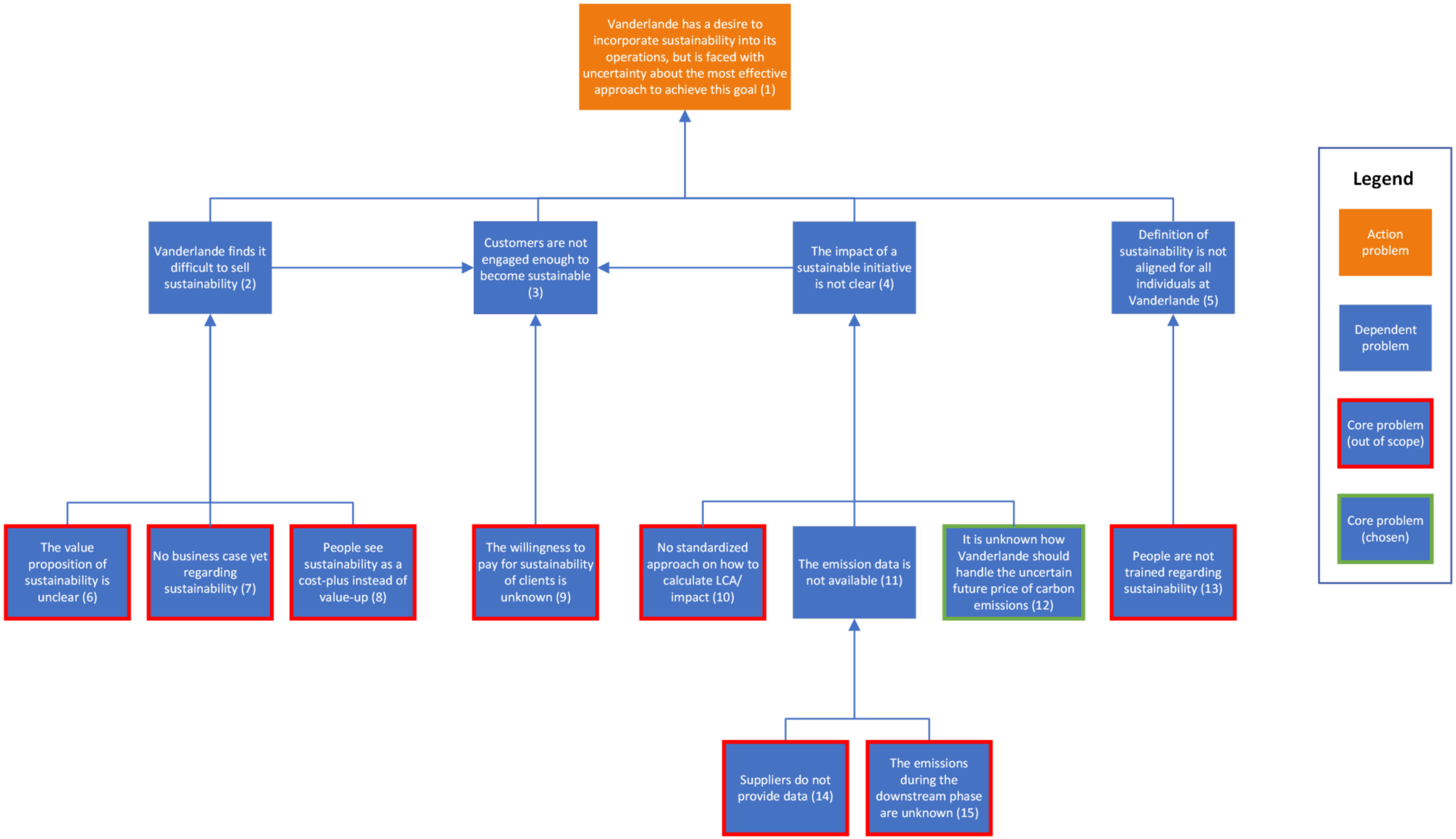

Figure 5: Problem cluster of VI showing the action problem and core problems and the relations between them, including a numeric reference between brackets.

2.2 Action problem

The action problem describes the difference between the current state (reality) and the desired state (norm) of a certain problem. Therefore, the action problem is described as follows:

Currently, VI does not know how to handle possible carbon pricing in the future and has no tools to help them monetize CO_2 emissions and make decisions regarding sustainability, which makes it challenging to incorporate sustainability into VI's operations.

2.2.1 Current state (Reality)

The reality signifies the current situation or state. In the case of the issue at hand, the reality of this challenge is that VI lacks a clear strategy to address the uncertainty surrounding carbon pricing, and they lack the necessary tools or methods to navigate this complexity. Furthermore, VI has not quantified or monetized the value associated with CO_2e emissions. However, it is valuable for VI to gain a monetized understanding of these emissions. Such knowledge can be key in addressing the growing demands of their customers, who inquire about the cost associated with reducing a specific amount of CO_2 emissions, such as the cost of reducing one ton of CO_2 emissions.

2.2.2 Desired state (Norm)

The norm describes the desired situation. The norm is to effectively manage uncertainties associated with carbon pricing. The objective is to establish a systematic approach for incorporating carbon pricing into business cases, enabling informed decision-making based on this information. This entails developing a methodology for calculating carbon prices and assessing discounted investments. Of particular significance for VI is the examination of variables that remain uncertain in the future, such as evolving legislation and fluctuating carbon pricing. This is crucial because the majority of projects currently being sold typically commence within an average span of 2 to 3 years. Thus it is valuable to know what laws, regulations, and prices there are in the future.

2.3 Elucidation of the problem cluster

This section discusses the problem cluster in more detail and we also derive the core problem in this section. The core problem is derived from the action problem. The core problem helps to get VI to the desired state as described in Section 2.2.2.

First, we discuss the problems that directly influence the action problem and after this, we discuss the different core problems. The action problem is directly influenced by numerous factors including:

- VI finds it difficult to "sell" sustainability (2) because they lack insight into what customers are willing to invest in it and the potential additional expenses associated with reducing carbon emissions;
- VI's customers are not engaged enough to become sustainable (3);
- The impact of a sustainable initiative is not clear (4);
- The definition of sustainability is not aligned for all individuals at VI (5).

These four problems are all caused by different core problems and these were all evaluated to reach the chosen core problem. For some core problems, VI was already working on, like training people regarding sustainability (13) and getting insights into the emissions during the downstream phase (15), as they started to measure the emission levels and energy usage more often. For certain other core problems, the company is not ready, or too much work still needs to be done and data needs to be gathered, including:

- No business case yet regarding sustainability (7);
- Suppliers do not provide data (14).

Additionally, some core problems are difficult and time-consuming to influence directly as VI like having a world standard on how to calculate a Life Cycle Assessment (LCA) (10) and the fact that people see sustainability as a cost-plus instead of a value-up (8). For the latter, a training that VI is providing contributes to the change of people's mindsets and is one of the most important steps to create awareness and increase the knowledge of the employees. The other possible core problems that are suitable for being the core problem of this master thesis, include:

- The value proposition of sustainability is unclear (6);
- The willingness to pay for sustainability of customers is unknown (9);
- It is unknown how VI should handle the uncertain future price of carbon emissions (12)

The last problem was chosen as the core problem due to the fact that a large impact can be made, VI has all the resources available to start this research, and it can help VI to start to include carbon emissions in business cases in financial terms. This core problem may become more relevant in the future as the legislative landscape is changing and plans for implementing a carbon pricing system are rising across the world (IMF & OECD, 2021; World Bank, 2021). Customers may abandon VI in the future if VI is not ready for this change while customers start asking for more sustainable products in the upcoming years. Therefore, it is relevant to research what the (internal) price of carbon should be and how different price scenarios should be handled by VI. So the core problem is:

It is unknown how VI should handle the uncertain future price of carbon emissions (12).

2.4 Research scope

This section discusses the scope of this research, which can be divided into different areas, namely the definition of sustainability, legislative environment, and carbon price development.

We decided to limit the scope of sustainability to the environmental element only and within these elements focussing on carbon emissions only and leaving out the other elements and interpretations of sustainability. These other elements are also known as the three pillars of sustainability: economic, environmental, and social also known as profits, planet, and people (Mollenkamp, 2023). Within the environmental pillar, the scope of carbon emissions is chosen due to the maturity of the topic as well as the fact that LCAs are widely used to measure the impact of a product, which is done in CO_2 emissions (Stucki, et al., 2021; Shi & Yin, 2021).

Secondly, we limit the scope with regard to the legislative environment as laws and regulations change in different parts of the world affecting the carbon pricing policy. This research focuses on European laws, and in particular Dutch laws and regulations as the headquarters of VI is situated in Veghel, the Netherlands (Vanderlande, 2023b).

To narrow the research down more we created a puzzle to visualise the problem in Figure 6. This puzzle shows the four elements that contribute and should be researched in order to decarbonize. We scope this due to the fact that researching all four elements would result in a thesis that is too broad, however, we do want to highlight that researching multiple areas is necessary in the context of decarbonization. We also visualized this because different individuals see different challenges when it comes to carbon emissions. The four angles in the puzzle pieces that should be solved are; 1) How many CO_2 emissions do we, as VI, produce? 2) What part of the CO_2 price will be included in the price for customers? 3) What will the price per ton CO_2 be? 4) What is the value proposition and Willingness-To-Pay (WTP) of sustainability? The area this thesis focusses on is shown in orange and concerns the price per ton of CO_2. For VI it is valuable to create an insight into how this price will develop and what carbon pricing will mean for their decision-making. The other three questions do serve as a foundation for VI to become more sustainable as a company and should be researched as well. However, due to the aforementioned limitations and arguments, and the data maturity of VI, they are not chosen in this thesis.

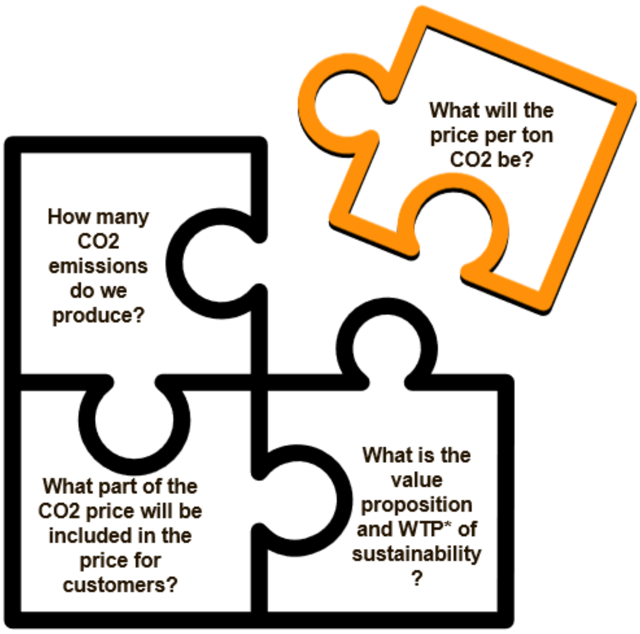

Figure 6: Visualised part of the scope showing the overview of key elements in achieving decarbonization. The focus area of this research is displayed in orange.

2.5 Research design

Now that the scope, core problem, and context are clear we dive into the research design. This section formulates the research design, which is derived from the DSRM. Additionally, the goal of the research and the corresponding research questions are formulated in this section, which help guide the research.

2.5.1 Research goal and deliverables

The second step of the DSRM is to define the objective of a solution. In this thesis, the overarching objective is:

To equip VI with valuable financial insights and an overview of cash flows to inform their business strategies and decision-making processes for product investments in response to varying carbon pricing scenarios.

The rationale behind this research goal is rooted in the growing recognition of the negative impacts of carbon emissions on the environment, economy, and society as well as the changing legislative landscape as described in Chapter 1. There is a need for accurate and reliable methods to quantify and mitigate carbon emissions is becoming increasingly pressing. In this context, the following deliverables are developed 1) forecasts of the possible carbon price paths, and 2) a Discounted Cash Flow (DCF) analysis tool that helps to make investment trade-offs using carbon pricing for VI under different policy scenarios.

Overall, the research goal of this thesis represents a significant contribution to the field of environmental accounting and management, as well as to the broader agenda of sustainable development. By developing a robust and user-friendly DCF analysis tool that can quantify the financial implications of carbon emissions, this research can inform and support more informed and responsible decision-making, thereby contributing to the transition toward a low-carbon and resilient future.

2.5.2 Main research question

To reach the research goal stated in Section 2.5.1 a main research question has been constructed:

> *How can VI incorporate carbon pricing scenarios into their decision-making process for product investments?*

This question is directly related to the research goals outlined in Section 2.5.1, as it aims to address the financial and strategic implications of carbon pricing policies for VI. Specifically, it seeks to investigate the different scenarios of carbon pricing policies and the effect they have on decision-making. By addressing this research question, this thesis aims to generate valuable insights and recommendations for VI regarding policy scenarios and to contribute to the wider discourse on sustainable development.

2.5.3 Research process

The research is structured using the DSRM approach, which is explained in Section 1.4. The first two phases, which are identifying the problem and defining objectives of a solution, of the DSRM approach are already executed in Section 2.1 until Section 2.5. In this section, we elaborate on steps 3 to 6, ‘Design & Development’, ‘Demonstration’, ‘Evaluation’, and ‘Communication’. These four steps of the DSRM are structured into six phases, which are displayed in Figure 7. The first four phases in Figure 7 are related to the ‘Design and Development’ step in the DSRM and create the artifact, which is the DCF tool, together. The ‘Demonstration’ step matches the fifth phase of using a case. Then the sixth step is the ‘Evaluation’ step in the DSRM after which the artifact is evaluated using an expert panel. Then the research is communicated and this rounds up the entire DSRM approach.

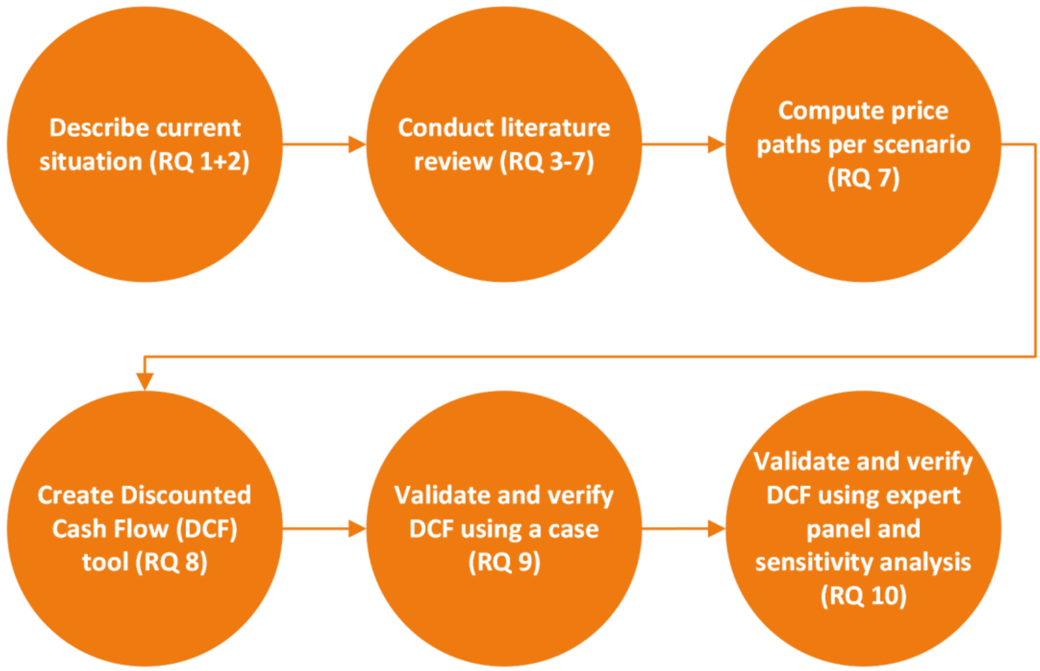

Figure 7: Visualisation of the six steps of the research process and sub-questions answered per step.

2.5.4 Sub-questions

This section discusses the sub-questions using headers, which are coherent with the research process as visualized in Figure 7. The sub-questions all include the motivation and research method.

Describe current situation

The current situation describes where VI and its customers are regarding decarbonization and (internal) carbon pricing. The first sub-question concerns how VI currently handles sustainability and carbon pricing.

1. **Sub-question**: How is VI currently handling decarbonization and carbon pricing in their product investment decision-making?
   Research method: Desk research and unstructured, open interviews
   Motivation: First, it is important to have more information about the current situation and goal of VI regarding carbon emissions and the challenges that VI is running into regarding those. Knowing where they want to be in 2030 and 2050 is important in giving context to this research. We focus on how VI currently makes product investment decisions and how sustainability is being implemented in the decision-making process. Together, this provides a clear overview of where VI currently stands with regard to sustainability and carbon pricing.

The second sub-question concerns the key customers of VI and how they include carbon pricing in their business operations. Therefore, the second research question arises:

2. **Sub-question**: How do key customers of VI incorporate internal carbon pricing into their business operations?
   Research method**:** Desk research
   Motivation: Knowing where customers of VI are regarding the use of an internal carbon price is important to provide a context to the business operations and maturity of the market. Desk research is used as the only method as interviews with key customers could nog be conducted for this thesis.

Conduct literature review

This step involves conducting a literature review of the relevant literature on carbon legislation, carbon pricing, price forecasting, and practices influencing the price of CO_2. This includes identifying the key theories, concepts, models, and empirical findings that inform the development and validation of the proposed model or tool.

3. **Sub-question**: How are carbon pricing methods utilized as a policy instrument for mitigating greenhouse gas emissions and promoting sustainable development?
   Research method**:** Literature review
   Motivation: The goal of this question is to explain which carbon pricing methods exist as a policy instrument and which carbon pricing policies there are in the Netherlands.

4. **Sub-question**: How are the current and anticipated laws and regulations in the Netherlands shaping the landscape of CO_2 emissions and their mitigation?
   Research method: Literature review
   Motivation: The goal of this question is to get familiar with the different laws and legislations regarding CO_2 emissions, both expected and already in practice in the Netherlands. This provides an important background on how VI and its current way of doing business will be impacted. These legislations can also affect the price of CO_2 and therefore, it is important to get this question answered.

5. **Sub-question**: What are the key factors influencing the CO_2 price on the carbon market?
   Research method: Literature review
   Motivation: The aim of this sub-question is to explore which factors influence the carbon price as often multiple factors influence a price next to its historical price. The answer to this research question provides a broader context into which elements influence the price of carbon and are thus important to track for VI as well.

6. **Sub-question**: How do various forecasting methods demonstrate advantages and disadvantages when used for forecasting the EU ETS carbon price?
   Research method: Literature review
   Motivation: The accurate forecast of carbon prices is crucial for effective decision-making and market participation within the EU Emissions Trading System (EU ETS). However, the diverse range of forecasting methods available presents a challenge in determining their relative strengths and weaknesses. This question explores and compares various forecasting methods used to forecast the EU ETS carbon price, examining their advantages and disadvantages. By identifying the most suitable forecasting approaches, VI can make informed decisions to navigate the dynamic landscape of carbon pricing and promote sustainable practices. The method that is chosen is used to forecast the EU ETS price and create a price path, which is used in the DCF. We also compare the chosen method to other methods to show the impact of the decision made for a forecasting model.

7. **Sub-question**: How do different policy scenarios impact the expected price paths of carbon?
   Research method: Literature review
   Motivation: The future trajectory of carbon prices is highly dependent on the policy scenarios implemented to address climate change. Understanding how different policy scenarios influence the expected price paths of carbon is crucial for VI in developing robust strategies and making informed decisions. The aim of this thesis is to investigate the impact of those different price paths on product investment decisions. For the different scenarios that are

identified a price path is determined with a time horizon until 2050. The following four policy scenarios are used in this thesis:

1. No carbon price
2. Tax-based carbon price
3. Market-based carbon price
4. Combination of tax and market-based carbon price

Create Discounted Cash Flow (DCF) tool

We create a DCF tool as it is important to look at the cash flows over the entire lifespan of a product and therefore discounting the future cash flows is valuable. The CDCF tool enables VI to do so and thus this method helps to create an insight into what the impact is of a certain carbon price path on product investment decisions. Such a cash flow also includes the investment cost, which may be different for a sustainable and less sustainable option. This method helps with decision-making as it provides insights into the cash flow and Net Present Value (NPV) over the total lifetime. As different scenarios, and thus price paths, influence the NPV it is valuable to see what their influence is on the NPV and therefore the following sub-question is formulated below.

8. **Sub-question**: How does an expected carbon price path influence the Net Present Value (NPV) of a product?
   <u>Research method</u>**:** Discounted Cash Flow (DCF)
   <u>Motivation</u>**:** The expected carbon price path has an influence on the NPV of a product, which is the output of a Discounted Cash Flow (DCF) analysis. Determining the tipping point at which a certain alternative becomes favourable is crucial in investment decision-making. This research investigates how the expected carbon price path impacts the NPV of a product, enabling a deeper understanding of the financial implications of carbon pricing and facilitating informed decision-making.

Validation and verification DCF using a case and expert panel

As a last step of the research, the model that was created is validated and verified. The validation proves that the outcomes are true and based on strong (scientific) evidence, while the verification proves that the method of the research has been used in the correct way and that it is suitable for the research topic. This step involves testing and validating the accuracy, reliability, and usability of the developed model or tool. This is done using a case, sensitivity analysis, and an expert panel. This includes verifying the assumptions, limitations, and uncertainties of the model or tool, and assessing its performance and robustness in different contexts. The case is used to test the created DCF and to see how it should be applied in practice. The case concerns the crossmember in the Twin Belt design decision. Furthermore, for this product, the carbon emissions also need to be mapped using an LCA. In the case of two different product development trajectories, the goal here is to use the tool to make a trade-off to decide which trajectory should be chosen. Lastly, an expert panel is conducted to check the usability of the DCF. The expert panel is conducted using a multidisciplinary team.

9. **Sub-question**: How will different carbon pricing scenarios influence the investment decision-making for VI and its customers based on the changing Net Present Value (NPV) of a product?
   <u>Research method</u>: Case
   <u>Motivation</u>: The decision that is made may depend on the (absence of) knowledge regarding the expected policy and thus carbon price path. Using the DCF created before, all carbon price policies can be calculated for a product creating the NPV under a certain policy. If there is no information the weighted average can be used. Using a case the created method can be tested, verified, and validated while doing a comparative analysis of different investment alternatives. The aim of this research is to create a generalizable method and therefore, a case helps to

achieve this and see where the challenges or difficulties of the method lie. This case should also help VI in their decision-making process of the ongoing case and provide insights into what to decide under different carbon pricing policies.

10. **Sub-question**: How does the sensitivity of the discount rate in the Discounted Cash Flow (DCF) analysis affect the decision-making?
Research method: Sensitivity analysis
Motivation**:** It is important to assess the impact of changing just one variable at a time on the decision-making. We conduct this analysis on the discount rate. This helps with seeing how this variable influences the outcome and thus the decision-making of VI.

2.6 Scientific relevance

Research in the field of carbon pricing and business is limited. Literature concerning carbon pricing mostly concerns forecasting of the ETS market prices, however, the implication this has on business and business decisions are not researched yet. Therefore, this section summarizes the scientific relevance of this thesis.

Research and insights are becoming more valuable as managing sustainability is one of the main challenges humanity is currently facing (Compernolle, Kort, & Thijssen, 2022). Much research is currently being conducted in the field of sustainability, however, not much research exists regarding the impact of legislation on carbon prices and business cases for more sustainable products. There is however, research regarding the impact that legislation has on total carbon dioxide emission and trade-related activities (Eskander & Fankhause, 2023; The Sustainanable Finance Platform, 2022; Green, 2021).

Additionally, some research is also conducted on EU ETS price forecasting algorithms and methods, however, there are only a few scenario-based price forecasts and none that combine the different policy uncertainties of either having a carbon tax, ETS market, or a combination of the two. Therefore, this research contributes to the knowledge gap existing in the literature on how companies can handle this uncertainty of carbon pricing in the future. Moreover, this research summarizes factors that have been researched that influence CO_2 price significantly, which has not been done before.

Another scientific contribution of this thesis lies in the creation of a DCF tool in which carbon pricing is included. The DCF method is a well-known method in finance, however, carbon pricing has not been included in a DCF so far. Thus we combine these two concepts is an addition to the current field of science. This thesis aims to create a generalizable method that can be used to monetize carbon emissions and make investment trade-offs. The DCF helps with providing an insight into the cost of carbon of a product and its alternatives. This information can then be used by key account managers and sales managers in companies to explain what the value of low-carbon alternatives is.

Lastly, there is no decision-making tool yet that helps companies handle the uncertainty in carbon pricing policies. The combination of a DCF, price forecast of EU ETS, and different policy scenarios is new and helps with decision-making. Creating more insights is even more important and relevant as the legislative landscape is changing around the world, including the rise of carbon pricing systems (IMF & OECD, 2021). It is valuable for a company to be ready for this change and have insights into what this will mean for their (day-to-day) business and possibly even their strategic decisions. Moreover, a shift in customer demand can be seen toward more sustainable and low-carbon alternatives. Assuring that VI is ready for this rising demand may become crucial to the survival of the company and maintaining its competitive market-leading position.

3 Current situation

This chapter is dedicated to describing the current situation of VI and its customers regarding carbon footprint reduction goals and (internal) carbon pricing and the limitations and obstacles that are faced. Section 3.1 examines the current product investment decisions as made by VI and the role of sustainability in these decisions. In Section 3.2, we delve into VI's mission and vision regarding the carbon footprint of VI and its key accounts. The objective of this chapter is to assess where VI is in its sustainability journey, where different customers of VI are, and whether customers already use carbon pricing internally.

3.1 Current product investment decision-making at VI

In order to assist VI in enhancing its product investment decision-making process and incorporating sustainability and carbon emissions considerations, it is crucial to understand the company's current approach to comparable decisions. This subsection aims to shed light on VI's existing framework for making product investment decisions.

3.1.1 Business case for investment alternatives

VI currently relies on business cases for product investment decisions to consider alternatives. These business cases include various factors like financial aspects, lead times, market demand, behaviour, growth, operational and functional requirements, and technological advancements. The product manager is responsible for making the decision. The primary tool for financial analysis is an Excel template, which calculates the NPV and payback period of investments. VI typically targets a payback period of 2 to 3 years, considering its time horizon and future uncertainties. Interestingly, both VI and their customers tend to focus on capital expenditures over operational expenditures due to their focus on short to midterm results and the risks associated with raising capital.

3.1.2 Limitations of the Excel business case template

The Excel business case template is predominantly used in larger projects, as it takes a considerable amount of time to fill it in. Consequently, smaller projects and investments often lack the usage of this tool. Sustainability is included in the template using a scale from 1 to 10 on which the product manager can subjectively rate the importance of each factor based on the frequency of 'Yes' responses. The scoring is based on the opinion of the product manager and the wishes of the customer. The following nine areas are scored with a 'Yes' or 'No' and result in a value from 0 to 10:

- Improved durability/repairability;
- Increased use of sustainable resources;
- Reduction of consumables/Energy;
- Reduction of raw materials required;
- Increased suitability for disassembly;
- Design for forward-compatible interfacing;
- Remove all/several registered materials from product;
- Sustainable Branding value;
- Reduced logistics footprint.

3.1.3 Challenges in integrating sustainability

While VI acknowledges the importance of sustainability and carbon emission reduction, the current extent to which these considerations are integrated into their product investment decision-making process is only limited and project-specific. The degree of emphasis on sustainability in the decision-making process largely depends on the individuals involved in making the decision. For example, when a team comprises of individuals who are intrinsically motivated to incorporate sustainability, the inclusion of sustainability aspects becomes more explicit compared to other cases. Additionally, in general, there is a lack of a systematic approach or tooling for integrating sustainability into the decision-making process (Russo & Fouts, 1997; Cherepovitsyn, Tsvetkova, & Komendantova, 2020). VI also observes this as they are trying to incorporate sustainability in the business. This absence of guidance leaves individuals feeling uncertain about how to incorporate sustainability effectively, particularly when faced with other critical factors such as the cost-competitive environment that VI is in. VI's employees state that part of the challenge arises from the fact that sustainability is still a broad and relatively new concept, making it challenging for individuals to translate it into actionable steps, especially in the absence of tools within the company. Additionally, only a limited number of customers are willing to pay a premium for more sustainable products. This poses a dilemma for VI on how to make sustainable product investments economically viable.

3.1.4 Conclusion

In conclusion, VI currently lacks a standardized method for making product investment decisions, regardless of project size, including considerations of sustainability. Therefore, there is significant value in creating an approach on how to make trade-offs between different products and to include the monetized element of sustainability. This thesis seeks to develop a user-friendly method to use for smaller investment decisions as well as larger ones, which also quantifies sustainability into monetary units (Euros) since financial considerations play a crucial role in product decision-making. Representing sustainability in the same unit facilitates informed decision-making by aligning it with other financial aspects.

3.2 Carbon footprint and sustainability goals of VI

In this section, we discuss the carbon footprint, mission, action, carbon pricing, and goals of VI. We start by providing an indication of the carbon emission levels of VI. Hereafter, VI's scope, action, and carbon pricing for VI and its customers.

3.2.1 VI's and carbon footprint

Firstly, it is key to have a clear definition of carbon footprint. VI also defines carbon footprint in an online environment called Vikipedia. The following definition is found in internal documentation of the carbon footprint:

"A carbon footprint is the measure of an activity, expressed in the total amount of greenhouse gases (GHGs) it emits – directly or indirectly. There are many GHGs, so we use the carbon dioxide equivalent (CO_2e*) as the measure of the global warming potential. Global warming potential (GWP) is the heat absorbed by any greenhouse gas in the atmosphere, as a multiple of the heat that would be absorbed by the same mass of carbon dioxide (*CO_2*). For example, the GWP of methane is 21 times that of* CO_2 *therefore, 1 kg of methane is equals to 21 kg* CO_2*e."*

In this thesis, we align the definition of carbon footprint with the one described earlier for VI. The carbon footprint of VI's solutions is computed using an LCA, which systematically calculates the environmental impacts associated with every phase of a product, process, or service's lifecycle (EPA, 2012). An LCA assesses the overall GHG emissions of a material handling solution, from the mining of resources to producing, transporting, using, maintaining, and removing the product.

Furthermore, we share the available data on carbon emission at VI. In 2022 the total number of tons of CO_2 emitted on ISO 50001 certified sites equaled 4071 tons. (Veghel, London, Birmingham, Mönchengladbach, Siegen (Vanderlande, 2022). However, this number does not include scope 3, which is discussed in Section 3.2.2.

3.2.2 VI's scope

VI emits CO_2e when using fossil sources i.e., electricity, heating, and transportation. These emissions also extend into VI's supply chain, encompassing their customers' facilities. VI acknowledges the need to address these emissions and has integrated decarbonization strategies and emission compensation efforts into the scope of their actions.

Figure 8 shows a simple display of the value chain and three different scopes as designed by VI, which is also in line with the three scopes in the literature. This thesis considers emissions from all three scopes. The three scopes to categorize carbon emission over the whole supply chain are:

- Scope 1 — This covers the emissions that a company makes directly, for example, while running its boilers and vehicles.
- Scope 2 — These are indirect emissions, produced when the electricity or energy a company buys for heating and cooling buildings is being produced on its behalf.
- Scope 3 — Emissions-wise, Scope 3 is nearly always the most significant category (90-97%) based on internal documentation within VI. In this category are all of the emissions that the company is indirectly responsible for, up and down its value chain, for example when buying products from its suppliers and from its own products when customers use them.

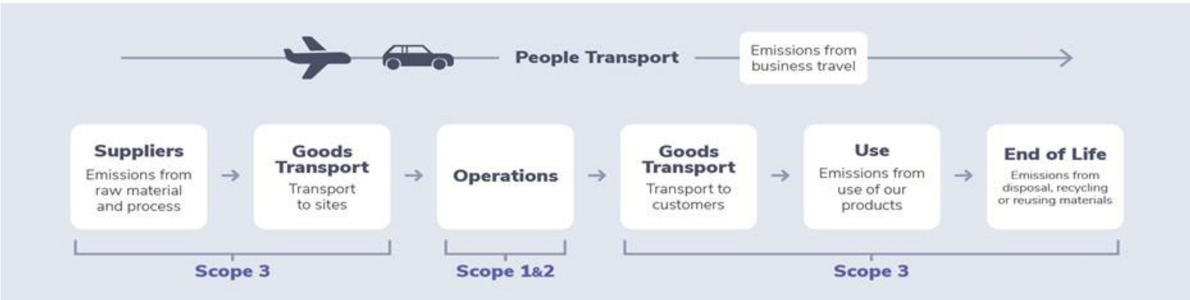

Figure 8: Three different scopes of carbon emissions as also seen in literature (Source: From internal documentation at Vikipedia within VI).

3.2.3 Carbon pricing for VI and its key accounts

Diverse approaches to carbon pricing are observed among companies, with some already incorporating an internal carbon price while others remain unaware of its existence. This section aims to summarize the findings from the desk research regarding whether VI's customers are currently utilizing internal carbon pricing in their decision-making processes.

Based on internal documentation and unstructured interviews it becomes clear that VI does not have an internal carbon pricing system in place. However, due to their energy-intensive products and heavy reliance on commodities like steel and aluminium, internal carbon pricing may become crucial, as their emissions affect their prices due to existing carbon taxes and the EU ETS system. With the expected Carbon Border Adjustment Mechanism (CBAM) in 2026 the business of VI may even be influenced more by carbon tax on imported goods. The concept of CBAM is explained in Section 4.2.3. Additionally, a possible future scenario may be that the EU ETS and carbon tax are extended to the entire industry making it even more important for VI to look at the impact of this price and their carbon emissions. To find the following information desk research is conducted using the following search strings:

1. “company name” AND “internal carbon (price OR pricing)
2. “company name” AND “shadow” AND “(cost OR price OR pricing)” AND “carbon”)
3. “company name” AND “true (price OR pricing)”
4. “company name” AND “marginal abatement cost”
5. “company name” AND “emission (cost OR price)”

These different search strings provided information regarding companies and internal carbon prices, which are summarized in Table 32 in Appendix A.0. In the table, the column that summarizes whether a company uses carbon pricing can be answered with yes or no, however, when the value inside the column is marked as N.A., the desk research question regarding the presence or absence of a carbon price cannot be answered with a yes or no due to a lack of information. This can also mean that when going through the sustainability report of the company no information could be found, which may imply that there is no carbon price in place at all. However, it may be the case that there is a carbon price internally but not externally, and thus N.A. is answered instead of no. If no is answered this means that sources are found in which it clearly states that the company does not use a carbon price. For the internal carbon price column it sometimes occurs that the carbon price itself is not stated or is confidential, this is then also mentioned.

We found that most of VI’s customers do not use a carbon price yet or have no information available on whether they use it or not. There are only a few customers that already use an internal carbon price, including Ahold Delhaize, Nike, and Delta. Only Ahold published the actual internal carbon price that they use which is 150 Euros per ton of CO_2. This is a valuable insight for Vanderlande as Ahold Delhaize actually values carbon emissions.

3.3 Conclusion

In conclusion, Chapter 3 provides a comprehensive overview of VI's carbon footprint, sustainability goals, and the current state of carbon pricing within the company. VI, together with its key customers, is actively committed to reducing carbon emissions and prioritizing sustainability as a central mission for the coming years. While some companies have already embraced carbon pricing mechanisms, offering valuable insights for potential future policies within VI, the majority have yet to integrate internal carbon pricing into their operation (RQ2). Consequently, no definitive trends or lessons can be learned from these early stages. The only key accounts that do use internal carbon prices are Ahold Delhaize, Nike, and Delta.

We find that VI presently lacks a standardized framework for decision-making across projects of varying sizes and therefore does not have a method to handle decarbonization or carbon pricing (RQ1). Notably, large projects employ a business case Excel template that incorporates a subjectively scored sustainability element. However, the integration of sustainability remains limited and often project-specific, contingent on the motivation of the decision-making team. This absence of a systematic approach or tool for objectively monetizing sustainability creates a lack of guidance.

The subsequent chapters of this thesis delve deeper into the calculation of an appropriate carbon price under various policy scenarios and explore the implications of such pricing on the business case and decision-making process. These discussions aim to provide comprehensive guidance for VI and its key customers in navigating the complexities of carbon pricing as they progress toward a sustainable future.

4 Literature review

The literature review presented in this chapter critically examines the existing body of knowledge. Section 4.1 explains the concept of CO_2e emissions. Hereafter, Section 4.2 shows the laws and regulations that are in place or expected regarding carbon emissions and the different carbon pricing systems that exist. Then, Section 4.3 summarizes other methods to monetize carbon emissions next to carbon pricing systems. Section 4.4 discusses different methods to forecast the price of the EU ETS and shows the performance of different methods. Lastly, we explain the concepts of discounted cash flow analysis and net present value in Section 4.5 and Life Cycle Assessments in Section 4.6. The review seeks to provide a comprehensive understanding of these interconnected topics within the context of addressing the pressing challenges posed by climate change. By synthesizing and analysing relevant scholarly works and research studies, this literature review serves as a foundation for the subsequent chapters of this master thesis, contributing to the broader discourse on informing decision-making processes under different carbon pricing scenarios.

4.1 Carbon dioxide equivalent emission

Carbon emissions, particularly those from human activities, have been identified as a significant contributor to climate change (Intergovernmental Panel on Climate Change, 2018). As such, there has been increasing attention to the need to reduce carbon emissions and transition to a low-carbon economy (UNFCCC, 2015). Moreover, the term carbon dioxide equivalents, CO_2e, is also often used and allows the combining of the global warming impact of different greenhouse gases. The emission levels are converted into CO_2 equivalents. The conversion is based on the Global Warming Potential (GWP), for example, the emission of 1 kg of nitrous oxide equals 298 kg of CO_2 equivalents (CBS, n.d.). It is important to look at the concept of CO_2e in the context of carbon emissions. However, in the remainder of this thesis, we solely focus on and mention CO_2 emissions due to the lack of carbon and research data in the field of CO_2e. Several studies have also explored the relationship between carbon emissions and financial performance, with some finding a positive correlation between high carbon emissions and company profitability (Wang, Li, & Gao, 2014). Others also confirm that there is a negative relation between financial performance and carbon emissions reductions (Busch, Bassen, Lewandowski, & Sump, 2022; Delmas, Nairn-Birch, & Lim, 2015). The latter clearly highlights that there is a need for further policy intervention to pave the way for a low-carbon economy.

4.2 Laws and regulations regarding carbon emissions

Climate change is a rising topic on the political agenda resulting in legislation in different parts of the world. In this research, the focus lies on the Netherlands and the legislation that is in place there. This section provides insights into the legislation that is in place as well as expectations regarding new legislation in the Netherlands to reduce environmental impact. First, an overview of European legislation is given regarding environmental impact. The focus lies on the carbon pricing mechanisms in place and expected in the Netherlands.

4.2.1 General European and Dutch laws and regulations

This section summarizes some key laws that are in place in the Netherlands and the European Union concerning environmental impact.

1. **European Climate Law:** This law is a legal objective for the European Union Green Deal to reach climate neutrality by 2050 (European Commission, 2023c). The goal of the law is to ensure that all EU policies contribute to this goal and that all sectors of the economy and society play their part. The Netherlands has created a similar climate law that aims to create policies aimed at reducing greenhouse gas emissions step-by-step until a reduction of 95% or higher has been reached in 2050 (Overheid.nl, 2023). The first goal that should be reached under the European Green Deal is a CO_2 emission reduction of 55% by 2030. The Fit for 55 is part of the Green Deal and it contains measures that will come into place to reach this target and execute the climate law (Delgado-Téllez, Ferdinandusse, & Nerlich, 2022; Frijters, 2021).
2. **EU taxonomy:** The EU taxonomy is a European guideline that obligates financial instances to classify investments based on their effects on nature, the environment, and society. This system should make it easier for investors and companies to make more sustainable investments (Frijters, 2021). This should make the system more transparent as one can see which activities contribute to the EU's environmental goals, such as reducing greenhouse gas emissions and promoting resource efficiency.
3. **Energy Efficiency Directive:** This directive states that companies with more than 250 employees, or a minimum revenue of 50 million or more or a balance total of 43 million, should get an energy audit once every four years in which all energy streams are being mapped. Moreover, all energy-saving measures that earn themselves back within 5 years should be implemented for certain large companies (European Commission, n.d.).
4. **Reporting directives**: The landscape of financial and non-financial reporting is also changing in the European Union with the Sustainable Finance Disclosure Regulation (SFDR) and Non-Financial Reporting Directive (NFRD). The SFDR forces large investors to be transparent regarding their Environmental, Social, and Governance (ESG) information and achievements. The NFRD is changed to the Corporate Sustainability Reporting Directive (CSRD), which obligates large companies, with more than 250 employees, to report on sustainability in their whole value chain (scope 1, 2, and 3) in their annual report (Frijters, 2021; NBA, n.d.). It is created to provide more transparency regarding the sustainability achievements of an organization and also to evaluate the sustainability performance of companies (European Commission, 2023a). Large organizations that are already obligated to report non-financial information will have to report from the financial year 2024 onwards. For all large companies reporting starts from the financial year 2025, in 2026 for listed Small Medium Enterprise organizations, or from 2027 for a non-EU organization with more than EUR 150 million (NBA, n.d.). This law will mean that numerous organizations will need to think about sustainability and integrate it into all activities. The CSDR will also make it mandatory to have an audit of the sustainability information that they report (European Commission, 2023a). This affects around 50,000 companies in Europe and the next step is to expand this CSRD to SMEs (Frijters, 2021). These reporting directives can be seen as the first step in actually paying a price for the carbon emissions of a company. Moreover, companies need to collect the correct data to be able to report on sustainability, which may also be challenging even though it may provide valuable insights. To be able to comply with this new reporting directive companies need to use the European Sustainability Reporting Standards, which include multiple concepts as shown in Table 2 (EFRAG, n.d.).

Table 2: European Sustainability Reporting Standards divided into three categories (EFRAG, n.d.).

Environment	Social	Governance
Climate change	Own workforce	Governance, risk management, and internal control
Pollution	Workers in the value chain	Business conduct
Water and marine resources	Affected communities	
Biodiversity and ecosystems	Consumers and end-users	
Resource use and circular economy		

4.2.2 Carbon pricing

Other types of regulations that are arising around the world include the pricing of carbon emissions. In recent years, there has been a growing interest in the use of carbon pricing as a policy tool to incentivize the reduction of carbon emissions (Yang, Yang, & Li, 2023; EEB, 2021; Delgado-Téllez, Ferdinandusse, & Nerlich, 2022). Carbon pricing mechanisms such as carbon taxes and emissions trading systems aim to create a market-based incentive for emissions reductions by putting a price on carbon emissions (EEB, 2021; Pietzcker, Osorio, & Rodrigues, 2021). Different countries have different carbon pricing systems. The main reasoning behind carbon pricing is the '*the polluter pays*' principle, which makes sure that the companies that pollute the most need to pay the most as well. Moreover, pricing carbon can create financial incentives for polluters to reduce emissions. Internal carbon pricing can be used by businesses in decision-making as it provides forward guidance to carbon pricing, which is becoming increasingly warranted (Lewis, 2022). There are multiple types of carbon pricing. In this research two common ones are discussed, a carbon tax or a cap-and-trade system also known as an emission trading system. The two different systems are explained in Sections 4.2.2.1 and 4.2.2.2.

4.2.2.1 Emission Trading System (ETS)

The Emission Trading System (ETS) is a system in which the trading of emission rights takes place (European Commission, 2023b). Such a cap-and-trade system sets the total amount of emissions that can be released ('cap'). The following step is that a government issues a limited number of emission permits per year, which decreases over time. These permits are currently partially freely given away and another part is being auctioned. The main reason for giving permits away for free is due to the fact that the competitive position of companies should be maintained, instead of companies moving away towards an area in which they do not need to pay for their emissions. This is also known as carbon leakage, which is discussed in Section 4.2.3.

In Europe, such an ETS is in place for companies in aviation, electricity and heat generation, and energy-intensive industry sectors, like iron and steel (European Commission, 2023b). The current plan for the EU ETS is to expand the EU ETS to the shipping, road transport, and construction sectors (Delgado-Téllez, Ferdinandusse, & Nerlich, 2022; Frijters, 2021). For each ton of emission that is being released, the emitter must have a permit also known as an allowance. In this way, emitters that cannot reduce their emissions have to pay for extra permits from emitters that are able to reduce. In this system, the resulting CO_2 price depends on supply and demand for the permits (Morris, 2022). This system provides certainty about emission reductions as the number of emission permits is decreased until zero by 2040. However, due to the market that determines the price there is no certain fixed price (Haug, Ferk, & Santikarn, 2015). Research shows that there is a positive correlation between the ETS price and emission reduction (Lin & Jia, 2019).

The EU ETS used to have a strong CO_2 price from 2005 until 2009, however, due to an oversupply of carbon permits and the Great Recession the price dropped rapidly. Growth can be seen in the price of

CO_2 in Figure 9 as it reached 100 Euros per ton of CO_2 in February 2023 (Trading Economics, 2023). The EU ETS is currently on the 4th of May 2023, 88.18 Euros (Trading Economics, 2023). It is important to note that European CO_2 prices have a high level of volatility (Lewis, 2022). In case we would only correct for inflation from the current carbon price we would have a price of 223.09 Euros in 2050. Here we use and inflation percentage of 3.5% and the EU ETS carbon price on the 30th of June 2023 is used which was 93.67 Euros (Trading Economics, 2023; WorldData, 2023).

Figure 9: EU Carbon Permits price in Euros from April 2005 until April 2023 showing an increase over time (Trading Economics, 2023).

4.2.2.2 Carbon tax

A carbon tax is another method that exists which directly sets a price per ton of emissions. The change in emitters' behaviour in response to this carbon tax will influence the number of emission reductions that will be seen in practice (Morris, 2022). A carbon tax provides much certainty regarding the price due to the fact that the price per ton of pollution is fixed, however, it offers less certainty regarding the extent of emissions that is being reduced. The government sets the carbon tax rate, which is ideally at a level that matches the marginal social cost of emissions, or the external cost of damages that result from each unit of emission (Haug, Frerk, & Santikarn, 2015). Compared to a trading system a carbon tax is more conducive for investment and purchase decisions (Dumitru, Kölbl, & Ryszka, 2022).

The Netherlands also has a CO_2 tax system in place since the 1st of January 2021, which is regulated by the Dutch Emission Authority (Rijksoverheid, n.d.). Industrial companies with high CO_2 emissions and that also fall under the EU ETS need to pay this national CO_2 tax. In 2021 the CO_2 price in the Netherlands equalled 24.97 EUR (OECD, 2022). Currently, the CO_2 price is 41.75 EUR, an overview of the different carbon taxes in Europe can be seen in Figure 10. Note that these are carbon taxes and that the EU ETS applies as well to all countries within the EU. The tax does not have to be paid if the carbon tax price is smaller than the EU ETS price per ton CO_2. Only if the tax is higher than the EU ETS price, a tax needs to be paid which is determined by the difference between the set tax level and the EU ETS price (Rijksoverheid, n.d.). An example of the tariff calculation is when the carbon tax is 125 EUR/ton and the EU-ETS price is 80 EUR/ton, then the national level of the carbon tax is the difference between the two, so 45 EUR/ton. If the carbon tax is 80 EUR/ton and the EU-ETS price is 125 EUR/ton, then the national level of carbon tax is 0 EUR/ton.

The carbon tax is designed to encourage companies to reduce their carbon footprint and shift towards more sustainable practices. In the first phases of the law, companies get an exemption for part of their emission over which they do not need to pay tax, giving them time to adjust their processes. This exemption will reduce in size over the years (Rijksoverheid, n.d.). Lastly, the tariff of the carbon tax will increase linearly in the Netherlands over time until 127 Euros as determined by the Dutch government (NEA, 2020; Koelemeijer, Hout, & Daniëls, 2022). According to the Dutch Emissions Authority, this cap is currently based on having 75% certainty of reaching the reduction goal of 14.3 Mton in 2030. Price studies conclude that a carbon tax of 90-165 EUR/ton CO_2 is necessary to reach the climate goals in the industry (Koelemeijer, Hout, & Daniëls, 2022).

There is a limited number of papers discussing the impact of a carbon tax. Dumitru et al. (2022) use three scenarios in which there is 1) a carbon tax in the Netherlands, or 2) in EU+, or 3) in all major economies beyond Europe. It discusses the impact of a CO_2 tax on combustion on the macro and sector levels compared to the current policy approach (Dumitru, Kölbl, & Ryszka, 2022). This research also states that 95% of the CO_2 price estimates are between 10 EUR and 200 EUR per ton of CO_2. The research of Dumitru et al. (2022) decided to use a carbon tax of US $100 per ton of CO_2.

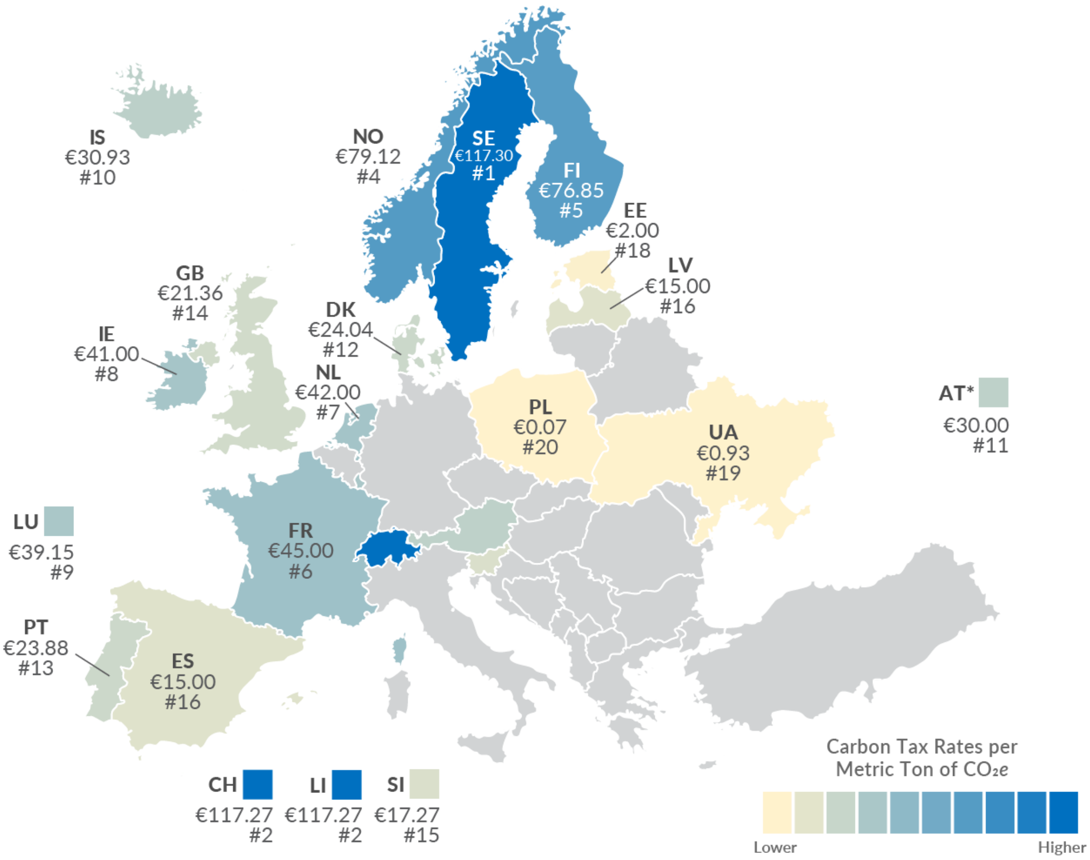

Figure 10: Different carbon taxes in Europe, rates per metric ton of CO_2e as of April 1, 2022 (Bray, 2022).

4.2.3 Carbon leakage and CBAM

Carbon leakage is the effect that regulation of emission in one country or sector has on the emissions in another country/sector, which are not subject to the same regulation (Barker & et al., 2007). It is the phenomenon in which companies relocate their production or operations to countries with lower environmental standards and less stringent carbon emission regulations, in order to avoid higher costs associated with complying with stricter regulations in their home country (Belloni, Kuik, & Mingarelli, 2022). This can result in an increase in carbon emissions globally, rather than the desired decrease.

To address this issue, the EU is implementing a Carbon Border Adjustment Mechanism (CBAM) regulation from 2026 onwards (European Parliament, 2023). CBAM is a proposed policy that would require importers of certain goods to pay a fee that is equal to the EU ETS price, which is provided in Section 4.2.2.1. The total price that should be paid is based on the amount of carbon emissions associated with the production of those goods at the production site multiplied by the EU ETS price which is per ton of CO_2. The goal of CBAM is to level the playing field for companies operating within the EU by creating a financial incentive for companies to reduce their carbon emissions (European Commission, 2023e). The price of these credits would be based on the cost of carbon allowances in the EU's Emissions Trading System. The CBAM will be implemented gradually, starting with a few sectors and eventually expanding to cover more goods.

Overall, the CBAM is a regulation that aims to reduce carbon leakage and encourage companies to reduce their carbon emissions. While it is still in its early stages, it has the potential to be a significant policy tool in the fight against climate change. This will mean that companies need to pay a significant additional cost pass-through from existing suppliers. Therefore, companies should already start to prepare and for example, investigate alternative product designs or suppliers.

4.3 Monetizing carbon

Next to legislation determining the price of CO_2 due to carbon taxes and trading systems, there are other methods to monetize carbon. These methods have different viewpoints on how to price carbon emissions compared to the previously discussed methods. Therefore, these other methods are discussed in this section to provide an overview of the different approaches that exist in the literature. The monetary value that these methods result in, so Euros per ton CO_2, is also provided in this section.

As stated above there exist other ways to account for the cost of carbon emissions. These are often based on the future costs that these emissions will have. A central estimate of the CO_2 price needed in 2030 to decarbonize by 2050 was set to 120 EUR per ton of CO_2 (IMF & OECD, 2021). Below the most important methods are considered and shortly explained:

1. **Social cost of carbon:** This cost is usually estimated as the NPV of climate change impacts of one additional ton of CO_2 emitted to the atmosphere today. It is the marginal global damage costs of carbon emissions (Watkiss, 2002; Backman, 2021). This method is also known as true pricing or true costing. This value is currently being estimated at around US $185 (Rennert, Errickson, & Prest, 2022). This is in line with research from the German Environmental Agency suggesting a price of 180 EUR (in 2016) (Matthey & Bünger, 2021). The price in this paper itself even rises to 205 EUR by 2030 and 240 EUR by 2050. Research from Kikstra et al. suggests that the carbon price per tCO_2 should be equal to US $3372 if all economic feedbacks are included (Kikstra, et al., 2021).
2. **Marginal abatement cost:** This is seen as a target-consistent approach to quantify CO_2 emissions. It provides monetary estimates for the GHG emissions based on the marginal abatement cost for achieving a given emissions reduction target, which means that it is the cost of abating the last metric ton of carbon dioxide needed to meet a particular emissions

target at least cost to society (RFF & NYSERDA, 2020). Actual numbers of the price of carbon dioxide that is connected to the marginal abatement costs are often related to the social cost of carbon.

3. **Internal carbon pricing**: Internal carbon pricing involves assigning a price to carbon emissions within a company or organization. A method that is used often is called shadow pricing, which is a hypothetical price for carbon emissions in order to internalize the cost of these emissions and to help with long-term business planning. By incorporating this price into decision-making processes, companies and policymakers can make more informed choices that take into account the full cost of their activities. The range for the shadow price of carbon is from $2-$893, however, often the price that is used is on the lower side of this range (United Nations, 2017).
   This price can be used to account for the costs associated with emissions and to incentivize reductions in emissions. Internal carbon pricing can be implemented through a carbon tax or through a cap-and-trade system, or by simply assigning a price to emissions that reflects their true cost. There are different kinds of studies that show how the internal carbon price should be set. A range that is seen more frequently is to have a carbon price between US $50-$100 by 2030 to be in line with the standards set in the Paris Agreement (Fan, Rehm, & Siccardo, 2021). However, the median internal carbon price is US $27 (Fan, Rehm, & Siccardo, 2021).

These are the most well-known concepts when it comes to monetizing carbon emissions, next to the carbon tax or ETS. Each method has its strengths and weaknesses, and the appropriate method will depend on the specific context and goals of the analysis.

4.4 Forecasting the price of EU ETS

This section provides literature on different forecasting methods for the EU ETS, which is used to create price paths for the carbon price until 2050. This price path can be used later on to analyze cash flows and include carbon prices. Section 4.4.1 gives an introduction to the data characteristics of the EU ETS market found in literature, and Section 4.4.2 provides an introduction to a widely known method, namely Geometric Brownian Motion (GBM), which is used as a benchmark. Moreover, other forecasting methods are shown which are used in literature to forecast the EU ETS market. The characteristics of these, their performance, and advantages and disadvantages are then summarized. Lastly, different factors influencing the EU ETS price are also summarized in Section 4.4.6.

4.4.1 Characteristics of the EU ETS market price

In literature, the EU ETS market prices have been described and analysed more often. To forecast the market prices it is important to know, which characteristics the historical data shows. These are summarized in this section, however, in Chapter 6 diagnostic tests are also conducted on some of these characteristics. The EU ETS price series shows the following features (Lin & Zhang, 2022):

- Nonlinear;
- Non-stationary, meaning that the price can move around without returning to a long-term level;
- Structural breaks or jumps due to for example policy adjustments;
- Heteroskedasticity, the variance is not constant over time.

4.4.2 General mathematical model

A mathematical model that is used often to describe the random movement of a financial asset's price over time is the stochastic process called Geometric Brownian Motion (GBM). The GBM is based on the Brownian motion model, which assumes that the logarithm of the price of an asset changes randomly over time, with the magnitude and direction of the change being proportional to the square root of time (Rickles, 2011). So, the more time passes, the greater the potential change in the asset's price. This model is frequently used to model stock prices, which often exhibit high volatility and frequent fluctuations. It can also be used to create sample paths. When sampling many paths and taking the average a long-term trend can be seen s the Brownian motion is canceled out. Brownian motion means that it undergoes random fluctuations with a constant variance over time as well as a constant drift, also known as trend (Reddy & Clinton, 2016). Some assumptions that are fundamental for a GBM model are (Sigman, 2006):

1. The stock prices are continuous in both time and value;
2. The continuously compounded return, which is the difference between prices of two consecutive days, for a stock is normally distributed;
3. The price follows a Markov process, so it is a random process and the future is independent of the past, given the present.
4. The price is expected to adhere to a deterministic drift in the long term but the price path itself moves randomly due to the Wiener process, which is a stochastic process;
5. The drift and volatility are assumed to be constant over time.

The formula of the stochastic differential equation following Brownian motion, also known as the Wiener process, is formulated as follows (Sigman, 2006):

$$S_t = S_0 \exp\left(\left(\mu - \frac{\sigma^2}{2}\right)t + \sigma * W_t\right) \tag{1}$$

where,

S_t	Price at time t
μ	Percentage drift (constant)
σ^2	Percentage variance (constant)
S_0	Initial value, which is >0
W_t	Wiener process or Brownian motion

The GBM can be used as a building block for more advanced econometric models but it can also be used as a benchmark model for testing the performance of more complex models and algorithms. It has not been applied to the EU ETS market in the literature. The assumptions of the GBM do not correspond to the highly volatile EU ETS market prices. Even though the EU ETS does not meet all these criteria based on findings from the literature, we do use the GBM as a benchmark model. Table 3 shows the advantages and disadvantages of GBM.

Table 3: Advantages and disadvantages of the Geometric Brownian Motion (GBM) approach.

Advantages	Disadvantages
Simplicity	Rigid assumptions that are often not in line with real-world situations, like constant volatility
Can capture trends, volatility, and serial correlation in data	Limited flexibility to capture complex relationships

We review more literature, which helps with choosing an appropriate method that matches the characteristics of the EU ETS. The method is chosen in Chapter 6 and then compared to the GBM.

There are numerous papers that review and compute price forecasting models for the EU ETS price. The rest of this section focusses on the models that exist to forecast the EU ETS price. The methods can be divided into different categories which can, and often do, overlap. Rudnik et al. (2022) clearly summarize different methods used to estimate the price of carbon and divide these methods into three categories:

- Forecast model using the econometric method;
- Forecast model based on artificial intelligence algorithms;
- Combined forecast model.

Another way to divide the models is by categorizing them into either time-series carbon price forecasting or multifactor carbon price forecasting (Zhang & Xia, 2022). This approach is, however, not used in this thesis to categorize them but Section 4.4.6 dives deeper into the multifactor approach.

4.4.3 Econometric method

Econometric models are used often to forecast the carbon price. The more modern techniques state that past behaviour, or historical prices, of a time series, is examined to tell something about its future behaviour. The more traditional approach searches for the effect of one or more variables on the forecast variable called explanatory variables (Xu & Wang, 2021). In this section, we show the two econometric methods, which are either traditional or modern.

4.4.3.1 Traditional econometric methods

More traditional econometric methods often involve the use of linear regression models, in which one assumes that the relationship between the dependent variable (i.e. the variable being forecasted) and the independent variables (i.e. the variables used to make the forecast) is linear. These methods often have strict assumptions, like normality and homoscedasticity, and they are often not able to account for nonlinear relationships or complex interactions between variables. As stated, traditional models are often linear models, like an autoregressive (AR) model or moving average (MA) models, or a mix of this ARMA model. However, the disadvantage of these models is that they are unable to represent most nonlinear dynamic patterns, including volatility clustering, asymmetry, and amplitude dependence (Kuan, 2002).

Table 4 shows the main advantages and disadvantages of traditional econometric methods.

Table 4: Advantages and disadvantages of the traditional econometric methods.

Advantages	**Disadvantages**
Well-established and widely used	Limited flexibility to model complex and dynamic systems
Simplicity	No complex relationships
Robustness to outliers and noisy data	Rigid assumptions that are often not in line with real-world situations

4.4.3.2 Modern econometric methods

Modern econometric methods have emerged to address some of the limitations of traditional methods. These methods include nonlinear regression models, time series analysis, panel data analysis, and machine learning techniques. The latter is discussed in Section 4.4.4. These methods are often more flexible and can capture complex relationships and interactions between variables. They can also handle non-stationary and non-normal data and can provide more accurate forecasts.

A deviation from the traditional ARMA model is the Autoregressive Integrated Moving Average (ARIMA) model. The benefit of this method is that it can model non-stationarity time series. It models the autoregressive and moving average behaviour of time series data. Traditionally an ARIMA model is an econometric model, however, hybrid alternatives already exist for this type of model (Xu & Wang, 2021). The advantage is that it uses less training data, however, the standard ARIMA model cannot capture complex nonlinear relationships (Rudnik, Hnydiuk-Stefan, Kucinska-Landwójtowicz, & Mach, 2022). This method uses historical prices only (Xu & Wang, 2021).

More recently numerous papers started to appear that show nonlinear time series models. However, these also have limitations, especially with regards to the computational time and risk of getting stuck in a local optimum. It is seen that for most nonlinear models the success of it depends on the data set to which it applies (Kuan, 2002).

Another popular nonlinear time series model is the Hamilton's Markov switching model, also known as the regime-switching model. The model uses different structures (equations) to characterize the time series behaviour in different regimes. The model allows switches between regimes to occur and thereby it captures more complex dynamic patterns, which could be useful for capturing changes in pricing behaviour or market dynamics in response to different carbon tax price scenarios (Rudnik, Hnydiuk-Stefan, Kucinska-Landwójtowicz, & Mach, 2022). This switching mechanism can be controlled by an unobservable state variable that follows a first-order Markov chain entailing that the current state depends on its immediate past state value. This model is suitable when describing correlated data that shows distinct dynamic patterns during different time periods. Markov switching models are mostly combined with other models like Auto Regressive or Vector Auto Regression models (Çanakoğlu, Adlyeke, & Ağrall, 2018).

Another alternative called structural changes is similar to Markov switching, however, the switches here occur only on occasion and exogenously while that of Markov switching can occur at random points in time (Kuan, 2002). This approach aligns with the heteroskedastic behaviour of the EU ETS price and non-constant trend.

The Markov switching model has proven to be valuable for the conditional mean. The next researched step was into conditional variance models. Here a widely used method is models based on the type Generalized Autoregressive Conditional Heteroscedasticity (GARCH), which estimates the volatility of carbon prices. A GARCH model uses historical prices only (Xu & Wang, 2021). GARCH models in themselves are often linear and thus have the disadvantage that they cannot describe nonlinear relationships. However, they can be extended and combined with, for example, Markov Switching to describe more complex behaviour and become nonlinear (Kuan, 2002; Zhang & Xia, 2022).

Moreover, multifractal models are used which forecast the long-term dependence and regime-switches (Rudnik, Hnydiuk-Stefan, Kucinska-Landwójtowicz, & Mach, 2022). Furthermore, other research developed a combination-MIDAS, mixed-data sampling, and regression model to perform real-time forecasts for the weekly carbon price, using high-frequency economic and energy data. Different variables were used to create a forecast and these were compared using the root mean squared errors (RMSE).

To summarize this section Table 5 is created comparing the advantages and disadvantages of modern econometric models. Per method there may be different advantages and disadvantages again, therefore, it is only done generally for modern econometric models.

Table 5: Advantages and disadvantages of the modern econometric methods.

Advantages	**Disadvantages**
Ability to handle nonlinear and non-stationarity interactions	Higher complexity
High forecasting accuracy	Much computational power needed
Robustness to outliers and noisy data	Risk of overfitting
	More challenging to interpret and explain

4.4.4 Artificial Intelligence (AI)

Another method to forecast the price of the EU ETS is based on Machine Learning (ML), such as neural networks (Rudnik, Hnydiuk-Stefan, Kucinska-Landwójtowicz, & Mach, 2022). Most machine learning approaches are able to deal with nonlinear systems. This is seen as a valuable method due to the nonlinearity of the carbon market, which often leads to difficulty in forecasting carbon prices (Zhang & Xia, 2022). However, a disadvantage is that a machine learning model often contains a large number of parameters, and it is prone to overfitting or poor convergence in the process of use (Xu & Wang, 2021). There are also some traditional machine learning methods that lack the ability to handle nonlinear and nonstationary carbon prices, which are affected by different factors (Zhang & Xia, 2022). In literature, there exist numerous ML methods already used to forecast ETS carbon price, which are summarized in the research by Rudnik et al. (2022) An example of this is Multi-Layer Perceptron (MLP) network model and Long-Short Term Memory (LSTM).

Generally speaking, machine learning methods can be perceived as more accurate and having a lower forecast error compared to traditional econometric methods. However, due to the complexity and black-box characteristics, it may be unnecessarily complex. The advantages and disadvantages are shown in Table 6.

Table 6: Advantages and disadvantages of Artificial Intelligence (AI) methods.

Advantages	**Disadvantages**
High flexibility and able to handle complex relationships	Prone to overfitting
High predictive accuracy	More challenging to interpret and explain

4.4.5 Combined forecasting model

Lastly, hybrid models can also forecast time series. These models combine econometric and AI models. Generally speaking, the disadvantage of these types of models is the computational complexity and the inconvenience to practical application (Xu & Wang, 2021). The advantage is the prediction accuracy which is higher than that of a single model. Numerous hybrid models exist in the literature, like a hybrid ARIMA and Least Squares Support Vector Machines model. It is key to note that there are lots of hybrid models that are used for ETS price determination (Xu & Wang, 2021; Rudnik, Hnydiuk-Stefan, Kucinska-Landwójtowicz, & Mach, 2022; Shahzad, Sengupta, Rao, & Cui, 2023). Another example is the ARMA-CNN-LSTM model, where ARMA, Convolutional Neural Network (CNN), and Long-Short Term Memory (LSTM) are combined. Table 9 shows the performance of these separate models and combined models. The advantages and disadvantages of combined methods themselves are shown in Table 7.

Table 7: Advantages and disadvantages of combined methods.

Advantages	**Disadvantages**
High forecasting accuracy	Much computational power and design effort needed
High flexibility and able to handle complex relationships	More challenging to interpret and explain
	Higher complexity

4.4.6 Factors influencing ETS price

From the previous sections, a division can be made that has models that are based on time-series data using price-only forecasting and methods that use variables that influence the carbon price under an ETS (Rudnik, Hnydiuk-Stefan, Kucinska-Landwójtowicz, & Mach, 2022). Models that use price-only data ignore important other factors, causing them to be less accurate in forecasting the carbon price. Both the supply and demand side that determines the EU ETS carbon price is influenced by different factors. This section explains what a factor model is and describes different factors that have been researched already.

Factor models are financial models that use factors, like technical, fundamental, macroeconomic or alternate, to define a price's risk and returns. Multi-factor models reveal which factors have the most impact on the price of an asset. In general, when constructing a factor model it is challenging to decide how many and which factors to include. Additionally, models are judged on historical numbers, which might not accurately predict future values. Multi-factor models also help explain the weight of the different factors used in the models, indicating which factor has more of an impact on the price of an asset (Chen J. , 2020). In the remainder of this section, we discuss the factors that have been researched already with regards to the ETS price.

The ETS price is pushed up when there are fewer industries, a higher annual decline factor, and a higher free allowance rate (Lin & Jia, 2019). This study focussed on the impact of carbon trading market design factors (industry coverage, annual decline factors, and free allowances) on the ETS price. Another important insight from this research is that the ETS prices are unpredictable when the mechanism is not fully determined yet, due to a high relationship between the ETS price and the mechanisms of ETS. For policymakers, this is an important insight as it shows that the market price can be adjusted by using these mechanisms. So, the impact of changing the carbon trading policies is larger on the CO_2 price, compared to changes in the industry itself.

Other influencing factors are researched, which include gas price, oil price, coal price, and DAX index as key determinants of CO_2 prices. Additionally, energy factors are the long-term influencing factors of CO_2 market fluctuations, and economic factors have a short-term impact on the CO_2 market (Li, Hui, & Lu-Tao, 2022). Additionally, weather factors have also been researched to see what their impact is on carbon prices (Rudnik, Hnydiuk-Stefan, Kucinska-Landwójtowicz, & Mach, 2022). In Table 9 the performance of research by Hao and Tian (2020) assessing different influence factors is shown. A research institute called DWS identified key drivers of European CO_2 prices. These include (Lewis, 2022):

- General economy;
- Policy;
- Fuel switching;
- Market Stability Reserve, which is a mechanism to curb oversupply on the ETS market;
- RePowerEU, which is a strategy to reduce the dependency on Russian fossil fuel imports;

- Industrial activity;
- Liquidity and volatility.

Recent research also showed the relationship between online news data and Google trends and the price of carbon (Zhang & Xia, 2022). The model created there using the LSTM algorithm to forecast carbon prices, shows that it outperforms traditional statistical forecasting models. An LSTM is in the domain of AI. Additionally, the carbon dioxide levels in the world may also be correlated to the carbon prices and these show seasonal behaviour (Global Monitoring Laboratory, 2023).

Concluding, there are numerous factors that have an impact on the price development of the EU ETS market. Next to those described in this section, even more research has been conducted describing the relation between additional factors and the ETS price. These insights are especially valuable if one wants to determine the impact a variable or multiple variables have on the stock price of ETS.

4.4.7 Requirements forecasting model, comparison of models, and performance measures

This section discusses which requirements need to be met for the forecasting model, the different models that exist are compared, and different performance measures. This information is used in Chapter 6 to choose an appropriate forecasting method when diagnostic tests are performed on the EU ETS time series.

To decide which method to use in this thesis to forecast EU ETS prices a comparison is made into what is needed for this thesis and what the advantages and disadvantages of the methods are. The requirements needed in the forecasting model for this thesis are:

- Global long-term price path is needed and there is no need for accurate day-to-day carbon prices and volatility;
- Data needed for the forecasting method should be available;
- The model should be well interpretable and explainable;
- There are different policy scenarios expected in the future including, no carbon pricing, EU ETS, carbon tax, or a combination of the two. These scenarios should be taken into account in the end in the final model. However, this is not necessary yet for the EU ETS price forecasting.
- Overfitting is not desired as there is a lot of uncertainty regarding the future of EU ETS prices and numerous factors that influence the price. Therefore, a complex model is not preferred.
- The method used should match with the data characteristics of the EU ETS carbon prices. To test this, different testing methods are used, which are shown in Chapter 6.

The characteristics of the discussed methods are summarized and provided in Table 8.

Table 8: Scoring of different forecasting methods along characteristics of complexity, accuracy, computation time, interpretability, non-stationarity, and autoregressive component, which helps later on in choosing an appropriate forecasting method.

Method	**Complexity**	**Accuracy**	**Computation time**	**Interpretability**	**Handles non-stationary data**	**Autoregressive component**
Traditional/Modern econometric methods	Low	Low	Low	High	Sometimes	Sometimes
ARIMA	Moderate	High	Medium	High	Yes	Yes
GARCH	Moderate	High	Medium	Medium	Yes	Yes
Machine learning	High	High	High	Low	Yes	Yes
Combined methods	High	High	High	Medium	Yes	Yes

The performance can be compared using different measures. The three most popular error measures are the root mean squared error (RMSE), the mean absolute error (MAE), and the mean absolute percentage error (MAPE) (Botchkarev, 2019):

1. The RMSE assesses the error magnitude and penalizes large errors by squaring them.
2. The MAE measures the average absolute error without under- or overprediction consideration, which is a measure to forecast accuracy.
3. The MAPE represents the sum of the individual absolute errors divided by the actual observed data.

The MAE, MAPE, and RMSE are used to measure the distance between the forecasted and actual value. So the smaller the values of those were the closer the forecasted value is to the actual value and the better the predictive performance of the model. It is important to note that these metrics are sensitive to outliers and from observing the EU ETS market it can be seen that there are sometimes outliers or extreme values due to various factors, like policy changes or market events. Moreover, a disadvantage of the RMSE and MAE is that it is more difficult to interpret when the magnitude of the response can vary. Relative errors, like relative RMSE (rRMSE) provide a better interpretation of how well the evaluated forecasting method performs compared to another method (Chen, Twycross, & Garibaldi, 2017). The four error performance metrics are given by:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Actual_i - Prediction_i)^2} \tag{2}$$

$$rRMSE\ (\%) = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(Actual_i - Prediction_i)^2}}{\overline{Actual}} * 100\% \tag{3}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|Actual_i - Prediction_i| \tag{4}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Actual_i - Prediction_i}{Actual_i}\right| \tag{5}$$

In this thesis when determining the performance of different methods the R-squared (R^2) value is also used. It is a well-known statistical measure of fit which indicates the proportion of variance of a response that is explained by predictors in a regression model (Fernando, 2023). An R-squared of 1 means that all observed variation can be explained by the predictors. The R-squared mostly ranges from 0 to 1, but it can also become negative. A negative R-squared is possible when the residual sum of squares, which is the numerator, is larger than the total sum of squares, which is in the denominator. This can especially be the case when one evaluates models separately on train and test data (Wei, 2022). The equation for R-squared is:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Actual_i - Prediction_i)^2}{\sum_{i=1}^{n}(Actual_i - \overline{Prediction})^2} \tag{6}$$

In time series forecasting it is a measure that compares the stationary part of the model to a simple mean model. However, some disadvantages of the R-squared are that it is sensitive to outliers and is often not a proper goodness of fit measure for time series models (Lendave, 2021). The R-squared gives an estimate of the relationship between movements of a dependent variable based on an independent variable's movements and checks how good of a fit it is (Fernando, 2023).

Table 9 gives the performance metrics as found in the literature of the different methods including econometric, AI, and hybrid models. Due to the extensive field of literature, the most relevant ones are chosen here based on the requirements for this thesis. Especially numerous combined methods exist, however, due to the fact that those are highly complex only a sub-selection is shown in Table 9. For all methods, only the non-relative error performance is provided due to the availability in literature. This makes it more challenging to compare models. We note that the performance of these models can vary depending on data availability, model assumptions, and the accuracy of the input variables. The best-performing model may also differ across different time horizons and market conditions. Therefore, it is advisable to compare and evaluate the performance of multiple models to assess their accuracy and reliability. It is important to note that some models are based on European Union Allowances (EUA) spots and others on the futures. The spot price of a commodity is the current cash cost of it for immediate purchase. The futures price locks in the cost that will be delivered at some point other than the present, often some months in the future (Nickolas, 2022).

Table 9: Performance of different forecasting methods on the EU ETS price in terms of MAPE, RMSE, and MAE.

AUTHOR (YEAR)	METHOD	MAPE	RMSE	MAE
TRADITIONAL/MODERN ECONOMETRIC METHODS				
(HE, YANG, JI, PAN, & ZOU, 2023)	ARMA	0.0413	1.2379	0.9122
(ZHU & WEI, 2013)	ARIMA	N.A.	0.2474	N.A.
(DUTTA, JALKH, BOURI, & DUTTA, 2020)	GARCH (1,1)	N.A.	9.21	2.17
MACHINE LEARNING				
(HE, YANG, JI, PAN, & ZOU, 2023)	MLP	0.0466	1.3771	1.0217
(HE, YANG, JI, PAN, & ZOU, 2023)	LSTM	0.1552	3.9867	3.3696
(HE, YANG, JI, PAN, & ZOU, 2023)	CNN	0.0621	1.7748	1.3474
(HAO & TIAN, 2020)	BPNN	2.57	0.91	N.A.
COMBINED METHODS				
(ZHU & WEI, 2013)	ARIMA-LSSVM2	N.A.	0.0311	N.A.
(HE, YANG, JI, PAN, & ZOU, 2023)	ARMA-CNN-LSTM	0.0400	1.2195	0.8837
(HAO & TIAN, 2020)	MOSCA-KELM model	2.17	0.73	N.A.
OTHERS				
(HE, YANG, JI, PAN, & ZOU, 2023)	Random walk	0.0415	1.2399	0.951
N.A.	GBM	N.A.	N.A.	N.A.
(HAO & TIAN, 2020)	Multiple influence factors	1.37	0.49	N.A.

4.5 Discounted Cash Flow analysis and Net Present Value (NPV)

Discounted cash flow and net present value are closely related concepts used in financial decision-making and investment evaluation. We use these concepts to provide information on the cash flows of different product investment alternatives. In the DCF tool, carbon prices can be used and included in business cases, which is the aim of this thesis. The output of the DCF analysis is multiple NPVs and these can be used to make investment decisions. Together, they provide a framework for assessing the profitability and value of projects, product investments, or business ventures. This section delves into their interconnectedness.

4.5.1 Discounted Cash Flow (DCF) analysis

A Discounted Cash Flow (DCF) is used to estimate the value of an investment based on its future cash flows. A DCF analysis helps to assess the viability of a project or investment by calculating the present value of expected future cash flows based on the concept of the time value for money, recognizing that a Euro received in the future is worth less than a Euro received today due to factors like inflation and the opportunity cost of capital. A DCF uses a discount rate (Hayes, 2021). A DCF is considered by companies when looking to buy assets and make investments for example in a more low-carbon product. The cost of purchase and the cost of its operations and maintenance are often separated on financial statements. The first term is also known as CAPEX, and the latter is part of operational expenditures (OPEX). Possible carbon prices should also be included in this calculation.

In making these computations a discount rate is often applied reflecting both the time value and uncertainty of future cash flows (Robicheck & Myers, 1966). This means that the investment should deliver more over the entire life cycle than the capital investment could otherwise have earned from bank interest on savings plus a safety margin. The discount rate changes per company. To give some general intuition, the higher the discount rate, the lower the initial investment needs to be in order to achieve the target yield. It is challenging to set the right discount rate even though there are standards that are often used (Attema, Brouwer, & Claxton, 2018; Mun, 2002). There are a few methods that can be used to determine the discount rate:

1. The risk-free rate of return is often used when investing in assets that have a zero chance of loss, however, this is only a theoretical concept;
2. The weighted average cost of capital (WACC) can be used as a discount rate, which is the average cost the company pays for capital from borrowing or selling equity (Hayes, 2021) It is the most commonly used discount rate. The equation of the WACC is:

$$WACC = \left(\frac{E}{E+D} * r_e\right) + \left(\frac{D}{E+D} * r_d\right) * (1 - Tax) \tag{7}$$

where,

E	Market value of equity
D	Market value of debt
r_e	Cost of equity
r_d	Cost of debt
Tax	Corporate tax rate

3. The cost of capital can also be used and it refers to the required return necessary to make a project or investment worthwhile. If financed internally, it refers to the cost of equity, which is often computed using the Capital Asset Pricing Model (Saalmuller, 2022). If it is financed externally, it is often referred to as the cost of debt, which is often the interest rate (Majaski, 2022; Brealey, Meyers, & Allen, 2010).

4. The hurdle rate can be used which is the minimum rate of return on a certain investment in order to offset the costs of the investment (Lioudis, 2021).
5. The Internal Rate of Return (IRR) provides the maximum discount rate which provides a nonnegative project value.

The discount rate used is often different for different industries, countries, and markets. When it comes to DCF analysis, the choice of the discount rate can dramatically change the valuation, especially for long-term investments. Therefore, it is valuable to conduct a sensitivity analysis to see how the Net Present Value, which is explained in Section 4.5.2, changes based on changes in the discount rate. Additionally, the estimation of future cash flows and carbon costs are also critical in a DCF analysis. The discounted sum of cash flows is the present value of a project, which is explained in the next section.

4.5.2 Net Present Value (NPV)

Another related financial metric is the NPV, which is an indication of the total value of a project, which can be positive or negative, calculated at today's value. So it is the difference between the present value of cash inflows and cash outflows over a period of time (Fernando, 2023). This indicates whether an investment will earn itself back and create a return to the business relative to the cost of financing the investment. An NPV larger than 0 can be seen as a signal to accept the investment. Typically the project with the highest positive NPV is chosen and not only a positive NPV. This can also help to compare different investments. The discount rate is often used in an NPV calculation to account for the time value of money. The future cash flow at time t is also discontinued over t periods of time. The NPV formula is as follows (Brealey, Meyers, & Allen, 2010):

$$NPV = \sum_{t=0}^{n} \frac{FCF_t}{(1+r)^t} \tag{8}$$

where,

FCF_t	Future Cash Flow at time t
r	Required return or discount rate
t	Number of time periods (years)

4.6 Life Cycle Assessment (LCA)

Numerous studies have used a variety of methods and tools to estimate and monitor carbon emissions, including one of the most used ones the LCA (Klöpffer, 1997; Chen, Yang, Yang, Jiang, & Zhou, 2014). This method is also used in this thesis due to the fact that it is widely acknowledged. This section explains the concept of LCAs.

A life cycle assessment, also known as LCA, is a methodology used for assessing environmental impacts associated with all the phases of the life cycle of a product, process, or service. This is a method that analyses the potential environmental burden of products at all phases of their life cycle; from the extraction of resources through the use to final disposal, i.e. from cradle to grave (Guinée, et al., 2002). An LCA is an iterative process, meaning that each of the four phases is performed iteratively, continuously adapting and improving the LCA. A general methodological framework has been defined by the ISO, as shown in Figure 11, depicting the four phases of the LCA (Guinée, et al., 2002):

1. **Goal and scope definition**: In this phase the exact question, target audience, and the intended application are formulated. The product or system that is analyzed is described in terms of a function, alternatives, and reference flows.
2. **Inventory analysis**: In this phase, the product systems are defined. The result of this phase is the life cycle inventory, which is an inventory table that lists all emissions to the environment, resource extractions, and land use.
3. **Life cycle impact assessment**: In this phase, the results of the inventory table are further processed and interpreted with regard to the potential environmental impacts. In this phase, we also classify the environmental interventions.
4. **Interpretation**: The fourth phase discusses the results of the analysis and all choices and the use of data based on soundness and robustness. Also, general conclusions are drawn.

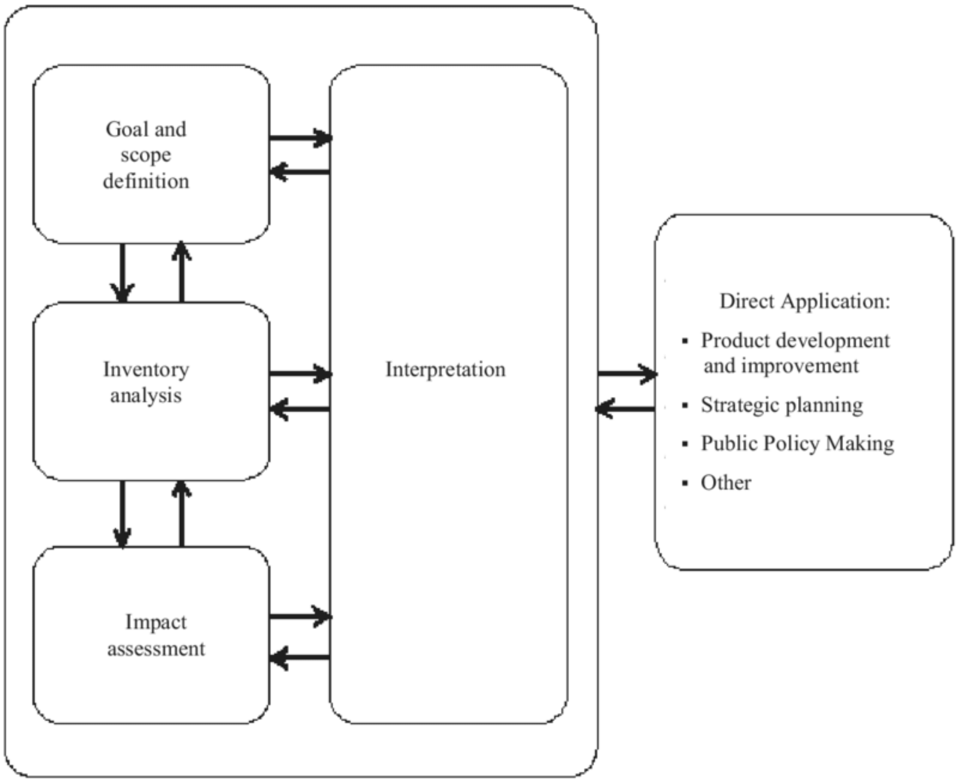

Figure 11: Methodological framework of LCA: phases of an LCA (Guinée, et al., 2002).

The life cycle assessment itself can also be divided into different phases from the start, also known as cradle, to the end-of-life, which is also known as grave. The different phases are shown in Figure 12. This method and these phases are also used in this thesis.

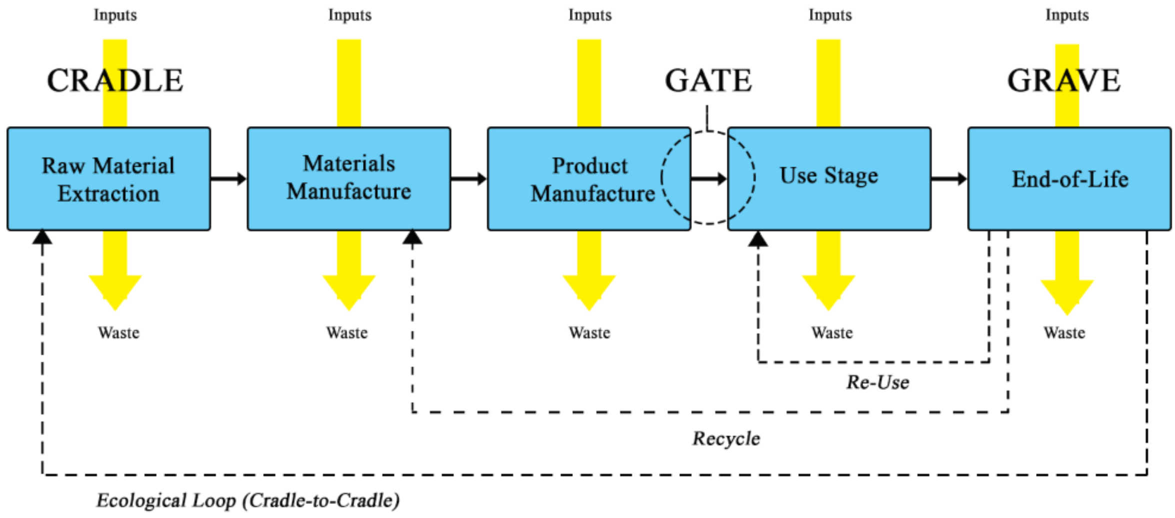

Figure 12: The LCA phases from cradle-to-grave (Klopffer & Grahl, 2014).

4.7 Conclusion

In conclusion, this literature review examined various aspects related to carbon pricing methods, price paths, CO_2 emissions regulations, market dynamics, and forecasting techniques. We combine different research fields in this study, which can also be seen in this literature review as we combine the field of finance, econometrics and sustainability.

Firstly, we explore how different countries worldwide utilize carbon pricing methods as policy instruments to mitigate greenhouse gas emissions and promote sustainable development (RQ3). We found that emission trading systems and carbon taxes or a combination of the two are the main pricing systems implemented in various countries, such as the Netherlands. Furthermore, this study discusses the anticipated expansion of laws and regulations in the Netherlands to mitigate carbon emissions, making it more relevant for VI and its customers (RQ4). We see that the regulatory landscape is changing every year and that carbon pricing systems are expanding to more sectors. The main changes that are planned for the upcoming years include CBAM from 2026 onwards, which puts a carbon price on imported goods from outside the EU which currently fall into the EU ETS sectors. Moreover, the number of free allowances will decrease in the future until zero allowances in 2040 and the number of sectors in which the EU ETS applies will increase, adding the transportation, maritime, and construction sectors.

This literature review also explored the key factors influencing the pricing of CO_2 and their impact on market dynamics (RQ5). The review emphasized the importance of these factors and keeping track of them. These factors include, but are not limited to, market demand and supply, regulatory frameworks, technological advancements, and gas and oil prices.

Then this literature review examined various forecasting methods used for forecasting and their advantages and disadvantages (RQ6). We conclude that traditional econometric models are generally less complex and are well-established and understandable methods that sometimes are able to handle nonstationary data and autoregressive behaviour. Machine learning methods are often more accurate, however, this comes at the cost of complexity and computation time. Lastly, traditional and machine learning methods can also be combined resulting in forecasts with the highest accuracy, however, these methods do become even more complex and hard to interpret.

Lastly, we investigate the impact of different carbon price policy scenarios on the expected price paths of carbon (RQ7). The price path under carbon tax is set to be 127 Euros in the Netherlands in 2030. The impact of the EU ETS price is provided later in this research in Chapter 6 and Chapter 7 by forecasting it. Lastly, the EU ETS and carbon tax combined will result in a price where the highest price is the one that should be paid and thus it depends on what the market price of carbon is.

Overall, this thesis combines various fields of research, including DCFs, carbon emissions, carbon pricing, and forecasting methods, providing valuable insights for business decision-making. The literature reviewed in this chapter serves as a foundation for further analysis and contributes to understanding the complex landscape of carbon pricing, CO_2 emissions regulations, market dynamics, and forecasting techniques.

5 Solution design

This chapter presents the solution design and systematic process taken in this research, which corresponds to the third step of the DSRM process model, 'Design & Development', the fourth step 'Demonstration', and the fifth step 'Evaluation'. The building of the model with the DCF tool and carbon price paths corresponds to the 'Design & Development', then the 'Demonstration' step is the case. Lastly, the expert panel is used in the 'Evaluation' step. The solution design describes the activities that are involved in answering the main research question:

How can VI incorporate carbon pricing scenarios into their decision-making process for product investments?

5.1 Introduction to the solution design approach of the model

This section describes the solution design approach for the model that was created in which the final output is a DCF analysis tool, which can operate under different carbon price scenarios. The DCF analysis also helps to provide insights into what the effect is of different carbon price policy scenarios on the NPV of investment decisions. These investment decisions may change for different policy scenarios.

Figure 13 shows the solution approach. The solution design elements that are discussed in this section are:

1. Different scenarios and price paths per scenario (First swim lane in Figure 13);
2. Discounted Cash Flow analysis (Second swim lane in Figure 13);
3. Life Cycle Assessment (LCA) (Third swim lane in Figure 13);
4. Case (Third swim lane in Figure 13);
5. Expert panel (Fourth swim lane in Figure 13).

The motivation for this solution design is mostly based on the fact that carbon pricing and the impact this has on business and decision-making is still uncertain. Therefore, it is valuable to provide a framework or method on how carbon prices may affect business decisions. This is also the reason why a scenario-based approach is chosen with multiple carbon pricing policies. In this approach, different elements are combined and we create a novel method that helps VI and also other companies to make better-informed investment decisions based on carbon emissions and prices. VI also wants a general idea and order of magnitude of the carbon price, instead of a very accurate price forecasting methodology. Monetizing carbon emissions holds significant value in the workplace, as many individuals lack a tangible understanding of the economic worth behind saving one ton of CO_2, and decisions are often directed by costs, which are expressed in monetary terms. This study helps in translating carbon emissions into a well-understood value, money. In creating a new method it is key to validate and verify this as well, which is done using 1) a case and 2) an expert panel. From here we provide recommendations to VI on how carbon pricing may influence their decision-making regarding investments and how they can handle this in future projects.

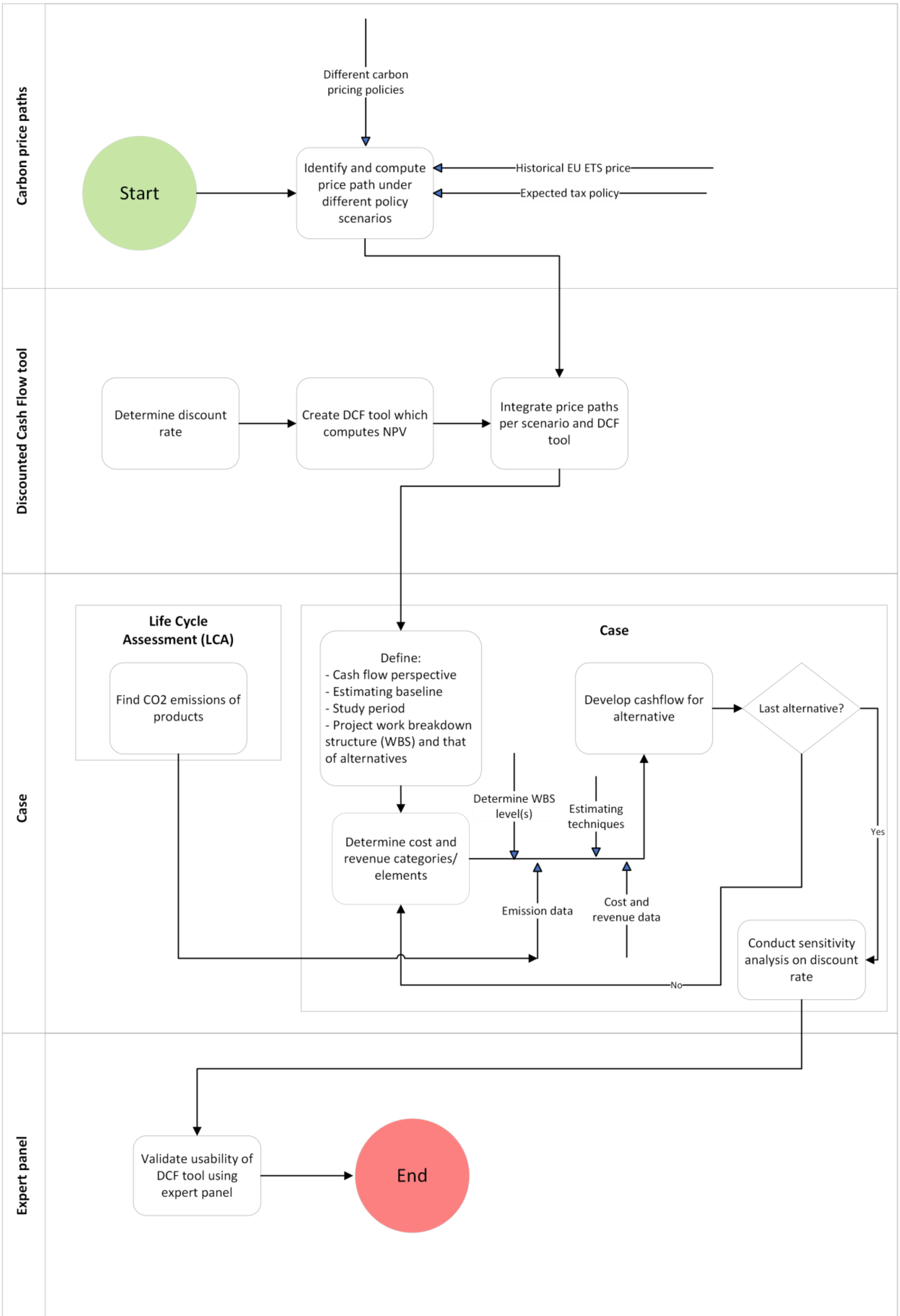

Figure 13: Flowchart of solution approach from carbon pricing literature until validation and verification of DCF analysis.

5.2 Different scenarios and price paths

In this thesis, we use different scenarios of carbon pricing in the Netherlands. These scenarios are used to create the different policy scenarios that the Netherlands can transition into. All of the scenarios have different characteristics, which are given using the mean, volatility, trend, or cap. Sections 5.2.1 until 5.2.4 describe the different scenarios and the expected price path per scenario. For the EU ETS price path, a forecast model is used, which is explained in Chapter 7.

5.2.1 First scenario: EU ETS price

The first scenario is the EU ETS carbon price. Here the price is determined by a market, meaning that supply and demand affect the price. For this scenario, a forecast is needed to know how the price will develop in the future as this is a dynamic process. To capture this process a time series forecasting model is used. As seen in the literature review in Chapter 4 there are numerous methods to forecast the EU ETS price. The decision on which method to use depends on the characteristics of the EU ETS price market and the specific aim of this study. To determine the characteristics of the EU ETS price in the market in which the permits are traded, diagnostic tests are performed in Chapter 6. This in combination with the literature on EU ETS market forecasting methods leads to an appropriate forecasting method. The decision on which method to use is made in Chapter 6.

5.2.1.1 Sub-scenarios within the first scenario

In this market scenario where prices are determined, it is crucial to account for various potential behavioural trends. To achieve this, we also examine two widely recognized forecasting methods: linear regression on time series and Geometric Brownian Motion. In the process of forecasting the European Union Emissions Trading System (EU ETS), it is essential to provide clear reasoning for the selection of benchmark models. In this study, we have chosen to compare the performance of our chosen model with two benchmark models: linear regression and geometric Brownian motion. These methods are used as a benchmark for forecasting the EU ETS price and are compared against another chosen method in Chapter 6. The reasons for this choice are as follows:

- **Linear Regression**: Linear regression is a widely used benchmark model in econometrics and financial modeling. By using linear regression, we aim to assess the performance of a simple, interpretable model that provides a baseline for comparison. The linear regression model assumes a linear relationship between variables, which makes it a straightforward choice for capturing any potential linear trends or dependencies within the EU ETS data.
- **Geometric Brownian Motion**: GBM is a fundamental model in the field of finance, particularly for modeling the dynamics of asset prices. This model is chosen as a benchmark to evaluate the performance of the chosen model against a widely recognized financial modeling approach. However, it is important to note that geometric Brownian motion only generates sample paths and does not provide a forecast. This means its performance may be less robust for long-term forecasting, and it serves as a reference point to understand how the chosen model compares to this stochastic process.

5.2.1.2 Model performance

The performance of the model is measured using the RMSE, MAE, MAPE, rRMSE, and R-squared error measures. These are defined and explained in the literature in Section 4.4.7. An additional verification step of the carbon price forecast is conducted by comparing the forecast with existing research that has forecasting models until 2050.

5.2.2 Second scenario: Carbon tax

The second scenario is a carbon tax, which starts at 41.75 Euros and linearly increases to 127 Euros in 2030 (Koelemeijer, Hout, & Daniëls, 2022). Then it is assumed to remain constant from 2030 until 2050 onwards as this is what is stated by the Dutch government at this moment. Figure 14 shows the expected trajectory of the carbon tax.

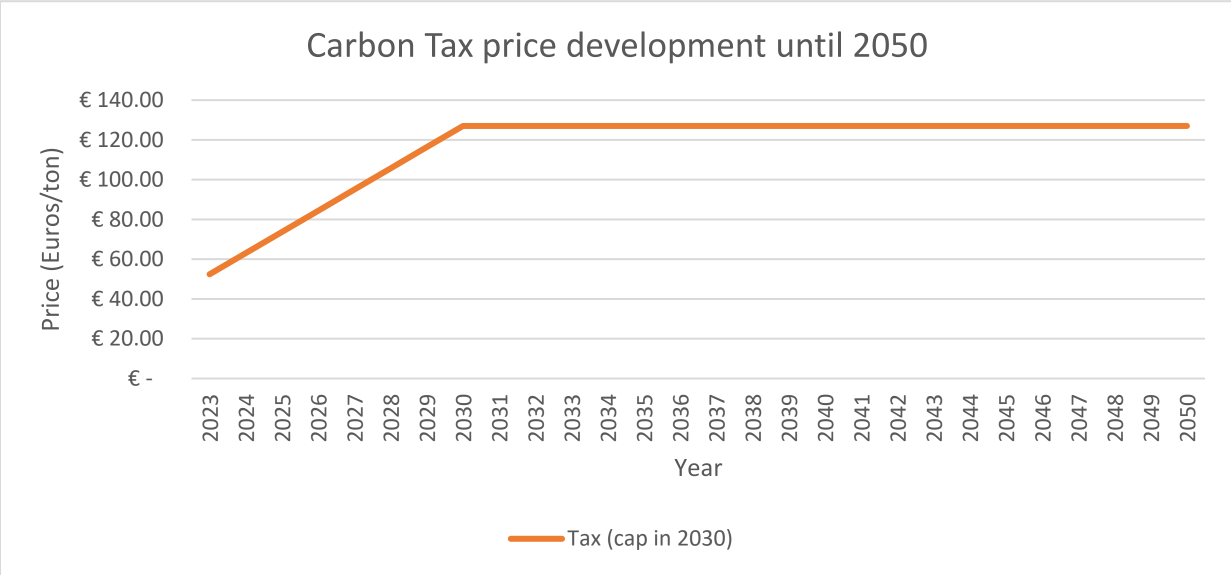

Figure 14: Carbon tax in EUR/ton per year, which is determined and set by the Dutch government until 2050.

5.2.3 Third scenario: No carbon price

The third scenario is simple and the carbon price is set to zero, as there is no carbon price. For the manufacturing industry that Vanderlande is part of there is no direct carbon price. Additionally, numerous countries outside the EU also have no carbon price at all in place. Therefore, it is valuable to research and observe what the impact is of having no carbon price in a business case. This can also be used as a scenario to compare the other scenarios with carbon pricing to.

5.2.4 Fourth scenario: Combination of EU ETS and carbon tax

The fourth scenario is a combination of the EU ETS and carbon tax, as is in place right now in the Netherlands in some sectors. The tax works as a minimum value that should always be paid, even when the ETS market price is lower than that of the tax, and the tax follows the same trend as the ‘Tax-based carbon pricing’ scenario. The EU ETS scenario follows the price trend of the method recommended to VI in Chapter 7. In this thesis, the distinction of who the tax should be paid to, which is based on the height of the ETS market price and tax-based carbon price is not relevant and, therefore, has been omitted from consideration.

5.3 Discounted Cash Flow (DCF)

The DCF analysis is a widely recognized methodology used to assess the financial implications of various factors on an organization's cash flows and investment decisions. We also decided to use this method as it aligns well with the current method that VI uses. In the context of this study, the DCF analysis serves as a powerful tool for evaluating the influence of anticipated carbon pricing policies on VI's current business decisions, particularly in comparing investment options based on their costs and carbon emissions. The output of the DCF is an NPV. In this section, we explain the key elements that come into play in the solution design of the DCF.

To achieve the goal of providing insights for investment decisions, the DCF analysis incorporates the following key features:

1. **Cash Flow Projections**: The DCF analysis requires robust cash flow projections for the investment options under consideration, such as Product A and Product B. These projections take into account both the traditional revenue and cost factors as well as the potential impact of carbon pricing policies. Specifically, the cash flow projections should reflect the investment costs and operational costs associated with the two products in the presence of carbon pricing. For example, Product A may have a higher initial investment but lower carbon emissions, resulting in lower operational costs due to the carbon pricing effect.
2. **Discount Rate**: The choice of an appropriate discount rate is critical in the DCF analysis. In the context of evaluating investment decisions with consideration of carbon pricing policies, the discount rate should reflect the cost of capital adjusted for the additional risk associated with uncertain regulatory and market conditions. Moreover, the discount rate should consider the potential impacts of carbon pricing on investment options. This can be achieved by incorporating the risks and uncertainties related to carbon pricing policies, such as the volatility of carbon prices, regulatory changes, and market dynamics, into the discount rate calculation. As seen in literature the WACC is often used as a discount rate. In this research, the discount rate used is the WACC of VI, which equals 12% based on internal information within VI. We decided to use the WACC as a discount factor because of the fact that VI also uses the 12% WACC in business cases. Therefore, it aligns best to do this as well. We conduct a sensitivity test to gain an insight into what the impact of the discount rate is on the investment decision. Another alternative is to use the IRR, however, when consulting people from the finance department within VI we concluded that there is no IRR yet. Therefore, we chose to align this research with the used measures within VI, which is the 12% WACC.
3. **Carbon Price Paths**: To compare investment options in light of carbon pricing policies, the DCF analysis incorporates multiple carbon price paths that correspond to different policy scenarios. By integrating these carbon price paths into the DCF model, the financial implications of carbon pricing policies on the cash flows and investment decisions of Product A and Product B can be evaluated under different policy scenarios. This enables a comprehensive assessment of the comparative financial attractiveness of the two options, considering both their investment costs and potential operational cost savings resulting from lower carbon emissions.

In conclusion, the DCF analysis, including considerations for investment costs and carbon emissions, provides valuable insights for investment decisions in the presence of carbon pricing policies. By incorporating cash flow projections, an appropriate discount rate, multiple carbon price paths, and a comparative analysis of investment options, this methodology enables VI to assess the financial attractiveness of different products and make informed investment decisions that align with their sustainability goals.

5.4 Case

To validate the approach a case is used where different alternatives are compared under carbon pricing scenarios. This is in line with the fourth step of the DSRM, ‘Demonstration’. In this case, a product with high sales volumes is chosen, namely the Twin Belt’s crossmember. This section discusses the solution design on how the DCF analysis can be used to make investment decisions. The first step is having insights into the CO_2 emissions using an LCA. The two alternatives within this case are discussed extensively in Chapter 8, but in summary, these are:

- Regular Twin Belt crossmember made from aluminium, which is the Business-as-Usual (BAU).
- Twin Belt crossmember made from steel.

To assess the impact of expected carbon pricing policies on VI's business decisions, a comprehensive methodology is employed, integrating the DCF analysis with the LCA approach. While the DCF analysis focuses on financial considerations, the LCA enables the evaluation of environmental factors, specifically carbon emissions associated with VI's operations. The LCA approach is chosen as it provides a systematic and holistic framework for quantifying the carbon footprint of a product, service, or process throughout its entire life cycle. Additionally, it is also a widely used and acknowledged method as explained in Section 4.6. It accounts for emissions associated with all phases, including raw material extraction, manufacturing, distribution, use, and disposal. By considering the complete life cycle, the LCA approach allows for a thorough assessment of carbon emissions and their associated environmental impacts (Grahl & Klöpffer, 2014).

To conduct the LCA, relevant data is collected on various aspects. These data points are then used to calculate the carbon emissions for a product and its alternative investment option. The EcoInvent database is used in the IDEMAT Excel sheet to retrieve the CO_2 emissions of the product in the case (Eco Cost Value, n.d.). This tool is an open-access database, which is free to use and can be used by VI as well. The estimated carbon emissions, obtained through the LCA, are subsequently integrated into the DCF analysis. By incorporating the environmental impact alongside financial considerations, this integrated approach provides a more comprehensive understanding of the implications of different carbon pricing policies on VI's business decisions. By quantifying the financial and environmental implications, this methodology offers valuable insights into how different carbon pricing policies may influence investment decisions between multiple alternatives.

In summary, the integration of the DCF analysis with the LCA approach enables a comprehensive assessment of the impact of carbon pricing policies on VI's business decisions. It provides a structured framework to evaluate financial viability, while also considering the environmental consequences by estimating carbon emissions throughout the life cycle of VI's operations.

5.5 Expert panel

As a last step, we validate the method created, which is done using an expert panel. We explain the design and aim of this expert panel in this section.

Validity is the extent to which the instrument measures what it is supposed to measure. While reliability refers to the stability of the research result (Heerkens & van Winden, 2017). This step is in line with the fifth step of the DSRM, ‘Evaluation’. Since there are numerous assumptions within this research, like the discount rate in the case, the validity and reliability are threatened. An expert panel is used to verify and validate the approach and DCF that are created. The expert panel gives feedback. This panel consists of people who are experts in either cost, investment decisions, sustainability, technology, or sales. After this expert panel, the feedback is summarized and a new version of the DCF and approach is given, which serves as the final version.

5.6 Conclusion

In this section, we summarize the solution design and systematic process, which aligns with the 'Design & Development', ‘Demonstration’, and ‘Evaluation’ steps of the DSRM process model.

The approach involves creating a DCF analysis tool that operates under different carbon price scenarios. The motivation for this approach and using scenarios lies in the uncertainty surrounding carbon pricing. We forecast the different carbon prices and use these in a DCF tool. The DCF analysis tool serves as a powerful tool for evaluating the financial implications of investment decisions under different carbon pricing policies. It incorporates cash flow projections, an appropriate discount rate, and multiple carbon price paths for comparing investment options based on costs and potential operational cost savings from lower carbon emissions. We use the DCF tool to demonstrate how the different carbon pricing scenarios impact the NPV of a product and how this impacts the decision made. The solution design also includes the ‘Demonstration’ phase from the DSRM, which is conducted using a case in which two products are compared under different carbon pricing scenarios. We gain insights into the carbon emissions of those products using an LCA. The entire methodology and tool are verified and validated using an expert panel that consists of a multi-disciplinary team.

In conclusion, the solution design offers VI a structured and comprehensive methodology for making informed and sustainable investment decisions considering carbon pricing scenarios. By integrating financial and environmental factors, this approach aligns with VI's long-term goals and enhances the decision-making process under uncertain carbon pricing dynamics.

6 Diagnostic testing

Diagnostic testing plays a crucial role in modelling price series. This thesis performs diagnostic tests on the historical data for the EU ETS. These tests are conducted to capture the patterns and characteristics present in the actual series and to select an appropriate forecasting technique based on these characteristics. By considering the properties of the time series identified through these tests, a well-supported decision can be made regarding the suitable modelling technique to employ. Based on the reviewed literature, a method is selected, taking into account the essential characteristics that the forecasting model should fulfill. The forecast technique chosen is also compared to linear regression and GBM as two benchmark methods.

This thesis conducts diagnostic tests for stationarity, autocorrelation/autoregressive behaviour, homoscedasticity, and normality. The order of testing follows a specific sequence due to interdependencies between tests, such as the influence of autocorrelation on normality testing. A significance level of 0.05 is used for all tests, aiming to gain a general understanding of the future price behaviour unless explicitly mentioned otherwise. This section is structured by providing a brief introduction of each test before performing it and presenting the results and conclusion in the same section. All tests are performed in Python and more information is provided in Appendix A.1. Before conducting the diagnostic tests, the data is introduced and transformed appropriately in Sections 6.1 and 6.2 for the diagnostic tests.

6.1 Data introduction

To forecast the EU ETS price, this thesis retrieves the EU ETS historical price data from FactSet (Factset, 2023). We obtain the data through an academic license. The time series dataset for the EU ETS spans from the 8th of April 2008 to the 9th of June 2023, providing daily prices. This results in 3,821 data points, representing daily spot prices, and excludes weekends and holidays when the market is closed. Consequently, there are inconsistencies in the data due to uneven representation of weekdays. However, for analytical convenience, the date gaps are ignored unless explicitly mentioned otherwise, assuming that the prices follow a continuous progression. While these gaps can be filled using methods like interpolation, this thesis does not employ interpolation to avoid making assumptions about the behaviour of the time series, as it could impact the forecast. It is important to note that these gaps do influence the model, particularly in relation to time lags. Regarding the dataset, there are no missing values for the price on trading days. However, the columns for change and % change contain missing values. Due to this reason and the lack of relevance in the context of this research, we do not use these columns.

The data is described using the summary function and data description functions in Python in Appendix A.1, yielding the following characteristics, as outlined in Table 10. Time series can show outliers in the data set. The outliers are not removed from this data set. We decided to do this because of the fact that removing extreme outliers ignores unexplained movements in the series, which is not wanted.

Table 10: Descriptive statistics for the daily spot prices,of the EU ETS carbon price from 08-04-2008 until 09-06-2023.

	Price	Change	% Change	Cumulative Change
Count	3,821	3,680	3,679	3,820
Mean	22.13	0.02	0.08	-11.04
Median	13.87	0.01	0.13	-44.25
Std. Dev.	23.74	1.06	3.17	95.46
Min	2.70	-13.36	-35.26	-89.14
25%	6.78	-0.19	-1.51	-72.75
50%	13.87	0.01	0.13	-44.25
75%	25.54	0.22	1.77	2.71
Max	100.34	24.87	27.03	303.46
Skewness	1.82	2.38	9.37	1.82
Kurtosis	2.22	104.19	0.13	2.22

Additionally, Figure 15 presents the EU ETS Carbon Market prices over time. When observing this figure, one can discern a difference in price behaviour, like mean and standard deviation, over time. The time series reveals two significant elements: 1) a drop at the beginning of 2020, which may be related to the onset of the COVID-19 pandemic, and 2) a substantial rise in 2021, coinciding with the stricter regulations of the EU Green Deal. Until roughly the start of 2018, the price remained relatively stable. From then onwards, it started to experience a more rapid rise, accompanied by an apparent increase in volatility. This observation possibly indicates the presence of heteroskedasticity, implying that the standard deviations of the forecasted variable are non-constant (Hayes, 2022). Moreover, there does not appear to be any time effects, also known as seasonal effects evident in the initial observations. However, when trying to confirm this using a decomposition of the model we conclude that there is in fact seasonality in the price series which can be seen in Appendix A.2. We do note that the range between which it fluctuates is small. We also expect this as the literature already shows that the carbon price is influenced by factors like energy and the weather and these are seasonal. As mentioned in Section 4.4.6 the carbon dioxide levels may also be correlated to the carbon prices and these show seasonal behaviour (Global Monitoring Laboratory, 2023). Thus, a similar cycle can be expected as well for the EU ETS price. We also look at the log return series as we will forecast this series and the price series itself already shows that the seasonal component is small. The return is the price change from one day to the next. A student t-test confirms that there is no significant seasonality in the log return series and therefore, we will not incorporate seasonality in the forecasting model as the seasonal component is not significant.

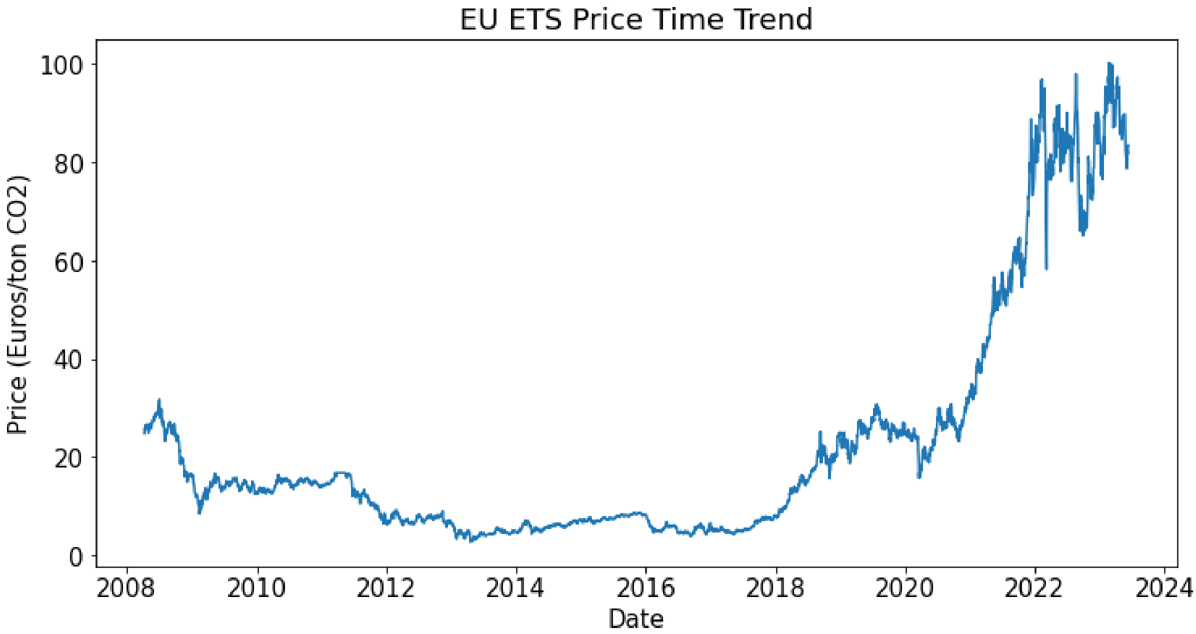

Figure 15: EU ETS Price Time Trend in Euros/ton CO2 showing a large growth from 2021 onwards.

6.2 Data transformation

Before conducting diagnostic tests, we perform specific data transformations, which are described in this section. Two primary transformations commonly observed in time series analysis are employed: 1) applying logarithmic transformations and 2) differencing the time series once to obtain the return series, this is also known as the interday price changes.

Firstly, we conduct a logarithmic transformation, the result is illustrated in Figure 16. Logarithmic transformations are often utilized to achieve variance stationarity in time series data (Kliestik, Sedláčková, Bugaj, & Novák, 2022; Rojko, Erman, & Jelovac, 2020). In Figure 16 we see the relative changes. The necessity to achieve variance stationarity is additionally demonstrated by the heteroscedasticity test explained in Section 6.5.

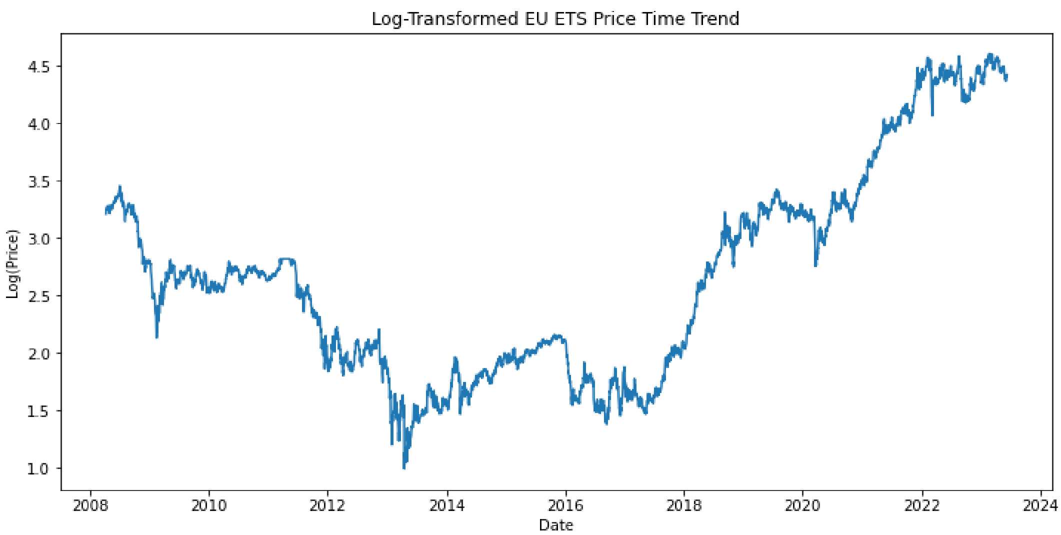

Figure 16: Log-transformed EU ETS price time trend from 2008 until 2023 in Euros/ton CO2 showing the relative changes.

Furthermore, the second transformation in this thesis involves taking the first difference of a price series, which provides the returns of a series. Logarithmic returns are defined by the following expression (Heeswijk, 2012):

$$x_t = \ln \left(\frac{X_t}{X_{t-1}}\right) \tag{9}$$

where,

X_t	The (logarithmic) price at time t
x_t	The (logarithmic) difference at time t

Diagnostic tests and time series forecasting typically focus on the return series rather than the price series. Conducting diagnostic tests on the return series proves more valuable due to its numerous analytical properties, which are not present in the price series. Logarithmic returns offer convenience from a mathematical perspective, particularly when performing operations like differentiation and integration. However, it is important to note that logarithmic transformations cannot handle negative values. Fortunately, negative prices are not present, eliminating this concern. This thesis employs logarithmic returns, aligning with the approach taken in most econometric analyses. Additionally, the stationarity test is performed in Section 6.3 on the original time series data as well to determine the necessity of differencing the time series (Müller, 2005). While the logarithmic return data is used in the forecasting method, all characteristics of the original data are important and thus presented in the diagnostic tests. In Python, the returns series is called 'log_returns', which is the logarithmic return.

Figure 17 displays the daily logarithmic return series for the EU ETS, revealing a highly volatile pattern. The return series also exhibits frequent occurrence of spikes. Notably, a significant spike was observed in 2013; however, no explanation for this spike can be identified from literature or the news. In this thesis when the term 'return' is used it always refers to the logarithmic returns.

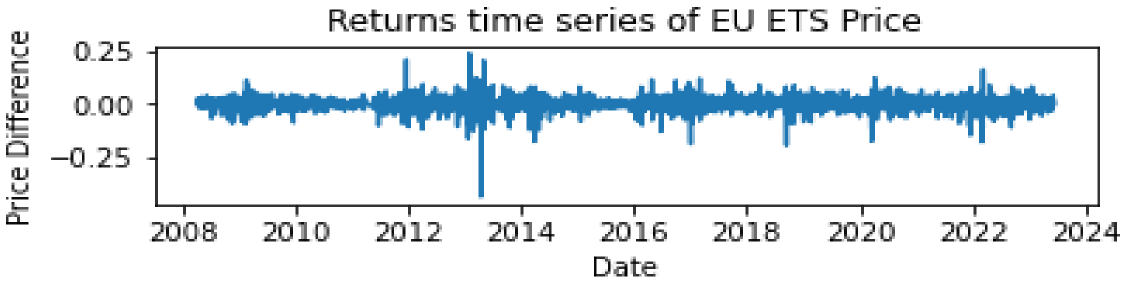

Figure 17: Logarithmic returns series of the EU ETS price from 2008 until 2023 in Euros/ton CO2.

The remainder of this chapter shows the results of different diagnostic tests. The theory behind each test and the results when applying it to the EU ETS price and return series are both discussed. As already mentioned, the diagnostic tests are applied on the log returns, however, the stationarity test is also conducted on the original series. All codes of the diagnostic tests, data descriptions, and data preparation and transformation can be found in Appendix A.1.

6.3 Stationarity

The first aspect this thesis focusses on is to see whether the time series is trend stationary, meaning that the characteristics of the data do not change over time. It implies that the mean, variance, and autocovariance structure of the series remain constant throughout the entire duration. It is advantageous to work with stationary series due to their favourable analytical properties, such as constant mean and variance, which are absent in nonstationary series (Alexander, 2001). Nonstationary series are usually transformed by taking the first difference of the series and creating a new series. In this way, a series becomes nonstationary or weakly stationary.

Testing whether a time series is stationary can be done in numerous ways, which include observing the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots, using an Augmented Dickey-Fuller (ADF) test, applying a Philip-Perron test, or a Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test (Wang & Tomek, 2004; Monigatti, 2022). In this thesis the ADF test is applied due to the fact that it is widely acknowledged as a method to test the presence of a unit root,- and therefore stationarity (Abugaber, n.d.). As a second test, the KPSS test is used to confirm the conclusions of the ADF test, which is done due to the limitations of the ADF test. A main limitation pointed out by Perron (1989) is that when a time series has structural breaks then the ADF is biased towards not rejecting the null hypothesis (Perron, 1989).

The null hypothesis of the ADF test states that the time series is non-stationary. Therefore, if the p-value of the test is less than the significance level (0.05) then the null hypothesis is rejected, meaning that the time series is stationary. So, in case that $p - value > 0.05$ then differencing is needed to transform a nonstationary series into a stationary series. When the calculated test statistic is lower (more negative) than the critical value at a significance level (1%, 5%, or 10%), then it provides strong evidence against the null hypothesis of non-stationarity at a higher level of confidence. Thus, the null hypothesis is rejected, which suggests that the data is stationary (Dickey & Fuller, 1979). The ADF test is performed on the following model:

$$\Delta x_t = c + B_t + (\rho - 1)x_{t-1} + w_1 \Delta x_{t-1} + \cdots + w_{h-1} \Delta x_{t-h+1} + \varepsilon_t \tag{10}$$

where,

x_t	Difference value at time t
c	Constant
B_t	Deterministic trend
ρ	Correlation between x_t and x_{t-1}, where x_t is the return at time t
h	Indicator for the lag size
w_{h-1}	Weight parameter
Δx_{t-h+1}	Lag term
ε_t	Error term at time t

The ADF test is conducted for both the original time series dataset and the log returns. This shows the characteristics of the original time series data and from there it can be observed whether differencing and taking the return series is necessary at all. Additionally, stationarity is also tested for the logarithmic returns to see whether this series is stationary or not. This helps with choosing the right forecasting method.

There are three versions of the ADF test, which tests for a lagged term, a lagged term with an intercept, and a lagged term with an intercept and a deterministic trend. The ADF test is conducted for a constant value and a constant value with a trend.

The ADF statistic for a constant at 5% significance level is 0.90 and for a constant and trend at 5% it is -0.97, which is still higher than the critical values of the ADF test in Table 11. The ADF statistic and the p-values corresponding to a 5% significance level are shown in Table 12 for both the original time series and log returns. From the ADF test, we find the following results:

- **Original time series**: The p-values are all higher than the significance level and the test statistics are also all higher than the critical values. Therefore, the null hypothesis cannot be rejected for the original time series tested here at a significance of 5%. This means that we cannot state that the original time series is stationary.
- **Log returns**: For the log returns low p-values are found which are lower than 0.05, and even below the 1% significance level. Therefore, the alternative hypothesis is accepted, which indicates the stationarity of the time series. This is also expected when taking the logarithmic returns of a nonstationary time series.

Table 11: ADF test critical values.

Significance level	Critical values ADF (constant) on original and log returns	Critical values ADF (constant + trend) on original and log returns
1%	-3.43	-3.96
5%	-2.86	-3.41
10%	-2.57	-3.13

Table 12: Performance of ADF on EU ETS time series data showing that the original time series cannot be proven to be stationary for both a constant and constant+trend and the log returns are stationary.

	ADF (constant) on original time series	ADF (constant + trend) on original time series	ADF (constant) on log returns	ADF (constant + trend) on log returns
ADF test statistic (5%)	0.90	-0.97	-11.40	-14.82
p-value	0.99	0.95	7.87e-21	2.72e-22

To confirm the results from this test and to overcome the barrier as mentioned by Perron (1989) of the ADF test, the KPSS test is also conducted. The KPSS test provides some advantages in terms of robustness compared to the ADF. It has the advantage that it is resilient to autocorrelation and heteroscedasticity (Kwiatkowski, Phillips, Schmidt, & Shin, 1992). The null hypothesis of the KPSS is different from the ADF test, as the null hypothesis assumes that the time series is stationary (Herranz, 2017). On the other hand, the ADF test has a null hypothesis, which states that a time series has a unit root, indicating non-stationarity.

The KPSS test is based on linear regression and it breaks up a series into three parts: a deterministic trend (βt), a random walk (r_t), and a stationary error (ε_t). These different elements combined result in the regression equation (Kwiatkowski, Phillips, Schmidt, & Shin, 1992):

$$x_t = r_t + \beta t + \varepsilon_t \qquad (11)$$

Conducting the KPSS test results in the output as shown in Table 13 and Table 14. The KPSS test rejects the null hypothesis, and therefore, states that the EU ETS carbon market data is non-stationary for both the original data and log returns as both p-values are lower than 0.05. This is thus a different conclusion for the log returns than when conducting the ADF test as the ADF test implies stationarity on the log returns. However, we do observe that the KPSS statistic is only slightly higher than the critical value for KPSS (0.55 > 0.463), while for the original time series, this difference is much bigger (4.79 > 0.463). Thus the log returns are nearly stationary according to the KPSS test as well. However, in later modelling steps, it is important to test whether the log returns series needs further differencing to make it stationary as most forecasting methods need stationary data. In this way, the forecast also performs better. A reason for inconsistent results from different stationarity tests can be found when a time series has moving average or autoregressive behaviour (Müller, 2005; Beran, 1995). Therefore, we test for autoregressive behaviour in the next section.

Table 13: KPSS test critical values.

Significance level	Critical values KPSS for original and log returns
1%	0.74
5%	0.46
10%	0.35

Table 14: Performance of KPSS on EU ETS time series data showing that the original time series and the log returns series are stationary as the p-values are lower than 0.05.

	Results for original time series	Results for log returns
KPSS test statistic (5%)	4.79	0.55
p-value	0.01	0.03

6.4 Autoregressive behaviour and autocorrelation

In this section, we determine whether the original and log returns time series show autoregressive behaviour and are autocorrelated. We define an autoregressive time series as one where observations from previous time steps serve as input for a regression equation to forecast the value at the subsequent time step (Diebold, Kilian, & Nerlove, 2006). This is an important test as for example normality tests and student t-tests depend on independent and identically distributed characteristics, also known as i.i.d. When the variables are autocorrelated this i.i.d characteristic does not hold. Moreover, the effective sample size would be smaller if the data is autocorrelated. The effective sample size is a metric that measures how much information content is lost due to the correlation in the sequence (MC Stan, n.d.). We test on both the original and log returns series to show what the impact if of taking the log return series.

To assess the presence of autoregressive behaviour in the data, researchers commonly employ autocorrelation tests. Autocorrelation signifies the correlation between two observations within the same time series, with the lag indicating the time interval between these observations (Taylor, 2008). A commonly used method to test autocorrelation is the Durbin-Watson test. The test results can range from 0 to 4. According to this test, autocorrelation is present when the Durbin-Watson statistic deviates from 2, with stronger autocorrelation observed as the statistic moves further away from 2, reaching either 0 or 4. Table 15 presents the findings, indicating a pronounced autocorrelation in the original dataset. However, in the log returns series, the autocorrelation is significantly smaller or even non-present when compared to the original time series.

Table 15: Results for autocorrelation when conducting a Durbin-Watson test showing there is no autocorrelation in the log returns data and that there is strong autocorrelation in the original time series data.

Data	Test statistic
Original time series	0.00 (more decimals: 0.00088)
Log returns	2.02

6.5 Heteroscedasticity

Heteroscedasticity refers to a pattern in data where the variability or spread of a variable is not constant over time (Hayes, 2022). In modelling, homoscedasticity is often assumed as it simplifies the underlying mathematics. Homoscedasticity is the opposite of heteroscedasticity and thus refers to a constant variance over time. However, in practice, data is often not homoscedastic but heteroscedastic. An example of this is if the price of a stock is high it often fluctuates (in absolute terms) more than if the price is low (Ferment, 2016). This has an effect on the validity of a test and therefore it is key to identify and address heteroscedasticity. Even though this thesis is not directly concerned with modelling the variance, it does affect the significance we attribute to model parameters.

There are numerous tests to test for heteroscedasticity like the White's test, Breusch-Pagan test, and Goldfeld-Quandt test. Another way to assess whether a time series is homoscedastic or heteroskedastic is by using a graphical analysis of the scatter plot of the residuals (Cerqueira, 2022). This thesis uses the Goldfeld-Quandt test as this is especially useful when there is a suspected heteroscedasticity pattern related to a particular subset or division of the data (Goldfeld & Quandt, 1965). The Goldfeld-Quandt test follows the following procedure:

1. Order the data by magnitude.
2. Divide the data into multiple parts.
3. Drop the observations of one part.
4. Estimate a simple regression on the smallest and largest observation sets, and calculate their sum of squared residuals.

5. Calculate the test statistic:

$$GQ = \frac{SSR_2/(n_2-k)}{SSR_2/(n_1-k)}, \tag{12}$$

   Where $GQ \sim F(n_2 - k, n_1 - k), n_i$ is the number of observations in set i, SSR_i is the sum of squared residuals of set i, and k is the number of parameters in the model.

Due to the nature of the dataset and the characteristics the order of the data is already, roughly speaking, in the correct order of magnitude over time. Therefore, this Goldfeld-Quandt test tests heteroscedasticity over time as well as over magnitude. Additionally, the dataset is divided into two time periods. Here a 20% split is used to remove the data. In the Goldfeld-Quandt test, the null hypothesis (H_0) states that heteroscedasticity is not present, and the alternative hypothesis (H_A) states that heteroscedasticity is present.

If the F-value is less than 0.05, then the null hypothesis can be rejected. In general, large F-values typically indicate that the variances are different. The test is conducted for the original time series and the log returns. Table 16 shows the F-value and test statistic.

Table 16: Results of Goldfeld-Quandt test indicating that the original time series is heteroscedastic and the log returns are not heteroscedastic.

	Original time series results	**Log returns results**
F-value	0.00 (more decimals: 0.000101)	1.00 (rounded up)
Test statistic	1.22	0.031

- **Original time series:** This time series shows an F-value lower than 0.05 and a rather large test statistic. This indicates heteroscedasticity as the null hypothesis can be rejected.
- **Log returns:** This series shows a high F-value and lower test statistic compared to the original time series. Due to the F-value, which exceeds 0.05, we cannot reject the null hypothesis and therefore, we cannot conclude that the returns are heteroscedastic.

6.6 Normality

A general test for normality is conducted to see whether the data is normally distributed. Often in price series modelling the assumption is made that returns follow a normal distribution. Therefore, the normality test is conducted on the logarithmic returns. If these returns are normally distributed, then Geometric Brownian Motion (GBM) can be used to model their price path (Alexander, 2008). Due to the simplicity of the GBM, return series are often tested for normality. Additionally, the normality test is also often applied to the residuals after constructing a model to see whether the error term can be modelled as a GBM.

A method that is used often is visual observation by plotting the returns in a histogram. If it is normally distributed, a bell bell-shaped curve should be seen. Formal ways of testing normality are the Shapiro-Wilk test, the Kolmogorov-Smirnov test, and the Jarque-Bera (JB) test, of which the latter performs best and is used most often in financial data analysis (Frain, 2007). In this thesis, visualization is used first to see if there is already evidence to reject the normality assumption of the logarithmic return series. If this is not the case the Jarque-Bera test is also conducted.

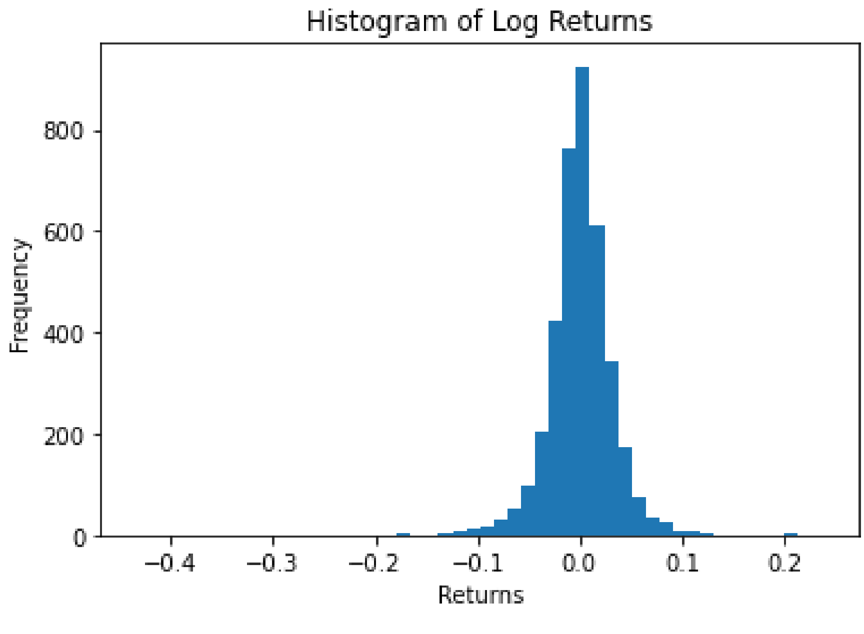

Figure 18: Histogram of the log returns, which shows that the log returns are approximating a normal distribution.

Figure 18 shows the histogram of the logarithmic returns. In this figure, an almost bell-shaped pattern can be seen which is not identical to a histogram with normally distributed data. However, due to simplicity reasons, we do assume normality. This is also supported by the Central Limit Theorem and the large sample size, which states that the data reaches normality. A formally adjusted Jarque-Bera test is still performed in Appendix A.3 to enable us to state something about whether this assumption holds. This test shows that the log returns are not normally distributed. This is an important finding that as i.e. a student-t test is used for testing seasonality which assumes the i.i.d. property. However, in this thesis, we do not account for this further.

6.7 Model decision

In order to make accurate and reliable forecasts, it is essential to select an appropriate forecasting method that aligns with the characteristics of the return series. The return series, also called the log return series, is the change in price from one day to the next. This section aims to motivate the choice of a forecasting method for EU ETS carbon prices based on the established criteria outlined in this thesis. We do this using diagnostic tests to find the characteristics of the return series and using those characteristics we can choose an appropriate method to forecast.

Before diving into the results of the diagnostic tests from this chapter the identified criteria to guide the selection of a suitable forecasting method are repeated. First, data availability is important to be able to forecast the time series. Additionally, we want a global long-term price path, so day-to-day fluctuations are not seen as important. Also, it is key that the model is interpretable and explainable to people without an econometric or quantitative financial background. Another constraint that should be considered is that we want to avoid overfitting the model. Lastly, the chosen model should align with the data characteristics of the EU ETS logarithmic return series. From the diagnostic tests conducted in this chapter, we retrieve the following characteristics:

- **Nonstationary**: The series does not exhibit a constant mean or variance over time.
- **Slight autoregressive behaviour**: There is a modest correlation between past and present values in the return series.
- **Homoscedasticity**: The variance of the series remains relatively stable.
- **Normal distribution**: The logarithmic returns approximates a normal distribution.

Considering the identified criteria and characteristics, a forecasting method that best addresses the unique nature of the EU ETS logarithmic returns series is sought based on the literature review. Based on the aforementioned criteria and characteristics, a suitable forecasting method found in literature for EU ETS carbon prices is the Autoregressive Integrated Moving Average (ARIMA) or GARCH model. Within the scope of this research we need to decide whether to use the ARIMA or GARCH model based on literature, the criteria for this thesis, and the characteristics. When reviewing these criteria we concluded that the ARIMA is the best fit due to the following reasons:

1) ARIMA models can handle nonstationary data by integrating the price series (Shweta, 2021);
2) ARIMA models can handle autoregressive behaviour (Shweta, 2021);
3) ARIMA models assume that the residuals, differences between actual and forecasted values, are homoscedastic (Sun, 2021);
4) ARIMA models are able to make global long-term price forecasts, which aligns with the criterion of emphasizing global long-term trends rather than day-to-day volatility (Bollerslev, 1986). As the main objective is to understand and forecast the general price direction, the ARIMA model's ability to capture trend patterns makes it suitable for this purpose;
5) ARIMA models are not too prone to overfitting;
6) ARIMA models are relatively explainable and interpretable due to the few parameters and mathematical transparency (Shweta, 2021);
7) ARIMA model is more interpretable and straightforward to implement compared to the GARCH model;
8) ARIMA models perform well as seen in Table 9, which shows the performance of different methods. When looking at the metric that is available for the ARIMA and GARCH model, which is the RMSE, we observe that the ARIMA model outperforms the GARCH model, with an RMSE of 0.25 and 9.21, respectively.

7 Forecast the EU ETS price

In the solution design in Chapter 5, the first step is computing the price paths per scenario. For the tax-based scenario and the scenario without carbon pricing, these are straightforward. However, for the EU ETS market-based scenario a more complex forecast should be made, which this thesis does by starting with implementing the ARIMA model. This section starts by explaining the ARIMA model itself and shows a flowchart of how the method is applied in this thesis in Section 7.1. Then this chapter guides the reader through all the steps to properly tune the model and make a forecast until 2050. Additionally, in Section 7.2 and 7.3 respectively the linear regression model and GBM model are also applied and compared with the ARIMA model's performance in Section 7.4. GBM and linear regression are used as benchmarks and compared to the ARIMA model.

7.1 ARIMA model forecast

An ARIMA model is a parametric model, meaning that it requires setting specific parameters before fitting the model. These components are the Auto-Regressive, Moving Average, and Integrated parts of the model, p, q, and d respectively. In an ARIMA model, the carbon price is a linear function of past values and error terms (Box, Jenkins, & Reinsel, 2015). ARIMA is made up of different components including an Auto-Regressive (AR) component, which places a certain weight on past observations. For Moving Average (MA) models something similar happens only for the past error terms. The Integrated (I) elements of an ARIMA model assume that the lag differences between past observations may have explanatory power as well and therefore, these differenced terms are used (Hyndman & Athanasopoulos, n.d.).

An ARIMA model, Autoregressive Integrated Moving Average, can also be written as follows, ARIMA (p, d, q) model. The equation consists of three terms in the equation (Shweta, 2021):

1. **AR term**: The time series is regressed with its previous values, i.e. x_{t-1} and x_{t-p}. The order of the lag is denoted as p.
2. **Integration**: The time series uses differencing to make it stationary and the order of the difference is denoted as d. The integrated component can be seen in the right-hand side of the equation where the difference of the difference is taken, based on the number of differences d set beforehand. We explain the concept of differencing in Table 17, where the number of differences and the corresponding formula can be seen.

Table 17: Integration of an ARIMA model explained using mathematical formulas (Duke, n.d.).

Integrated component	Formula	Order of differencing
$\boldsymbol{d = 0}$	$x_t = X_t$	No differencing
$\boldsymbol{d = 1}$	$x_t = X_t - X_{t-1}$	1st order differencing
$\boldsymbol{d = 2}$	$x_t = (X_t - X_{t-1}) - (X_{t-1} - X_{t-2})$	2nd order differencing

3. **MA term**: The time series is regressed with the residuals of the past observations, i.e. error ε_{t-1} and error ε_{t-q}, where the order of the error lag is denoted as q.

The ARIMA model can be mathematically expressed as:

$$x_t = u_t + \varphi_1 * x_{t-1} + \varphi_2 * x_{t-2} + \cdots + \varphi_p * x_{t-p} - \theta_1 * \varepsilon_{t-1} - \theta_2 * \varepsilon_{t-2} - \cdots - \theta_q * \varepsilon_{t-q} \quad (13)$$

where,

x_t	The differenced/log return series at time t
ε_t	(Hypothetical white noise) is assumed to be independently and identically distributed with a mean of zero and a constant variance of σ_ε^2
φ_i	Model coefficient of the AR term where p is the order of the AR time with, $i = 1,2, \ldots p$
θ_j	Model coefficient of the MA term where q is the order of the MA term and ε_t is the error, with j $= 1,2, \ldots q$
u_t	The value at time t (in our case the price/returns at time t)

The key assumptions of the ARIMA model are summarized (Liu, Hoi, Zhao, & Sun, 2016):

- Stationarity
- Linearity
- No residual autocorrelation
- Constant variance of residuals (Sun, 2021)
- Independent errors (independent and identically distributed (i.i.d))
- Normality of errors

Figure 19 shows the ARIMA process in the form of a flowchart as programmed in Python for this thesis extensively. The exact Python code files can be found in Appendix A.1. This process consists of the following steps and starts with collecting the original data (1), which is transformed by taking the logarithm of the data (2). The return series, one-time differenced series, is used in diagnostic testing in Chapter 6. This returns series is also used as a starting point to train the ARIMA model on (3). After having the log return series, we split the data into a training and test model using a 90/10 split (4). This split is chosen since the behaviour of the time series has changed much in the last 2 years and we want to capture this change. In most training and test splits a split of 70/30 or 80/20 is used, however, 90/10 splits also occur based on the aim of the study and data features (Dobbin & Simon, 2011; Vakayil & Joseph, 2022).

The first decision node in Figure 19 shows a check on whether a time series is stationary (5). If this is not the case yet, then differencing once is again necessary and the model checks the stationarity constraint again until it is stationary. This thesis checks stationarity by conducting ADF and KPSS tests.

Once the time series is stationary the number of differences d is determined (6). This differenced series is then used to further tune the ARIMA model's parameters. From there the tuning parameters p and q are set based on ACF and PACF plots (7). These concepts are explained in the following sections.

Once the parameters p, d, q are set the ARIMA model is fitted on the training data (8). In this ARIMA fitting it is important to note that the training data is not the return series but the log training data only. This decision is made due to the fact that the ARIMA model itself can difference a time series and thus putting in the log original train series is most in line with the ARIMA model's function in Python. In this manner the order of differencing d as entered in the Python 'ARIMA(p,d,q)' function is equal to the total number of differencing needed to create the best forecast of the EU ETS time series.

Hereafter, a forecast is made on the time period of the test set and it is compared to test the performance (9). Then the model checks whether there are other model orders that result in a better performance in terms of the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and the used performance measures, which are RMSE, MAPE, and MAE (10). Both AIC and BIC are methods used for scoring and selecting a model. The AIC is an estimator of prediction error and thus a relative quality of statistical model for a given data set (Akaike, 1998). The BIC method is similar to the AIC only it penalizes complex models more and it is based on Bayesian probability and inference instead of frequentist probability (Schwarz, 1978). Once the model reaches a point where achieving a superior model order is no longer feasible, then a forecast is made until 2050 (11). We make this forecast using parameter settings from the previous steps, however, it is forecasted using all available data and not just the training set. The motivation to do this is that we want to include all available data to make a forecast as the behaviour in the last two years may impact the future values of the EU ETS. Additionally, it is important to remember that all previous transformations should be undone after creating a forecast in order to get a forecast on the correct scale. Once we have the forecasted values for the log returns series, we reverse the differencing process to obtain the forecasted prices. This is necessary to get back to the original price series from the forecasted log returns. The process involves accumulating the log returns to construct the price series. This process is repeated for all forecasted log returns to obtain the forecasted price series. This can be done using the following formula:

$$X_{t+1} = X_t * \exp\left(x_{t+1}\right) \tag{14}$$

The structure seen in Figure 19 is used for the remainder of this section until we create a forecast using the ARIMA model until 2050 in Section 7.1.4. Hereafter, in Sections 7.2 and 7.3 we show the benchmark models linear regression and GBM, respectively, after which we compare the performance.

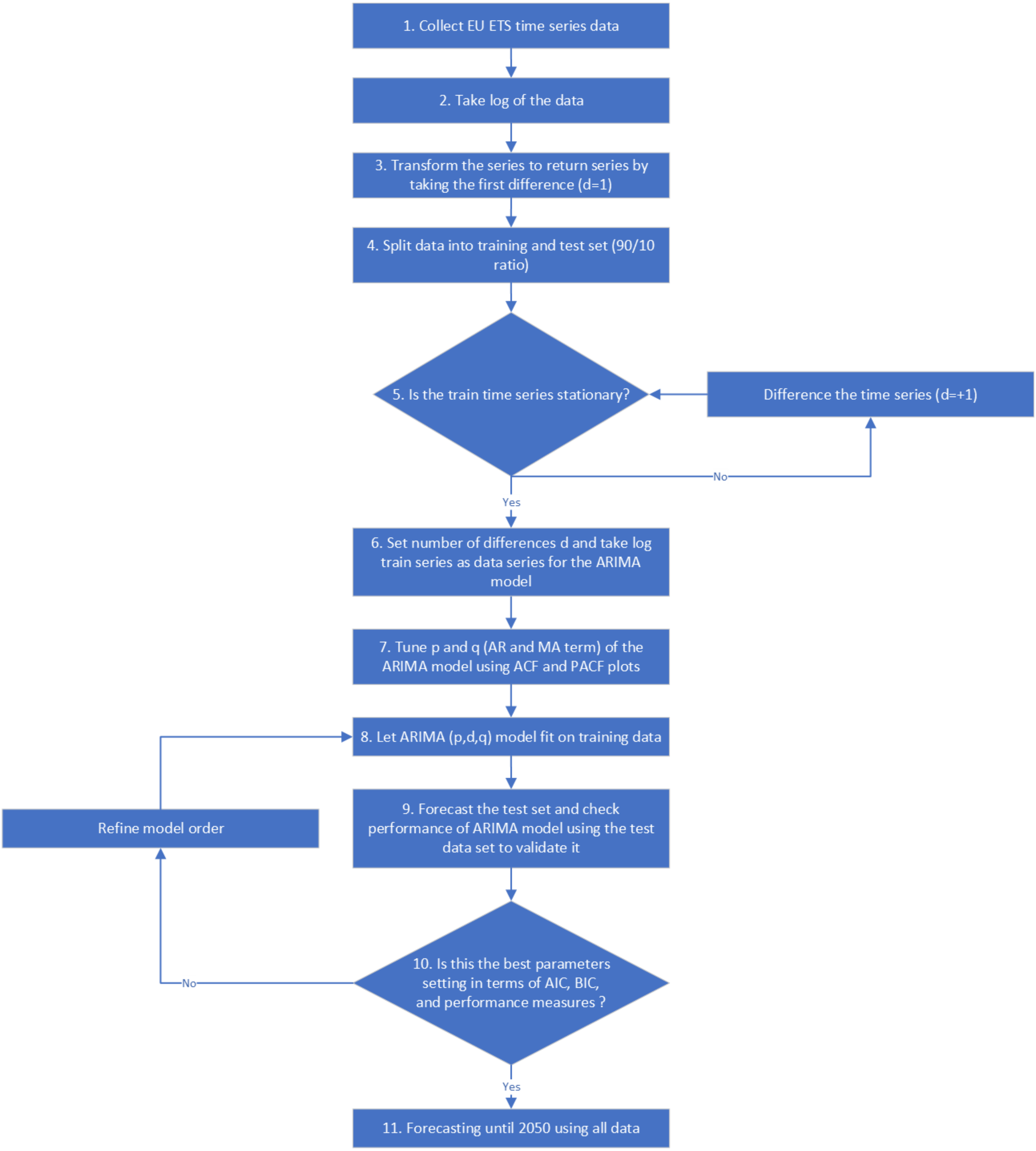

Figure 19: Flowchart of the ARIMA (p,d,q) model approach as programmed in Python.

7.1.1 Data preparation for ARIMA model

This section described the data preparation step of the ARIMA forecast as well as the process to determine the order of differencing (d), the AR term (q), and the MA term (q). This results in the initial parameters for the ARIMA model.

In Table 10 and Figure 15, the general characteristics and visual graphs of the EU ETS data are represented. In the ARIMA model, the log return series serves as an input for tuning all parameters. For the ARIMA function fitting itself the log data series are used and not the return. The ARIMA function itself is able to difference the data further, so manual differencing is not needed for this method. The manual differencing is only performed to see what the ACF and PACF plots show for tuning the p and q parameters.

This research starts with determining the structure of the ARIMA model and estimating the parameter values (p, d, q). The order in which this is determined is first determining the order of differencing d, then the order of the AR term p, and lastly the order of the MA term q. Additionally, the data is divided into a train and test set with a 90/10 split. The data split is shown in Figure 20, here the log data is used. The log returns train set is used to set the ARIMA model's parameters.

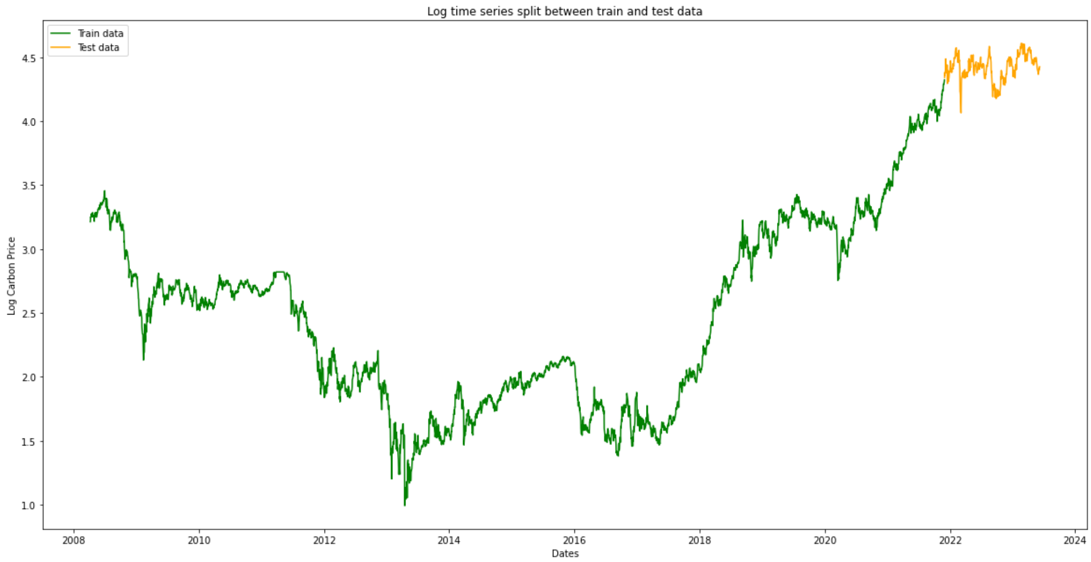

Figure 20: Log time series and the test and train data set using the 90/10 split.

7.1.1.1 Differencing the data (d)

Based on the stationarity tests in Section 6.3 on the EU ETS time series we draw the conclusion that the time series data is not stationary. The ARIMA model, however, needs stationary data and therefore the (log) train data should be differenced. Differencing is subtracting the previous value from the current value, and for some time series, it is necessary to do this more than once. Mathematically speaking it can be written like this when combined with the first step of taking the log gives (Duke, n.d.):

$$x_t = \ln(X_t) - \ln(X_{t-1}) \tag{15}$$

where,

X_t	The price at time t
x_t	The logarithmic difference/return at time t

The d value is the minimum number of differencing needed to make time series stationary. If a time series is already stationary then $d = 0$. It is important to note that one should not over-difference a time series as this will affect the model parameters (Shumway & Stoffer, 2017).

This thesis determines the order of differencing d in an ARIMA model by the minimum differencing required to get a near-stationary series. An ACF plot is a statistical technique that we can use to identify how correlated the values in a time series are with each other (Zvornicanin, 2023). The ACF plot starts at lag 0, which is the correlation of the time series with itself, and therefore this results in a correlation of 1. The general rule is that if the autocorrelations are positive for many number of lags, 10 or more, then the series should be differenced further (Shumway & Stoffer, 2017). If the lag 1 autocorrelation itself is too negative, then the time series is possibly over-differenced (Shumway & Stoffer, 2017). In case that two orders of differencing may seem appropriate, then the order of differencing is given by the one that gives the least standard deviation in the differenced series (Curtiss, et al., 2023). Here the results from looking at the ACF show that the time series should be differenced once. It should be emphasized that this approach is not strictly based on empirical evidence. Consequently, the number of differencing is further validated by performing the ADF and KPSS tests once again on the differenced data.

The results of differencing two times can be seen in Figure 21 and Figure 22, respectively the time series plots and ACF plots. Figure 21 provides an insight into what happens to the (log train return) time series itself when differencing it. We take a closer look at the autocorrelation plot in Figure 22 to determine the order of differencing. Based on the aforementioned explanation on the ACF we do not want a plot that becomes negative too fast, like in lag 1. In the first ACF plot, there is a minor drop to the negative side, however, when this log return series is differenced once more a large negative drop can be observed at lag 1, which may indicate over-differentiation. Therefore, we draw the conclusion that differencing in the order of 1 is necessary. So, $d = 1$ is the order of differencing, this means that we will use the log return series as this is already differenced once. In the ACF plots, however, we can also observe that the later lags deviate from positive to negative.

To confirm stationarity the ADF and KPSS tests are conducted again. The results are shown in Table 18. This test also confirms that the return series is already stationary according to the ADF test as the p-value is lower than 0.05. For differencing the log returns series an additional 1 and 2 times we also see that they return stationary, which is in line with the line of expectations. Note that the ADF statistics and p-value for the log train returns are different from the log returns as tested in Section 6.3 on stationarity. This also makes sense as the test here is only on 90% of the data while the other stationarity test is on the entire data set.

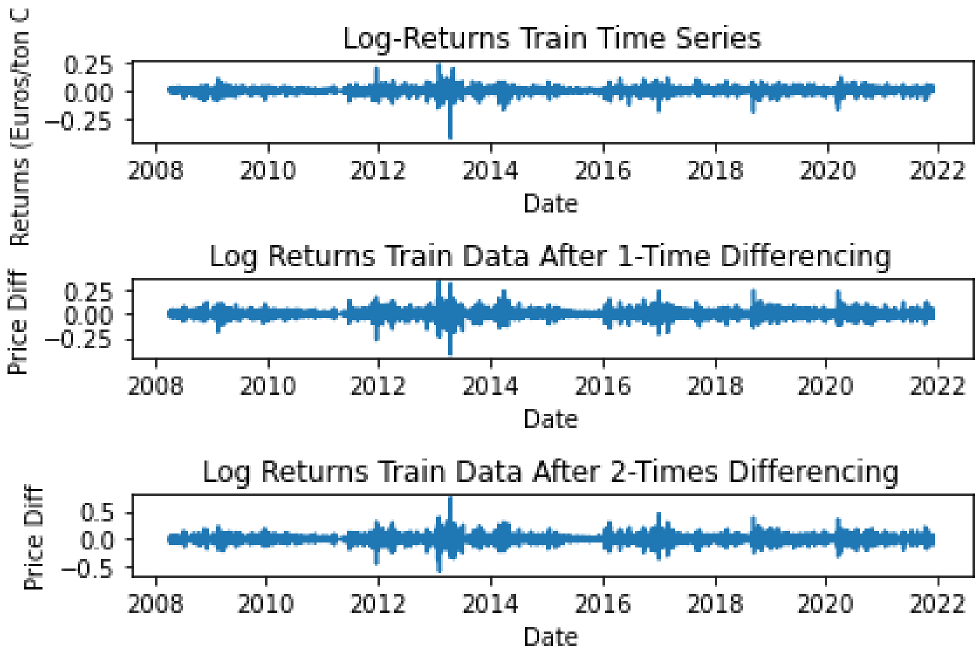

Figure 21: Times series in the log-train return time series and after 1st and 2nd order differencing.

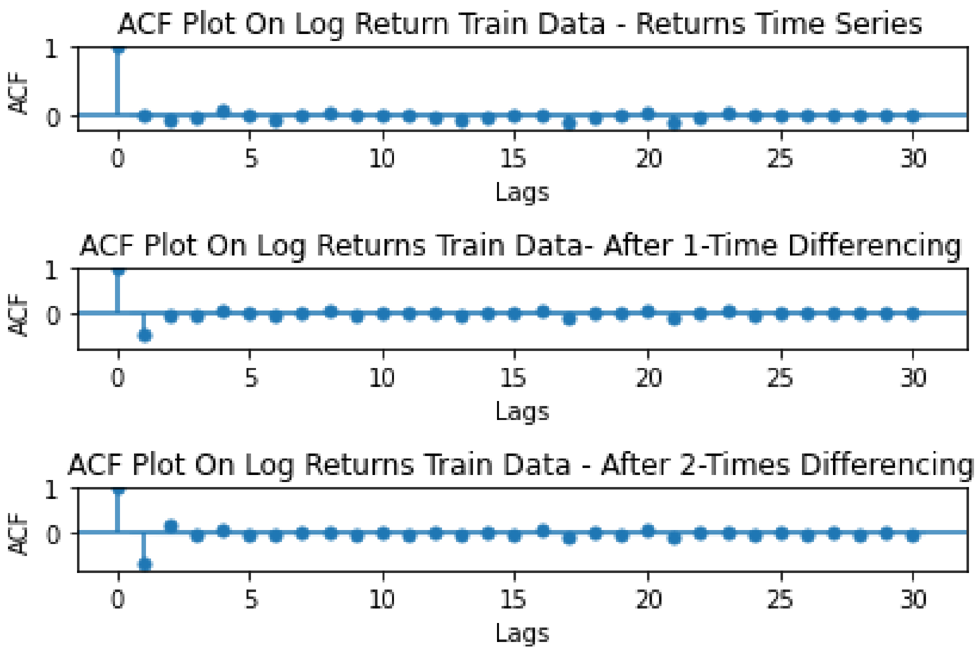

Figure 22: Autocorrelation plots on log train return time series after 1st and 2nd order differencing.

Table 18: ADF test on log train time series and after 1st and 2nd order differencing.

	ADF (constant) on log train returns	ADF (constant + trend) on log train returns	ADF (constant) on 1^{st} difference	ADF (constant + trend) on 1^{st} difference	ADF (constant) on 2^{nd} difference	ADF (constant + trend) on 2^{nd} difference
ADF test statistic (5%)	-12.53	-15.05	-20.69	-20.68	-24.61	-24.61
p-value	2.50e-23	2.07e-22	0.00	0.00	0.00	0.00

Additionally, the KPSS test is also conducted on the log returns train series and the differenced series which shows that the train log returns are non-stationary, and the 1^{st} and 2^{nd} differences, are stationary. This is not the same conclusion as that of the ADF tests in Table 18, as this showed that the log train returns are stationary. However, it is similar to the outcome in Chapter 6, where a difference is observed as well in the conclusion on stationarity between the KPSS and ADF tests. Table 19 shows the p-values and test statistics of the KPSS test. Thus, we set the order of differencing to $d = 1$ to initially fit the ARIMA model. After determining this order of differencing the order of the MA and AR terms can be determined, which the next sections do.

Table 19: KPSS test on log train time series, and 1st and 2nd order differenced series.

	KPSS on log train returns	KPSS on 1^{st} difference	KPSS on 2^{nd} difference
ADF test statistic (5%)	0.70	0.025	0.021
p-value	0.013	0.1	0.1

7.1.1.2 Order of the AR term (p)

The order of AR terms can be found by inspecting the PACF plot (Wegner, 2018). The PACF can be seen as the correlation between the series and its lags, after excluding the contributions from the intermediate lags. This provides information on whether a specific lag is needed in the AR term or not. As Section 7.1.1.1 determined that an order of 1 is needed for differencing, the data of the PACF used is the data that is differenced once, so on the log returns. This gives the output as seen in Figure 23.

To determine the value of p (the AR term) one should look at the last significant spike before the plot enters the non-significant range (Jayaraj & Hoe, 2022). In the PACF plot, and the ACF plot as well, a blue area can be observed around 0, which depicts the 95% confidence interval and is an indicator of the significance threshold (Monigatti, 2022). In other words, the lag value should be identified for which the PACF plot, as seen in Figure 23, crosses the upper confidence interval for the first time.

When looking at the figure it can be observed that for the first lag already the plot is in the non-significance range. Therefore, the AR term p is set to 1, as the lags are not significantly out of the limit. We observe that there are significant spikes later on in later lags, possibly indicating the need for including an additional AR term to capture the underlying patterns in the data.

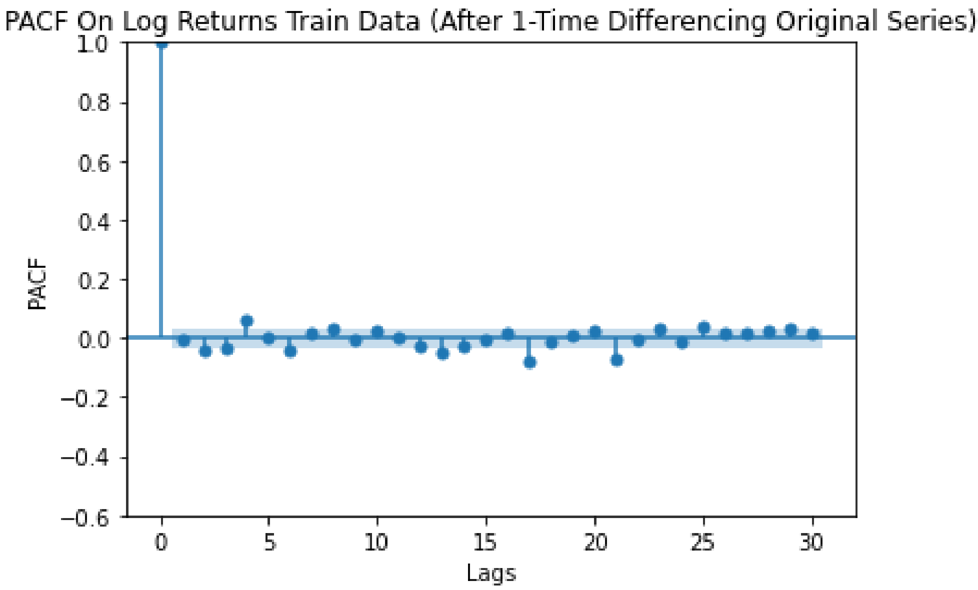

Figure 23: Partial Autocorrelation Function (PACF) plot on log train time series after 1st time differencing, which is the log return train series.

7.1.1.3 Order of the MA term (q)

The last step of determining all ARIMA parameters is determining the order of the MA term. The ACF plot is also used to determine the order of the MA term q. The MA term is technically, the error of the lagged forecast (Monigatti, 2022). Analysing the ACF plot to determine the order of the MA term, works similarly to the PACF plot in Section 7.1.1.2. Figure 24 shows the ACF plot on the log returns train series. This plot shows that lag 1 is already slightly negative and in the non-significance range. Therefore, we choose the MA term of $q = 1$. However, we do note that some later lags do rise above the significance range, like lag 4. This indicates a substantial positive correlation between the log returns and their values four time points ago. Such a correlation might imply the presence of underlying patterns or trends in the data that occur with a lag of four time intervals.

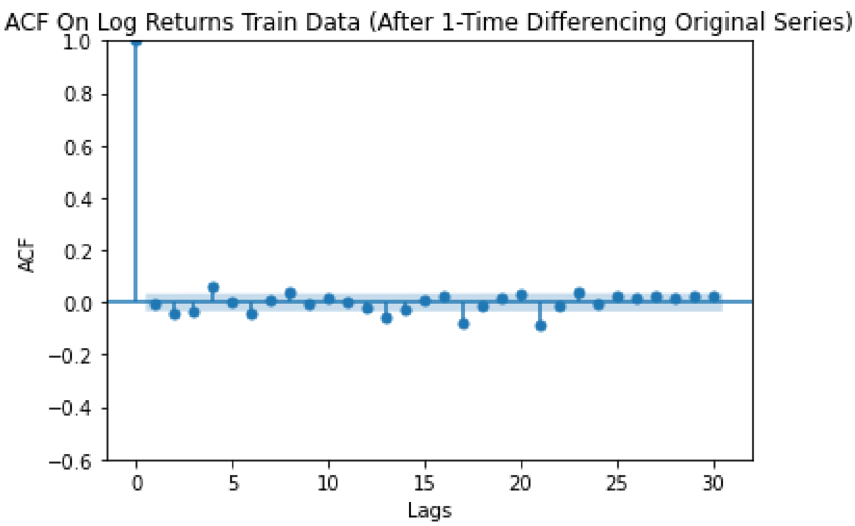

Figure 24: Autocorrelation Function (ACF) plot on log train time series after 1st time differencing, which is the log return train series.

7.1.2 Setting ARIMA model parameters

Once the parameters of the ARIMA model are determined and set to $(1,1,1)$ it is time to make forecasts and compare those to the test set. This forecast is called out-of-sample, which refers to the fact that the period of data is independent of the in-sample data and thus not used during model training. It is the future or unseen data that the model has not seen yet. The purpose of using out-of-sample data is to evaluate the performance of the trained model within a realistic forecasting scenario. The forecasts are compared to the actual values in the test data and in this way, the performance of the model can be measured using the performance metrics; RMSE, MAE, and MAPE. Additionally, the AIC and BIC values are also observed for the model. The model can also perform poorly. This can be when there is a better AIC and BIC value when changing a parameter within the ARIMA model. In that case, the new parameter is set and iteratively the other parameters are changed until we end up with the best configuration. First, this section shows the results of the ARIMA (1,1,1) model.

When making a forecast for the ARIMA (1,1,1) model a poor forecast is found, with a nearly flat horizontal line as forecast. The figures of this forecast can be found in Appendix A.4. Due to this poor performance and higher AICs and BICs in other configurations, we look further at better parameters for our forecasting model. This thesis uses the algorithm of Hyndman-Khandakar with some adjustments. This method consists of the following steps (Hyndman & Khandakar, 2008):

1. The number of differences $0 \leq d \leq 2$ is determined using repeated KPSS or ADF tests.
2. The values of p and q are chosen by minimizing the AICs after differencing the data d times.
   a. Four initial models are fitted:
      - ARIMA (0,d,0)
      - ARIMA (2,d,2)
      - ARIMA (1,d,0)
      - ARIMA (0,d,1)
   b. The best model (with the smallest AIC value) fitted in step (a) is set to be the 'Current model'.
   c. Variations on the current model are considered
      - Vary p and q from the current model by ± 1

      The best model considered so far becomes the new current model.
   d. Repeat step 2(c) until no lower AIC can be found.

The first step is already done in Section 7.1.1.1 and was set to 1. However, there is some uncertainty about whether the time series is fully stationary when differencing it 1 time in the diagnostic testing. Therefore, setting the parameter to $d = 2$ is also tested here to optimally tune the model and see if it performs better when differencing twice. The results of the algorithm to optimally tune the ARIMA model are shown in Table 33 in Appendix A.5. The ARIMA (0,2,0) and ARIMA (1,2,0) have the best AIC and BIC, however, when plotting these configurations very extreme forecasts until 2050 are observed, which rise exponentially until 1.4e51 or 1.50e55 respectively. These results are also shown in Appendix A.6. Due to this extremely exponential behaviour we look at other well-performing configurations, which results in the ARIMA(2,2,2) model.

7.1.3 Performance and forecast of the ARIMA(2,2,2) model

This section demonstrates the performance of the ARIMA(2,2,2) model through out-of-sample testing. Out-of-sample testing involves utilizing a model to make forecasts or estimates on data points that were not included in the model's training dataset, allowing for an assessment of the model's performance on unseen data (Hastie, Tibshirani, & Friedman, 2009). The ARIMA model is trained and the parameters are set using the training data. Subsequently, a forecast is generated for the values of the test data, enabling a comparison with the actual test data. The code for this forecast can be found in Appendix A.1. The evaluation of the model is presented through three graphs, each providing different insights. Figure 25 illustrates the logarithmic forecasts and log returns of the training dataset. We observe that the forecast runs through the test data and seems to follow the average trend. Figure 26 presents a closer view of the forecasts and test data, represented on the original scale. Figure 27 displays the forecasts and the original time series, also depicted on the original scale. The graph resulting from the ARIMA(2,2,2) model reveals a consistent trend in the form of a nearly straight line, which appears to represent the average behaviour. However, it is important to note that this trend does not capture any significant variations or fluctuations in the data. This suggests that the ARIMA model might have limitations in capturing more complex dynamics present in the time series. However, in this research the aim is to get a general price path and therefore, this limitation is of less importance.

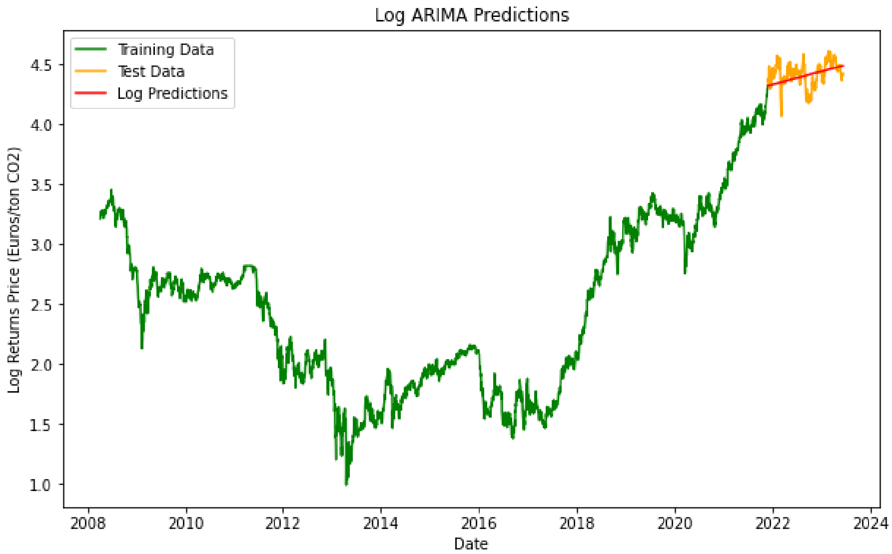

Figure 25: Training and test data split from 2008 until 2023 showing the forecast of the log returns (out-of-sample) of the ARIMA(2,2,2) model from 1st of December 2021 until 9th of June 2023 compared to log test data.

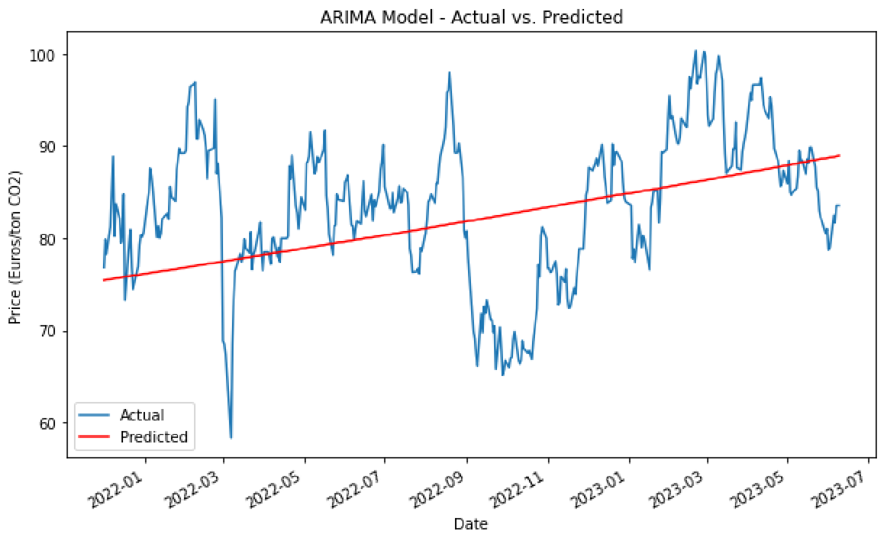

Figure 26: Out-of-sample forecast of ARIMA(2,2,2) model from 1st of December 2021 until 9th of June 2023 compared to actual test data, which shows that the ARIMA model follows an increasing trend.

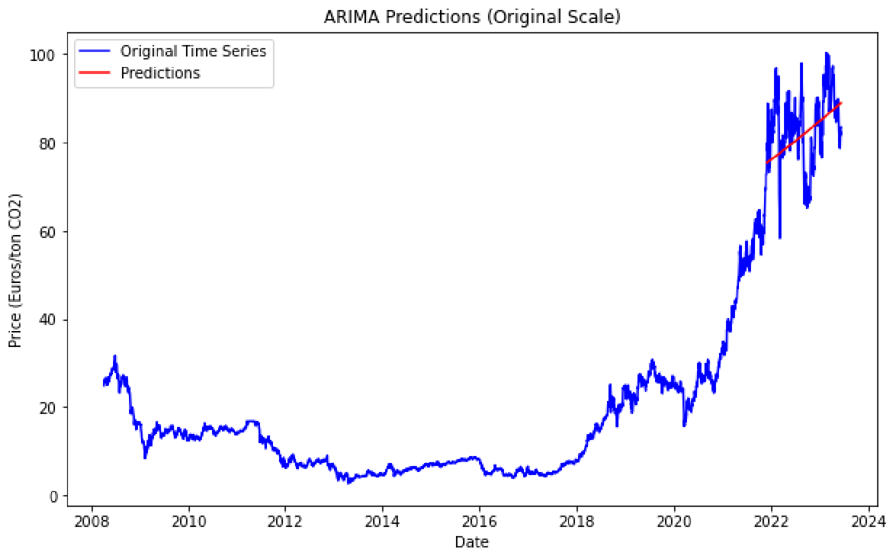

Figure 27: Original data series from 2008 until 2023 showing the out-of-sample log forecast of the ARIMA(2,2,2) model from 1st of December 2021 until 9th of June 2023 compared to original data.

In addition to the graphical evaluation, the performance of the ARIMA(2,2,2) model is quantitatively assessed using five key metrics:

- **Mean Absolute Error (MAE):** The MAE is determined to be 6.45, indicating an average absolute deviation of 6.45 units between the forecasted and actual values.
- **Mean Absolute Percentage Error (MAPE):** The MAPE is calculated to be 0.079, suggesting an average relative error of 7.9% between the forecasted values and the actual data.
- **Root Mean Squared Error (RMSE):** The RMSE value is found to be 7.99, representing the average magnitude of the residuals between the forecasted and actual values.
- **Relative Root Mean Squared Error (rRMSE):** The rRMSE of linear regression equals 9.58, which is a relative RMSE that is perceived as a reasonable but not an extremely accurate fit. It suggests that on average forecasts deviate from the actual values by approximately 9.58% of the mean of the EU ETS price.
- **R-squared (R^2)**: The R-squared is calculated to -0.024, indicating that the historical prices give a poor explanation for the variation of the future prices. A negative R-squared is not common as it performs below simply forecasting the trend line of a series. However, when looking at the formula, $R^2 = 1 - \frac{\sum_{i=1}^{n}(Actual_i - Prediction_i)^2}{\sum_{i=1}^{n}(Actual_i - \overline{Prediction})^2}$, we see that a negative value can only occur when the numerator, also known as the sum of squares representing variation in the data that is not explained by the fitted model, exceeds the value of the denumerator, also known as the total sum of squares which represents the total variation in the data measured by the sum of squares of the difference between expected and actual values. This can be the case when we evaluate models separately on train and test data, which is what is happening in this thesis.

These metrics provide insights into the accuracy of the ARIMA(2,2,2) model. The average MAE and MAPE values, along with the moderate RMSE value, indicate that the model generates reasonably accurate forecasts with respect to the actual data.

7.1.4 ARIMA(2,2,2) forecast until 2050

Now that we investigated how the ARIMA(2,2,2) model performs we adjust the parameters p, d, q again using all data as input, instead of only the training set. In this way, all information is taken into account when making a forecast on the returns. This section describes the process of tuning all three parameters again as well as assessing the ARIMA model based on the AIC and BIC values. Hereafter, a forecast is made until 2050, which can be found in Appendix A.1.

First, the parameters of the ARIMA model are tuned starting with the number of differencing d. Table 20 presents the results of the ADF test on all log return data. These results show that all time series, log returns, differenced once, and differenced twice, are stationary. Additionally, when looking at the ACF plots in Figure 28 the same conclusion is drawn that the ACF plot on the log return data is already stationary and in the 1-time differenced plot a large negative drop can be seen, which may indicate over differencing. Therefore, initially, the order of differencing is set to 1. This can still be altered later on when looking at the BIC and AIC values.

Table 20: ADF test on log time series (all data) after 1st and 2nd order differencing.

	ADF (constant) on log returns	**ADF (constant + trend) on log returns**	**ADF (constant) on 1st difference**	**ADF (constant + trend) on 1st difference**	**ADF (constant) on 2nd difference**	**ADF (constant + trend) on 2nd difference**
ADF test statistic (5%)	-11.40	-14.82	-21.82	-21.81	-25.79	-25.79
p-value	7.871e-21	2.72e-22	0.00	0.00	0.00	0.00

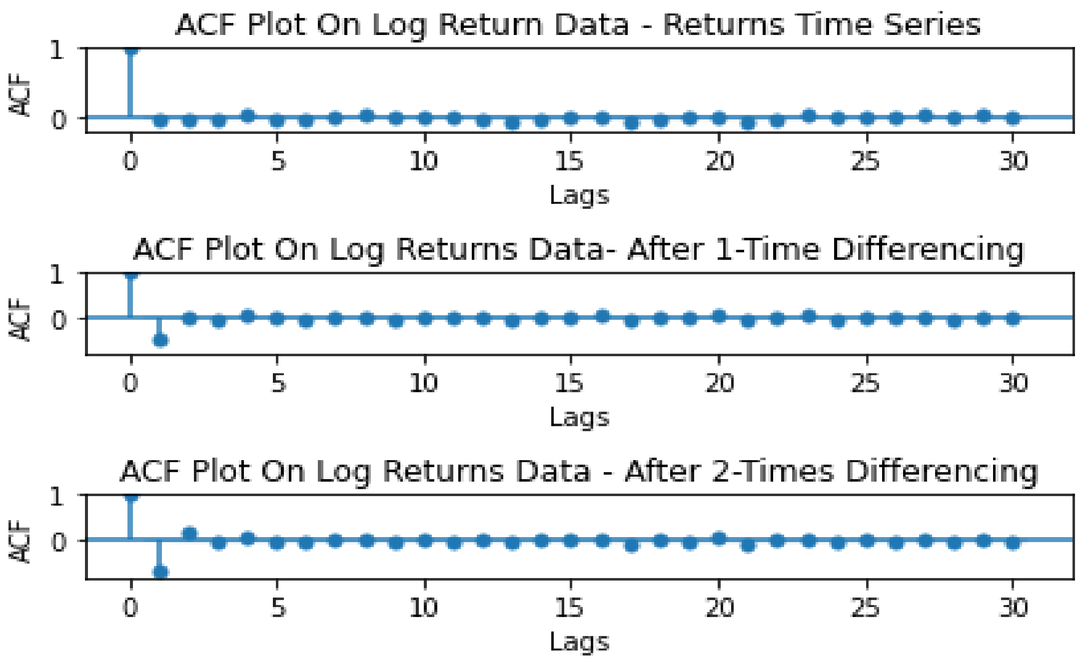

Figure 28: Autocorrelation plots on log return time series (all available data) after 1st and 2nd order differencing.

Secondly, the order of the AR term is determined by observing the PACF plot. Figure 29 shows the PACF plot which displays that the first lag is already non-significant and therefore, the order of the AR term is set as $p = 1$.

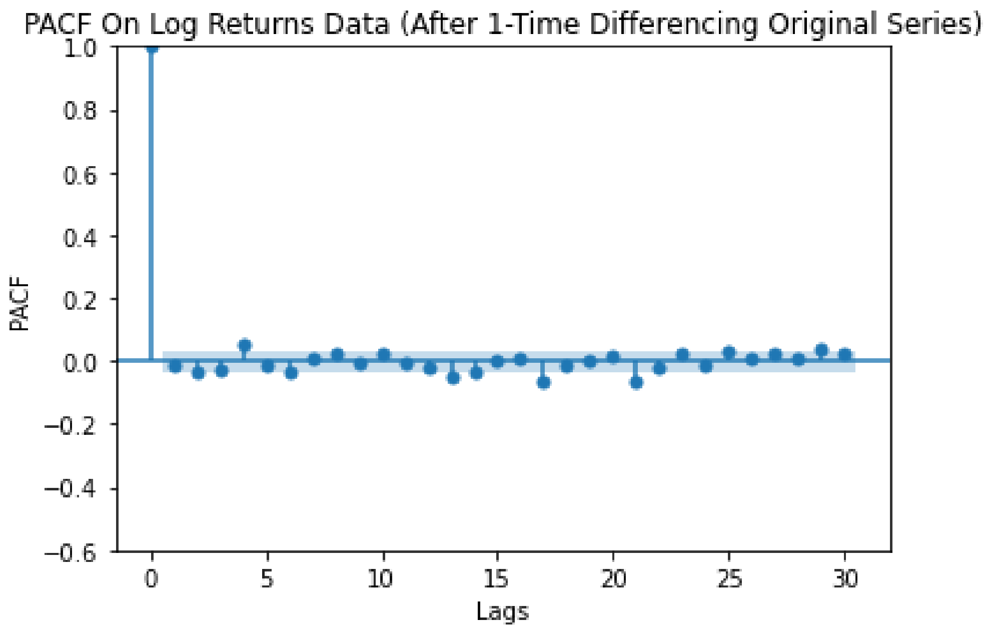

Figure 29: Partial Autocorrelation Function (PACF) plot on log train time series after 1st time differencing, which is the log return series.

Thirdly, the order of the MA term is determined by observing the ACF plot on the log returns data. Figure 30 shows the ACF plot and as the first lag is already non-significant we conclude that the order of the MA term can be set to $q = 1$.

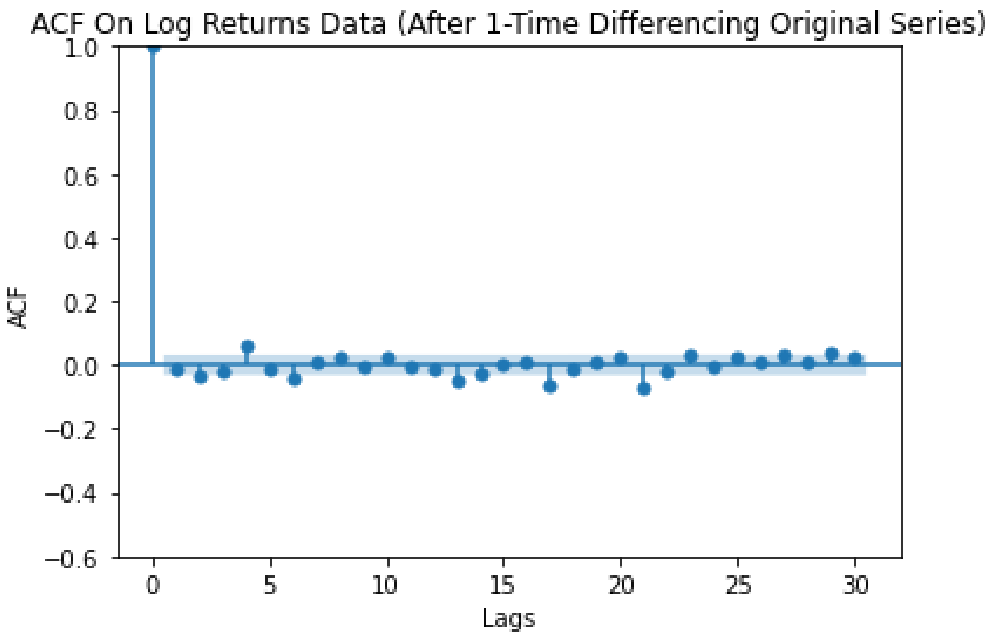

Figure 30: Autocorrelation Function (ACF) plot on log train time series after 1st time differencing, which is the log return series.

Combining the three conclusions of the order of differencing, AR term, and MA term we start at the ARIMA(1,1,1) model. The AIC and BIC values are used again to set the best parameter combination of the ARIMA model as it is now trained on all data. However, the forecast is still poor and therefore, we adjust the parameters again using the algorithm of Hyndman-Khandakar.

When using this algorithm we conclude that the ARIMA(0,2,0) and ARIMA(1,2,0) seem like good fits, however, when observing their forecast they both produce a horizontal line as forecast. This behaviour changes when either adding 1 to the autoregressive component or 1 to the moving average component, it then turns into a more exponential type of behaviour. When looking at step a) the third best parameter settings are those of the ARIMA(2,2,2) model. Therefore, further alterations in step c) are made to get to the optimal parameters. When testing more we can observe that when increasing the order of d the model always seems to perform better in terms of AIC and BIC, however, the forecast itself becomes more extreme meaning that the price develops more exponentially and rises very steeply towards the end of the time horizon. The ADF tests show that the time series is already stationary for differencing 1 time, $d = 1$. We do keep in mind that we do not want to over difference the series even though the performance seems to become better in terms of AIC and BIC. Due to not wanting to over difference, the horizontal line forecast of ARIMA (1,1,1), and better AIC and BIC values for a time series that is differenced twice, $d = 2$, we chose to set $d = 2$.

Furthermore, this thesis tests different AR and MA terms while setting the number of differences at $d = 2$. In altering both of these terms an optimum can be seen when looking at the AIC and BIC. The results can be seen in Table 21. From there, we observe that setting both the AR and MA terms to 3 results in the best BIC and AIC values.

Table 21: AIC and BIC results of using the Hyndman-Khandakar algorithm to optimally tune the ARIMA model based on all data.

Performance of different ARIMA models	**AIC**	**BIC**
Initial models fitted (step a)		
(1,1,1)	-15,617	-15,599
(0,2,0)	-12,919	-12,913
(0,1,0)	-15,618	-15,612
(2,1,2)	-15,639	-15,608
(2,2,2)	-15,601	-15,569
(1,1,0)	-15,617	-15,604
(1,2,0)	-13,960	-13,947
(0,1,1)	-15,617	-15,604
(0,2,1)	-15,605	-15,592
Variations of current model fitted (step c)		
(2,1,1)	-15,615	-15,590
(1,1,2)	-15,617	-15,592
(0,1,2)	-15,619	-15,600
(2,3,2)	-15,223	-15,192
Variation with $d = 2$ fixed		
(1,2,1)	-15,603	-15,584
(1,2,2)	-15,603	-15,578
(2,2,1)	-15,606	-15,581
(3,2,2)	-15,604	-15,567

(2,2,3)	-15,601	-15,563
(2,2,4)	-15,603	-15,559
(3,2,3)	15,600	-15,557
(4,2,3)	-15,606	-15,556
(3,2,4)	-15,608	-15,558

However, the performance indicators (RMSE, MAE, and MAPE) are also used on the top four model parameters as the AIC and BIC values only provide limited insights. Table 22 shows these performance indicators per parameter setting of the ARIMA model. When looking at these performance measures the ARIMA(2,2,2) model is the best-performing model and therefore this is the final model parameter setting in this thesis.

Table 22: Performance indicators of top four parameter settings for the ARIMA(p,d,q) model.

Parameters	MAE	MAPE	RMSE	R-squared
(2,2,2)	6.45	0.079	7.99	-0.024
(3,2,3)	34.92	0.42	42.54	-28.02
(2,2,3)	31.49	0.38	38.26	-22.47
(2,2,4)	42.40	0.51	51.96	-42.29

To capture all information of the ARIMA model the model is initially fitted on all data available, meaning the test and train set together. Fitting the ARIMA(2,2,2) model on this data results in the price forecast in Figure 31. This more extreme forecast in terms of exponential increase is also expected. The last part of the available data set, from 2021 until 2023, shows a different trend compared to the period before, namely from 20 to 90 Euros approximately. The behaviour in Figure 31 can be explained by the fact that there were significant positive coefficients of the log returns in the last part of the data set. These significant positive coefficients may be captured by the AR and MA terms. The AR term captures the influence of past values on future values and in the returns of the EU ETS an increasing past value is observed, which results in increasing forecasted values. The MA term accounts for any residual patterns in the original time series and as these residual patterns are increasing drastically as well it is also expected that the forecasted values are adjusted to this rapid trend. It is also important to state that forecasting on a very long horizon, like until 2050, often results in more extreme values as the forecast interval increases for an ARIMA model (Brockwell & Davis, 2016). Additionally, more parameter configurations are used, but they all result in the same or even more exponential forecasts or a flat horizontal line.

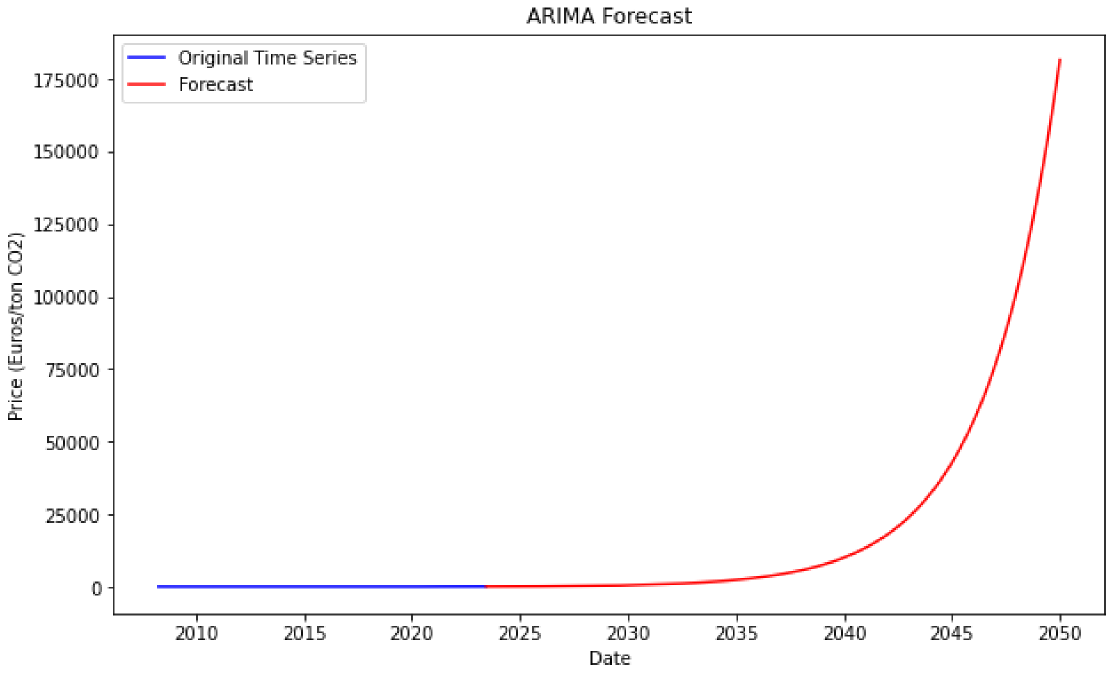

Figure 31: ARIMA(2,2,2) model forecast until 2050 and original EU ETS time series when setting the parameters on all data, which shows an exponential increase until 175,000 Euros by 2050.

To create additional insights a forecast is also made according to the ARIMA(2,2,2) model, only using train data. Figure 32 shows the results of this forecast until 2050 and we observe that the result is less extreme than the results when trained on all data. These results are also expected as the AR and MA terms are not trained on the period of 2021 until 2023 and thus do not incorporate the trend in those years.

In this thesis, we have decided to use the forecasted values of the forecast as shown in Figure 32 based on the ARIMA(2,2,2) model trained on the train data. The motivation to do so is two-folded. Firstly, the test data set shows a distinct shift in behaviour in terms of trend and volatility. This behaviour starts after the Green Deal is announced, which shows the ambitious plans of the EU. When observing the price in October 2023 we see that the price is more stable now, which may imply that the carbon price does not keep the same trend and volatility as the one present in the test set. However, when training the ARIMA model on all data the model's AR and MA terms are important to observe as well. The AR term is of the order 2 and therefore looks back two time periods, with 30 lags each lag presents 127 days, and thus the model looks back for slightly more than 2/3rd of a year. However, when forecasting this means it only looks at the more extreme behaviour in the last 2/3rd year. The MA term is also of the order 2 and it captures the relationship between the current value of the time series and the random error terms. Upon comprehensive examination, it is evident that the ARIMA model trained on all data tends to generate forecasts characterized by a more pronounced, exponential price development. This development, however, does not seem to align with the observed price stability as of October 25th, 2023, where the EU ETS price stands at 84.28 Euros, signifying a two-year period of relative stability. Therefore, the price behavior, as illustrated in Figure 31, appears less likely. Given the overarching aim of our study - the creation of a general price path - we prioritize employing a model that does not overfit the data. Furthermore, based on discussions with the board at Vanderlande, it is apparent that a more conservative approach is favored. Consequently, we have made the informed decision to utilize the ARIMA(2,2,2) model trained exclusively on the train data to make forecasts extending up to 2050.

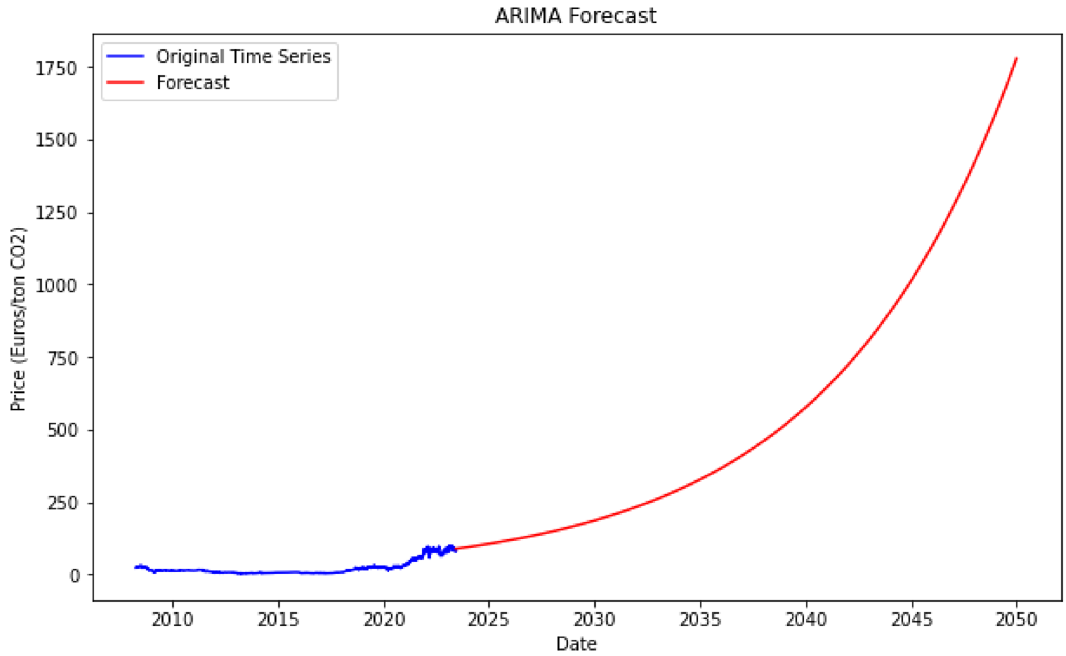

Figure 32: ARIMA(2,2,2) model forecast until 2050 and original EU ETS time series when setting the parameters on the train data, which shows an exponential increase until 1,776.84 Euros by 2050.

Next to the ARIMA model we also use two benchmark methods to which this model is compared. The two methods are GBM and linear regression and the motivation as to why these are used is provided in Section 5.2.1.1. The forecasts and price paths are also made using the log returns as input series. Sections 7.2 and 7.3 delve into the other two forecasting methods. Together, the ARIMA(2,2,2) model, linear regression model, and GBM form sub-scenarios within the EU ETS market-based carbon pricing scenario. Through this comprehensive approach, we illuminate diverse facets of the EU ETS market and uncover valuable information to inform our analysis.

7.2 Forecast EU ETS price using linear regression

This section discusses the first alternative to the ARIMA model, which is linear regression. Linear regression is explored as an alternative method to forecast the price of EU ETS. We show the results of the forecast by linear regression and the performance metrics in this section. The details of the linear regression are provided in the 'Forecast_Excel.csv' file. However, first, the concept of linear regression is shortly explained in the context of forecasting the EU ETS price until 2050.

Linear regression is a statistical method used for modelling the relationship between a dependent variable and one (or more) independent variables (Freedman, 2009). The primary aim of linear regression is to find a linear equation that best describes the association between the variables.

One of the main advantages of linear regression is its simplicity and interpretability, a change in the dependent variable is associated with a one-unit change in the independent variable(s). However, linear regression also has its limitations. Firstly, it assumes linearity between the dependent and independent variables. Secondly, it is sensitive to outliers as they can significantly impact the estimated coefficients. Additionally, linear regression assumes that the errors are normally distributed and have constant variance (homoskedasticity). Violation of these assumptions can lead to biased estimates (Bonamente, 2023).

In the context of using linear regression to forecast the future EU ETS price based on historical price data, the approach involves fitting a straight line to the historical price points. The Excel forecast works using a linear formula (Microsoft, 2021):

$$x_t = a + bt \tag{16}$$

where,

x_t	The log return series at time t
t	Time (in days)
a	The intercept, which represent the value of the log return when time is 0
b	The slope, which represent the change in log returns for a unit change in time

The historical returns are used as the independent variable, and time is used as the dependent variable. The linear regression model estimates the slope and intercept of the line, allowing us to project the future EU ETS price based on the assumed linear relationship between historical and future returns. However, it is important to be cautious about this approach as it assumes a linear trend in the return data, which might not always accurately capture the complex and nonlinear dynamics that can affect financial markets.

To create a linear regression model in Excel, we need to handle inconsistencies in the data first. In the data, there are dates missing that are not business days, like weekend days and holidays. These days are given the price of the day before, i.e. the price on Saturday was based on the price of that prior Friday. This method is also known as forward filling or last observation carried forward. It is a method of imputing missing values in a time series by propagating the last observed value forward in time until a new value is observed. It should be noted that this method of imputing missing values has an impact on the forecast itself as these are non-existing values (Lachin, 2015). Once the missing values are replaced a forecast can be made, which is based on linear regression. The first step is similar as in ARIMA and the data is split by a 90/10 train-test split. Using the training data a forecast is made on the test set and then transformed back from the return to the price series, which is visualised in Figure 33. We observe that the linear regression line seems to forecast close to the average trend of the time series. To further analyse the performance of linear regression on forecasting the EU ETS the four performance metrics are used as well. These show the following results:

- **Mean Absolute Error (MAE):** The MAE is determined to be 8.04, indicating an average absolute deviation of 8.04 units between the forecasted and actual values.
- **Mean Absolute Percentage Error (MAPE):** The MAPE is calculated to be 0.094, suggesting an average relative error of 9.4% between the forecasted values and the actual data.
- **Root Mean Squared Error (RMSE):** The RMSE value is found to be 9.58, representing the high magnitude of the residuals between the forecasted and actual values.
- **Relative Root Mean Squared Error (rRMSE):** The rRMSE of linear regression equals 11.48, which is a relative RMSE that is perceived as a reasonable but not extremely accurate fit. It suggests that on average forecasts deviate from the actual values by approximately 11.48% of the mean of the EU ETS price.
- **R-squared (R^2):** The R-squared is calculated at 0.032, indicating that the historical prices give a poor explanation of the variation of the future prices. We can explain this by looking at the graph in Figure 33 where we see that the actual price has a high variability and thus data points fall further from the regression line.

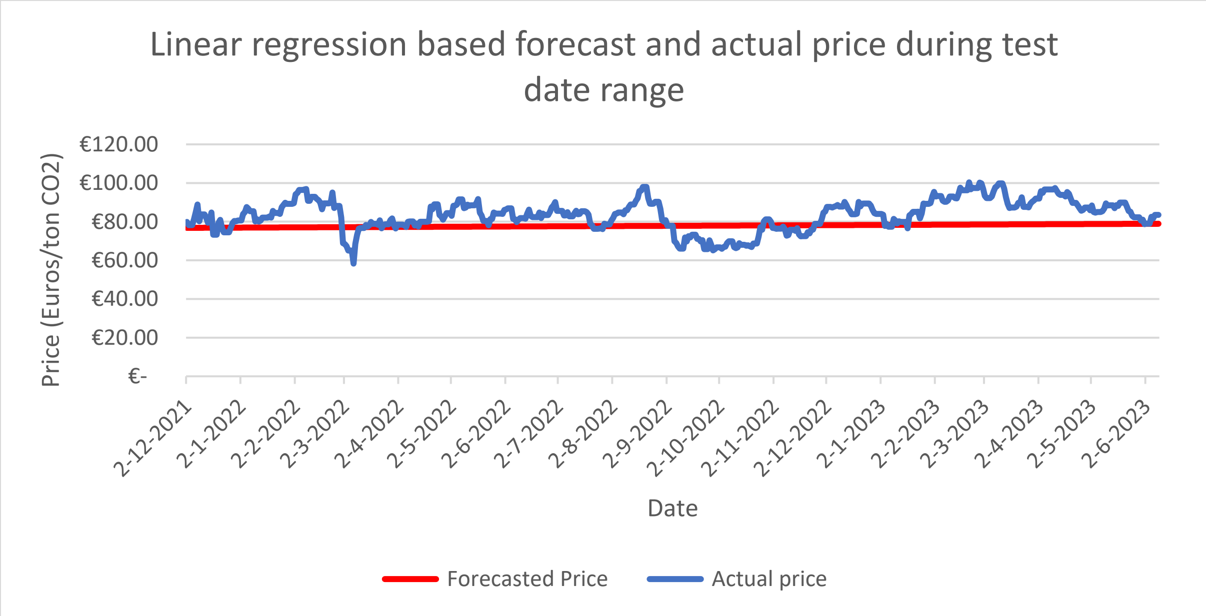

Figure 33: Forecasted and actual test price from 2021 until 2023 during the date range of the test set, which shows that the linear regression follows the average trend of the test series.

For the forecast until 2050, we use all available data and not just the train data. Using linear regression to forecast until 2050 results in the forecasting interval and forecast visualised in Figure 34. The Excel FORECAST function forecasts future values using linear regression. This graph shows the forecasted price as a red line and the lower and upper confidence bound in light and dark orange respectively. The confidence bounds show the confidence interval which is the range surrounding each forecasted value, in which 95% of the future points are expected to fall based on the forecast with normal distribution. A smaller interval implies more confidence in the forecast for a specific point. We observe that the confidence interval increases and becomes wider as time passes, which suggests less confidence on the longer horizon and more price uncertainty. The price itself will increase to 175 Euros per ton of CO_2 in 2050, with the upper bound running until around 1,300 Euros. The lower bound drops below zero, however within the scope of this research we assume that there is no negative price. Therefore, we crop the image and do not show the full trajectory of the lower bound.

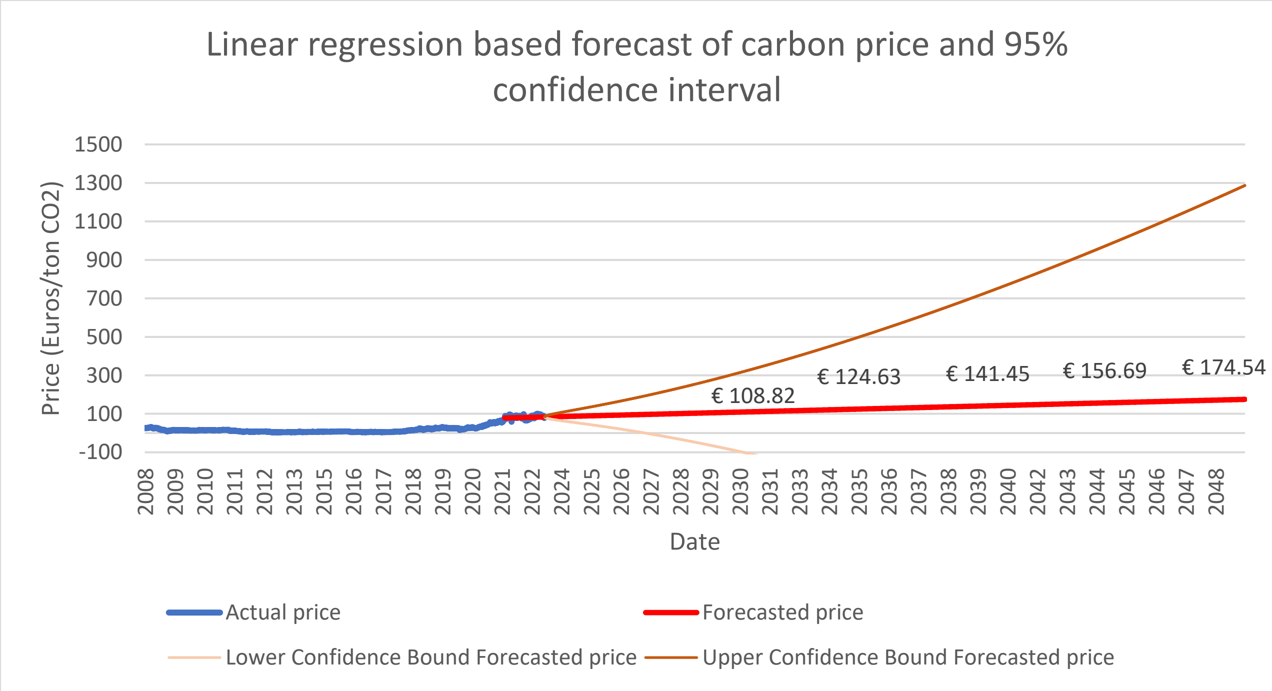

Figure 34: Forecast and the 95% confidence interval of the EU ETS carbon price until 2050, where the upper bound reaches 1,300 Euros by 2050.

7.3 Forecast EU ETS price using Geometric Brownian Motion (GBM)

The third method that is explored to forecast sample paths of the EU ETS is Geometric Brownian Motion (GBM). In this section, we present the results obtained from applying the GBM model to the return series of the data. The GBM model is utilized as a third benchmark and explores its ability to create sample paths of the price behaviour. In Section 7.4, we evaluated the performance of the GBM model and compared it with the ARIMA(2,2,2) and linear regression model to assess its effectiveness in capturing the complex patterns present in the return data. For the GBM model, we use an average sample path, which is compared to the actual test data and this can provide insights into the performance metrics.

GBM is the most basic model to generate a price path (Hull, 2008). In the Black-Scholes framework, asset prices are assumed to follow the GBM. The formula that describes GBM is also discussed more extensively in the literature review (Sigman, 2006) equation 1. It is important to mention that the actual empirical validity of the GBM is widely debated (Mandelbrot, 1963; Luenberger, 1998). The assumptions of the GBM model are discussed in the literature review Chapter 4.

Before applying the GBM model, the return series data was pre-processed to ensure that it was suitable for the model. Additionally, the assumption is made that there are 252 business days per year (Samuelsson, 2023). Unlike for the linear regression model no forward filling is needed for the GBM. The data is also transformed into the logarithmic returns data and a 90/10 split is used for training and test data. All the Python code can be found in Appendix A.1. First, ten sample paths are made using the training data on the test data, which forecasts the log returns. These are then transformed back to the original scale prices and compared to the test data. Figure 35 shows the ten sample paths that are created from the train data set. Figure 36 shows the average sample path when computing the average price at each point in time of the ten sample paths in Figure 35. This average sample path is used to provide some information on the performance of GBM. We see that the GBM forecasts lower values than the actual EU ETS price. This can be reasoned as the GBM function is based on the mean and standard deviation in the entire train data set, which are lower than in the test data set. The standard deviation is higher in the test set compared to the train set.

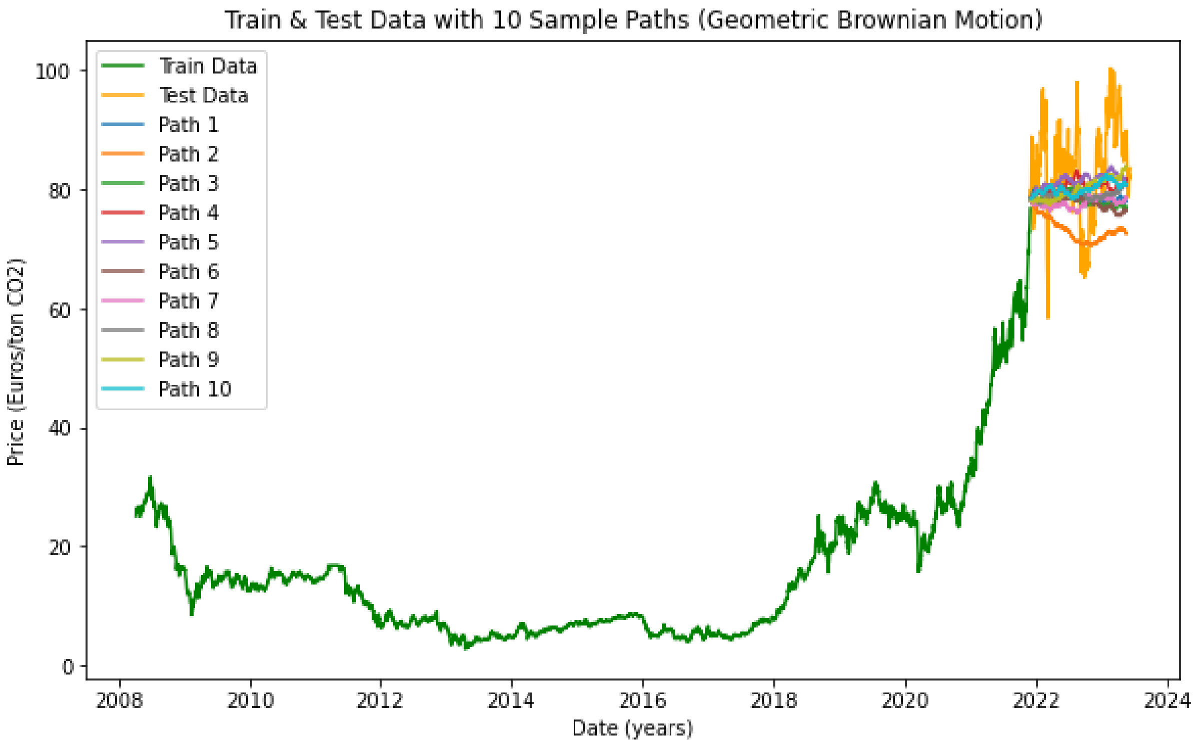

Figure 35: Ten sample paths created from the train data on the period of the test data based on Geometric Brownian Motion (GBM).

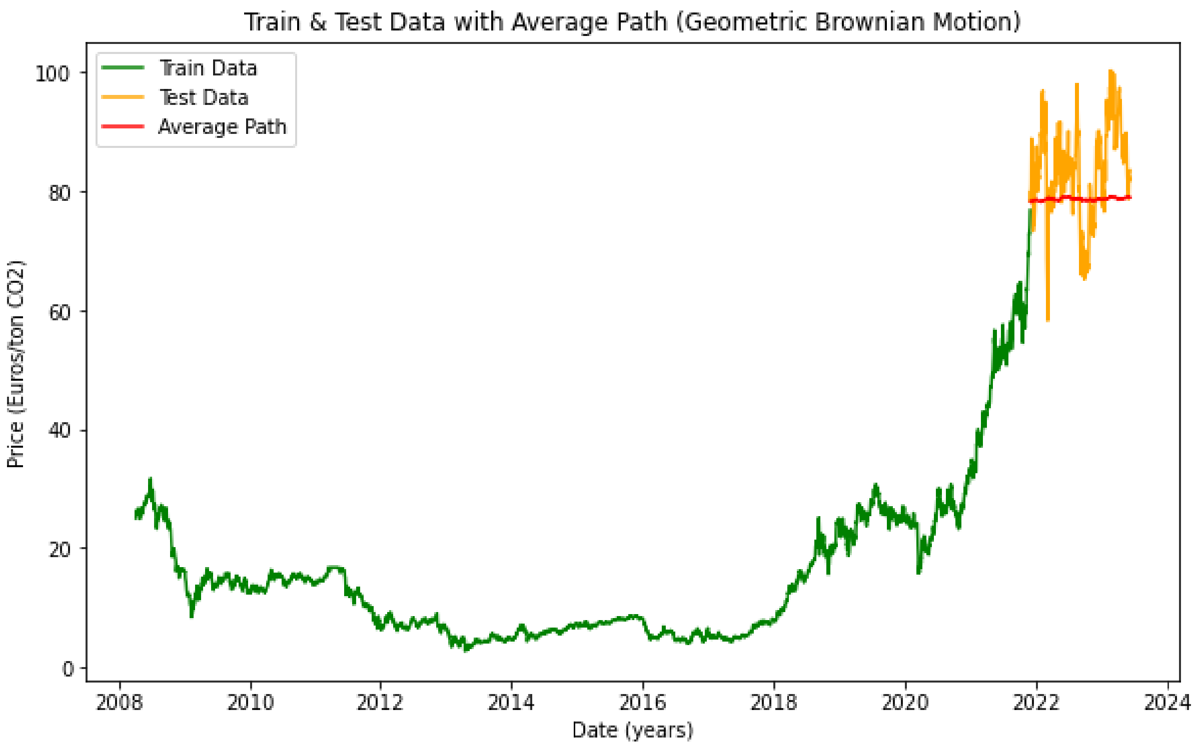

Figure 36: Average path calculated from the 10 sample paths from the train data on the period of the test data based on Geometric Brownian Motion (GBM).

The performance of the GBM is found with the following values:

- **Mean Absolute Error (MAE):** The MAE is determined to be 7.57, indicating a high absolute deviation of 7.57 units between the forecasted and actual values.
- **Mean Absolute Percentage Error (MAPE):** The MAPE is calculated to be 0.089, suggesting a rather high relative error of 8.9% between the forecasted values and the actual data.
- **Root Mean Squared Error (RMSE):** The RMSE value is found to be 9.16, representing the average magnitude of the residuals between the forecasted and actual values.
- **Relative Root Mean Squared Error (rRMSE):** The rRMSE of GBM equals 10.98, which is a relative RMSE that is perceived as a reasonable but not extremely accurate fit. It suggests that on average forecasts deviate from the actual values by approximately 10.98% of the mean of the EU ETS price.
- **R-squared (R^2)**: The R-squared of GBM is -0.34, which is a very poor R-squared value as it performs worse than fitting a trend line on the data.

After finding the performance of the model based on training and testing the data, we use all available data to set up the parameters of the GBM model when using all data. This results in slightly different but almost similar sample paths. Figure 37 displays the ten sample paths until 2050 that are created from the entire original data set based on GBM. Figure 38 shows the average path when averaging all ten sample paths. We see that the GBM price remains very stable and has a small trend making it rise from 83 Euros to 86.29 Euros per ton of CO_2 in 2050. This is also confirmed when looking at the value of the drift term, which is very small but positive indicating a small increase over time.

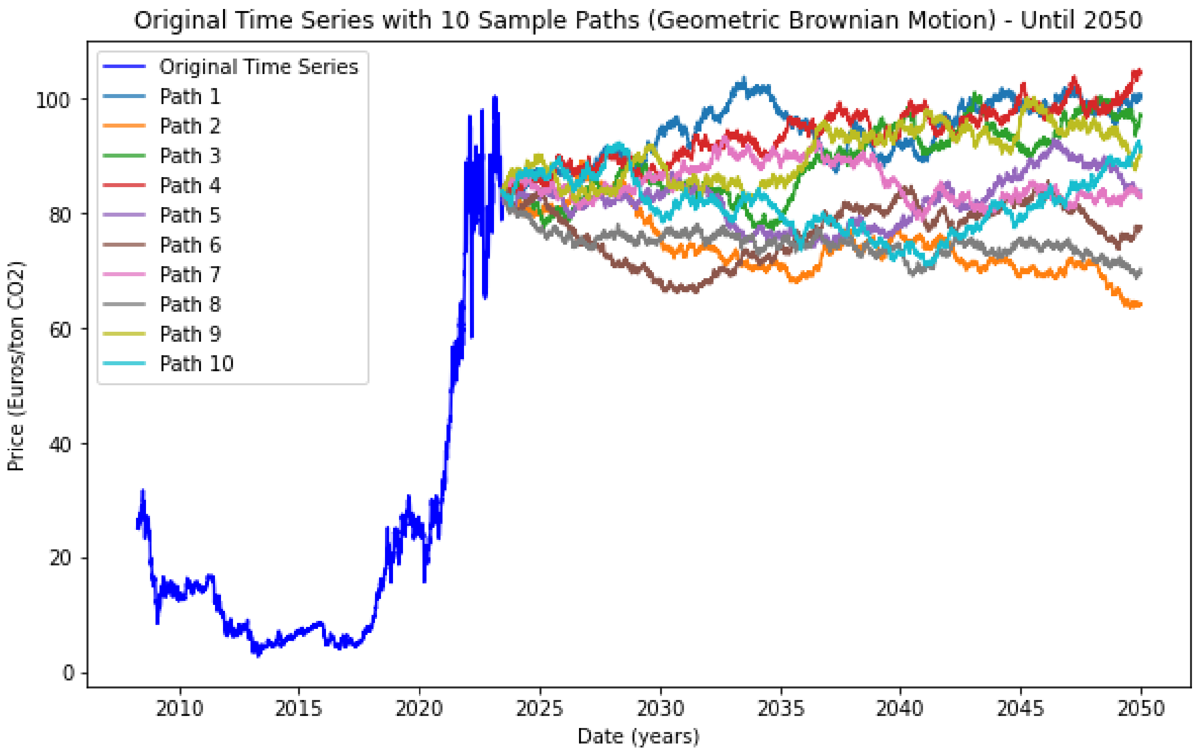

Figure 37: Ten sample paths created from original data based on Geometric Brownian Motion (GBM) until 2050.

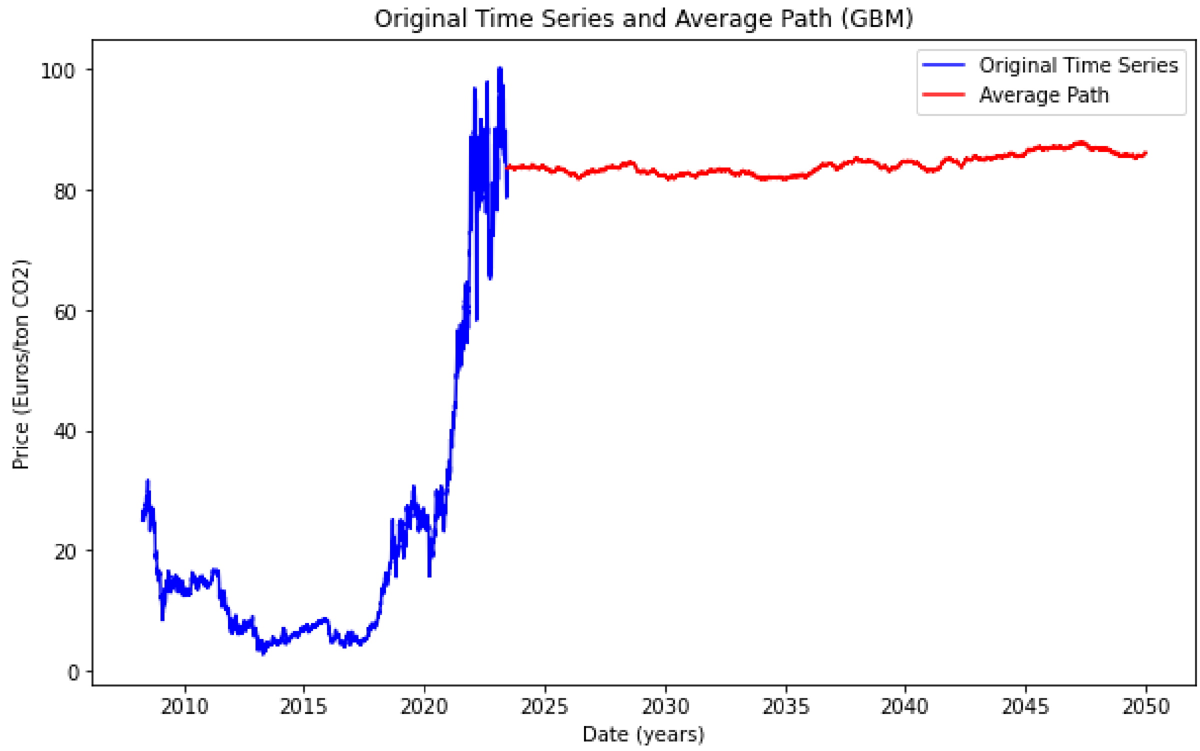

Figure 38: Average path calculated from the 10 sample paths created from original data based on Geometric Brownian Motion (GBM) until 2050.

7.4 Performance comparison

This section presents the outcome of our comparative analysis of three forecasting methods – GBM, ARIMA, and linear regression – to forecast the EU ETS price trajectory on the test set and until 2050. The aim of the forecast is twofold, we want 1) to recommend a short-term forecasting method to VI with which they can forecast what the price will do in the next 1 to 2 years, and 2) a long-term price path that can be used in the DCF analysis.

We begin by evaluating the performance of each forecasting method to see which method should be used in the short-term. In general, all three forecasts show an upward trend in the price and thus we imply that the price will increase until 2050. It is important to note that these performance measures are based on using the training set and forecasting the test set with it and then comparing the performance of the forecast versus the actual price during the test set. The forecast itself until 2050 is made on all available data. This should be kept in mind when looking at the performance measures.

Table 23: Performance comparison of the GBM, ARIMA model, and linear regression showing that the ARIMA model performs best.

	GBM (MU, SIGMA)	**ARIMA(2,2,2)**	**LINEAR REGRESSION**
RMSE	9.16	7.99	9.58
RRMSE	10.98	9.58	11.48
MAPE	0.089	0.079	0.094
MAE	7.57	6.45	8.04
R^2	-0.34	-0.024	0.032

Table 23 summarizes the performance of each method and enables us to compare the different methods. In terms of RMSE, MAPE, and MAE the ARIMA(2,2,2) performs the best, while in terms of R-squared the linear regression performs best. We can conclude that the GBM is the worst-performing method in terms of all performance measures. We reason this due to the fact that GBM is a relatively simplistic model, which assumes a constant drift and volatility. This assumption is proven not to be true for a complex market like the EU ETS and thus the quality of the forecast is worse than the other two models. However, the limitations of these performance measures should be considered as well (Lendave, 2021). These present the limitations per performance measure:

- **RMSE**: It is sensitive to the presence of outliers in the data. Large errors for outliers can significantly impact the RMSE and may not accurately reflect the model's overall performance. This statistic penalizes great errors more.
- **rRMSE**: The rRMSE depends on the mean of the actual data, which can be heavily influenced by outliers. Therefore, the rRMSE itself is also sensitive to outliers (Yu, et al., 2015). Furthermore, rRMSE does not provide information about the bias of the forecasts. It only measures the dispersion of the errors, but not their direction. This means that a model with a low rRMSE may still have a systematic bias, leading to consistently over- or underestimating the observed values.
- **MAPE**: The MAPE can be problematic if the actual values are zero or close to zero as it involves division by the actual value. Additionally, MAPE is asymmetric so it penalizes underestimations more heavily than overestimations (Armstrong, 2001).
- **MAE**: The MAE is insensitive to magnitude and treats all errors equally. Therefore, it can be difficult to distinguish large and small errors.
- **R-squared**: Linear regression has a different sample size due to forward filling which makes it difficult to compare the models as R-squared is dependent on the sample size. Additionally, R-squared does not provide information on how well a model can make accurate future forecasts, as it only tells something about how good of a fit the model is for the observed values.

The strength of this assessment lies in combining various performance measures to gain a comprehensive perspective on the model performance. When combining all performance measures we conclude that the ARIMA(2,2,2) model is the best model for forecasting the test set. However, it is important to acknowledge that this model yields higher values in the long term. We also compare the price paths of the different scenarios with each other to see where they deviate from each other. Figure 39 shows all price paths and we see that until 2025 the GBM, linear regression, and ARIMA are still relatively close to each other. Only from then onward the ARIMA forecast starts to rise rapidly.

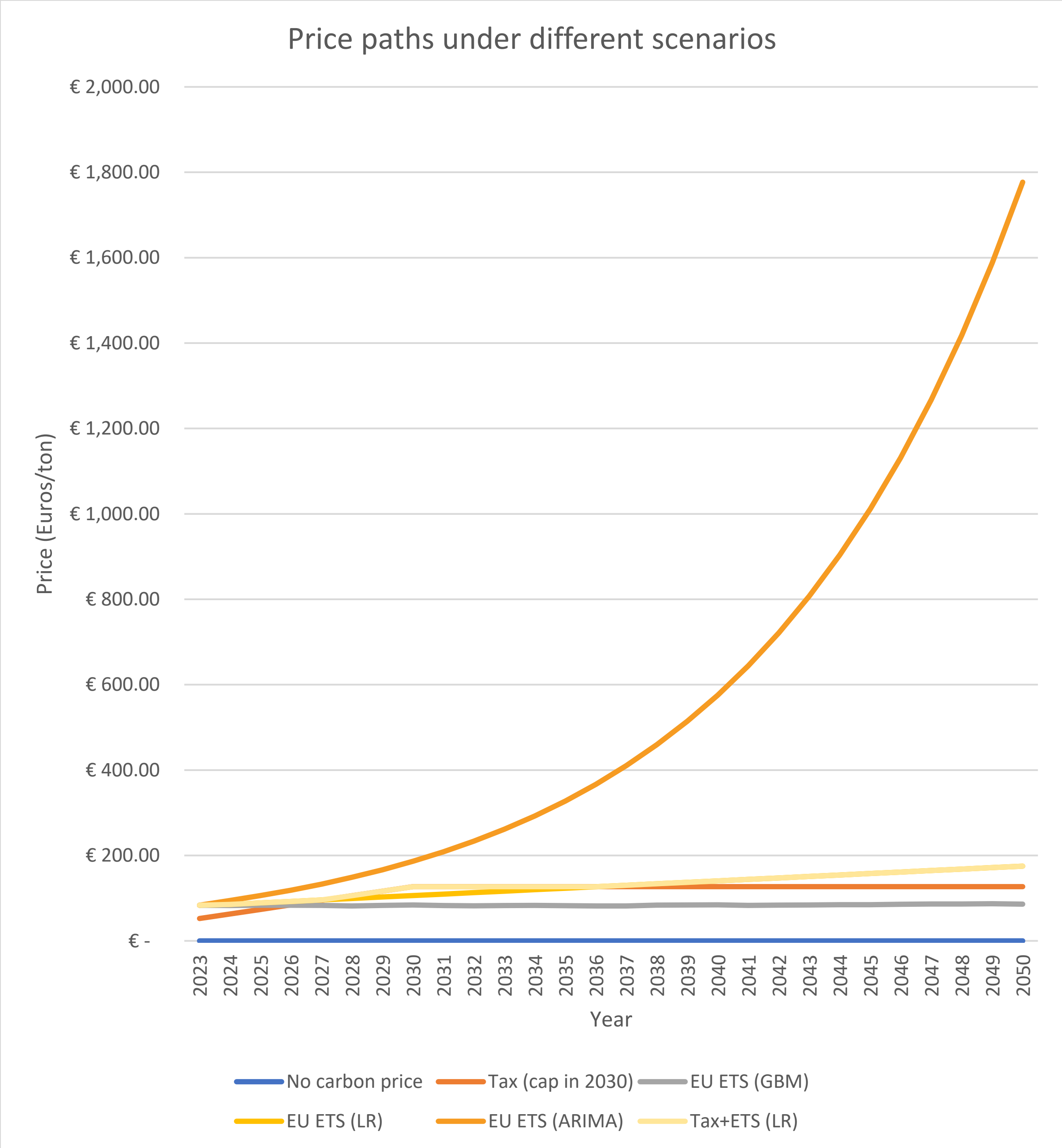

Figure 39: Graph of price paths under different scenarios showing the difference in behaviour between all methods.

When observing the performance of the difference models in the long term we see that the ARIMA(2,2,2) model projects a value of 1,776.84 Euros in 2050, while linear regression and GBM forecast 86.29 Euros and 100 Euros, respectively. This wide range of outcomes prompts us to compare our results with existing literature. This comparison is critical since our forecasting objectives are twofold: firstly, recommending a short-term forecasting method (2-3 years ahead) for VI, and secondly, constructing a long-term price path suitable for DCF analysis.

One of the largest research that forecasts a carbon price until 2050 is from the NGFS, which sets a standard for global climate scenarios. These scenarios are based on the type of policies that are in place compared to the Net Zero ambitions (NGFS, 2021). Figure 40 shows the prices under different scenarios and these range from US$0 to $780 per ton CO_2. In this study, we have chosen not to rely on price paths derived from existing literature, such as those from the NGFS. This decision stems from the need to provide a truly independent and data-driven analysis of EU ETS pricing. Using externally generated price paths could introduce biases or assumptions that may not align with the specific characteristics of our dataset or the model's goals. By conducting our own price forecasting, we maintain control over the assumptions and methods, ensuring transparency and reliability in our analysis. Comparing the price paths in this thesis to these price paths from the NGFS is however valuable as it shows that the research is in line with carbon price developments found in literature.

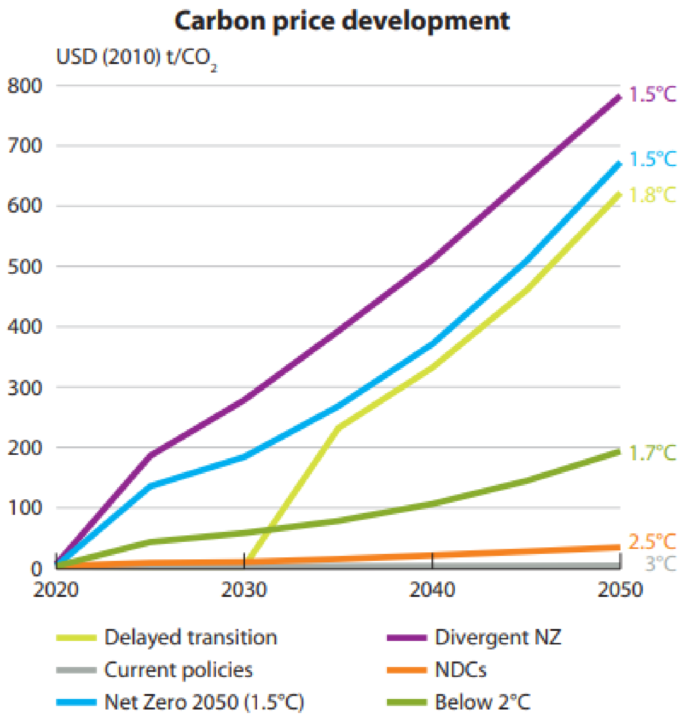

Figure 40: Carbon price development until 2050 in USD. Source: (NGFS, 2021)

Other research from EY suggests that the price will range somewhere between US$60 and US$275, with the highest probability that it will range between US$150-200 (EY, 2022). The European Investment Bank also created a forecast, which shows a price range between 300 and 1,150 Euros, with a median price of 800 Euros per ton CO_2 in 2050 (EIB, 2020). Additional research shows that the price will move between US$300-950 by 2050 under different scenarios (Napp, et al., 2019). None of these forecasts reach the 1,776.84 Euros price that the ARIMA(2,2,2) provides as output. Due to the high value of the ARIMA forecast and the high level of uncertainty of future developments, we do not use the price path of the ARIMA model even though it performs well according to the performance metrics. Another well performing method, which is linear regression, is well in line with the forecasts found in literature. Due to this we recommend to use linear regression as forecasting method to describe the general price paths in the DCF analysis. Additionally, using all different price paths can provide valuable insights and these can serve as different price scenarios.

7.5 Conclusion

To summarize, in this chapter, we created price paths using three different methods of which the linear regression and GBM serve as a benchmark, and the ARIMA(2,2,2) model is selected based on literature, diagnostic tests, and the goal of this study.

For the ARIMA model, we ended at a configuration of (2,2,2), which resembles the autoregressive term, degree of differencing, and the order of the moving average which are all set to 2. We set these values based on PACF plot, observations of the stationarity tests and an ACF plot, and the ACF plot respectively. From the evaluation we observe that the price path from the ARIMA(2,2,2) model increases to 1,776.84 Euros per ton CO_2 by 2050, for linear regression this value is 175 Euros and for GBM this is 86.29 Euros (RQ7). These prices all increase but the degree to which varies a lot. In the literature, we also see a spread between almost no increase in price to a maximum of 1,150 Euros per ton CO_2. The performance of the different models on train and test set is computed. When observing the results we conclude that the ARIMA model performs best, compared to the GBM and linear regression in terms of RMSE ($7.99 > 9.16 > 9.58$), rRMSE ($9.58 > 10.98 > 11.48$), MAPE ($0.079 > 0.089 > 0.094$), and MAE ($6.45 > 7.57 > 8.04$). The order of results of the performance measures as provided in the brackets is always ARIMA first, then GBM, and then linear regression. Thus, linear regression performs the worst. However, in terms of R^2 linear regression performs best ($0.032 > -0.024 > -0.34$), compared to the ARIMA(2,2,2) model and GBM, respectively.

We created an advice on the short and long-term based on the fact that we want a long-term forecast until 2050 within this research and VI also wants a 2-3 year forecast due to the shorter horizon that VI looks at with general price developments. Our evaluation indicates that the ARIMA(2,2,2) model is the best fit for short-term forecasting based on the performance measures. However, for long-term forecasts, given the significant variation in forecasted values, a more cautious approach is recommended, which can be found in linear regression. Linear regression provides a more stable forecast and especially due to the high degree of uncertainty until 2050 we recommend a price path and forecasting model that does not provide extreme forecasts in the long-term. Additionally, linear regression is also more in line with the forecasted carbon prices found in the literature and has a better R^2.

These findings provide crucial insights for policymakers and stakeholders navigating the complex landscape of carbon pricing strategies, offering a comprehensive view of short-term and long-term forecasting approaches tailored to specific needs and contexts. In this way, there are two methods for VI to say something about the price developments on the short horizon, but also to use the linear regression model in business cases.

8 Results and Discussion

In this section, we share the final results of this thesis. Section 8.1 starts with the expert panel and then Section 8.2 shows the final DCF analysis tool and build-up of the tool and assumptions using the input from the expert panel. Then the DCF tool is tested with a case in Section 8.3. Lastly, we perform a sensitivity analysis on the discount factor in Section 8.4.

8.1 Expert panel

The goal of the expert panel is to validate the DCF tool and give room for possible improvements and comments. The concept of the DCF tool is explained in literature and the first version of the DCF tool can be found in Appendix A.7. In this section we will provide feedback retrieved from the expert panel, which is used to come to the second version of the DCF tool which is explained in Section 8.2. This section summarizes the key findings found from the expert panel that is conducted.

The expert panel followed an open structure in which no questions were prepared with the aim of providing a free flow of feedback. The expert panel consists of two groups with individuals from different disciplines within the company, including sustainability project managers, innovation engineers, a director of strategic costing, a financial controller, a program manager, a director of warehousing, and a commercial sustainability lead. The total number of people per expert panel equalled 4, resulting in a total of 8 individuals. Due to the different backgrounds of people, insights from different angles can be provided and included in reviewing the first version of the DCF tool. During the panel, an extra member was added who also took minutes. These feedback remarks that resulted from the two expert panels are all taken into consideration when improving the first version of the DCF analysis. The feedback can be summarized in the following topics:

Improvements:

- It would be valuable to split the general input from the product-specific input into two separate sheets as it becomes more clear to the users how to use the DCF tool;
- It would be valuable to use a large case that shows the impact of carbon pricing on a larger scale as the current steel versus aluminium case for this project is only a small project compared to the total revenue of VI;
- It would be valuable to see what the impact is of carbon pricing and CBAM on the cost of VI as currently around 25% of the expenditures can be found in raw materials;
- It would be valuable to show information on how much the standard product would cost without carbon pricing and then also compare it to the scenario with carbon pricing and the alternative with and without carbon pricing;
- It would be valuable for VI to be advised on how we should use carbon pricing and which carbon price to use. A concept that is valuable to include here as well is the social cost of carbon;
- It would be valuable for VI to get an overview of what is going to change, like the CBAM in 2026.

Strength:

- This method aligns well with the current methods used by VI as concepts like DCF and NPV are often used;

8.2 DCF analysis

Creating the DCF tool is an iterative process between the DCF analysis approach and the case chosen. The first step consists of creating a DCF tool that is able to include all the elements that come into play for the case. Before applying the case an expert panel evaluates the DCF tool resulting in an updated version. This updated version is then used to iteratively create the final DCF tool, which is presented and explained in this section, including the input parameters, assumptions, calculations, and results. Consecutively, the DCF tool is generalized more so that it can be used on all kinds of product investment decisions, by for example adding elements like energy usage which is irrelevant for the case later.

8.2.1 Discount rate and other general assumptions

Firstly, we should decide which discount rate to use. As described in literature Section 4.5.1 there are numerous ways in which this can be chosen. The Weighted Average Cost of Capital (WACC) is frequently employed as a discount rate, providing insights into VI's cost of capital. VI uses the WACC already for making investment decisions. Therefore, the same WACC is used as the one that VI is already using, which is 12%. This is the average rate of return VI needs to earn on its investments to maintain its current capital structure. Additionally, a sensitivity analysis is conducted in Section 8.4 on the 12% discount rate. Moreover, the DCF analysis tool is based on other assumptions, including:

- The carbon tax has a cap of 127 Euros by 2030
- The default long-term price path is based on linear regression
- Cost per employee per hour is, for example, 59 Euros based on internal information within VI

8.2.2 DCF tool with integrated price paths

In this section, the DCF tool is shown per sheet. Here the price paths are integrated into a DCF tool, which can be used to make investment analysis. The DCF tool consists of multiple sheets.

8.1.2.1 General Input

The first sheet is the general input sheet, which can be seen as a dashboard in which manual adjustments can be made. In Appendix A.7 the previous version can be seen where both the general input and product-specific input were combined, however, they are split out now to bring more clarity to the user. Table 24 shows the general input sheet, where the following elements are presented:

- Current year
- Discount rate of 12%
- Time period (years), which refers to the lifetime of a product
- Project duration, which refers to the number of years until the operation starts
- Cost per employee per hour, which is set to 59 EUR
- Cost per employee per hour is calculated from the monthly salary
- Carbon price scenario, which is a dropdown menu, however, the linear regression model is recommended

After filling in the general input variables the carbon-related variables should be filled in in the product-specific sheet. However, in the general sheet, one should fill in the carbon price scenario that is chosen from a dropdown menu. Each scenario has a different price path. Then the carbon price that matches the current year is displayed in the cell below the scenario selection.

Table 24: General input sheet in DCF analysis tool.

Input DCF		
Current year	2023	
Discount rate	12%	
Time period (years)	25	
Project duration (years until the start of the operation)	0	
Cost per employee per hour	€ 59.00	
Carbon costs		
Carbon price scenario	EU ETS (LR)	*Dropdown menu*
Current carbon price under scenario	€ 77.91	

8.1.2.2 Product Specific Input

The second sheet called 'Product Specific Input', has two input fields for two product investment alternatives that are compared in the DCF analysis tool. Table 25 shows the input that is needed on a product-specific level including the:

- Initial investment;
- Hours needed for investment, in case it is a one-time investment. Else this time investment can be left out of consideration as it can influence the individual business case heavily, while the time investment can be spread over all future projects that use the new product alternative.
- Maintenance cost per year;
- Energy cost per year;
- Carbon emissions before the use phase (ton);
- Carbon emissions during the use phase (ton);
- Carbon emissions End-of-Life (ton).

The carbon emissions before the use phase, during the use phase, and end-of-life can be filled in to use for calculating the carbon costs. These carbon emissions should be retrieved by filling in the Simplified LCA tool of VI or another LCA tool.

Table 25: Product specific input sheet in DCF analysis tool.

Input DCF - Aluminium Crossmember			
Initial investment	€	876.53	
Hours needed for investment		-	
Maintenance cost per year	€	-	
Energy cost per year	€	-	
Carbon emissions			
Carbon emissions Before Use phase (ton)	6.73		*Fill in based on LCA calculation*
Carbon emissions Use Phase (ton)	0.00		*Fill in based on LCA calculation*
Carbon emissions End of Life (ton)	-5.62		*Fill in based on LCA calculation*

Input DCF - Alternative (Steel crossmember)			
Initial investment	€	326.78	
Hours needed for investment		-	
Maintenance cost per year	€	-	
Energy cost per year	€	-	
Carbon emissions			
Carbon emissions Before Use phase (ton)	1.34		*Fill in based on LCA calculation*
Carbon emissions Use Phase (ton)	0.00		*Fill in based on LCA calculation*
Carbon emissions End of Life (ton)	-0.10		*Fill in based on LCA calculation*

8.1.2.3 Price paths

The third sheet includes the carbon prices per scenario and subdividing the EU ETS scenario between the three different methods that are used to forecast the price path, GBM, linear regression, and the ARIMA model. Table 26 shows the different carbon price scenarios and their price paths. The following price scenarios are included:

1. **No carbon price**, here the carbon price is set equal to zero at all times;
2. **Tax (cap in 2030)**, here the current tax is 51.41 EUR and this increases to 127 EUR by 2030 and then it is assumed to remain constant until 2050;
3. **EU ETS (GBM)**, here the scenario is described by the EU ETS market following the average sample path of the GBM;
4. **EU ETS (LR),** here the EU ETS price path is determined by linear regression;
5. **EU ETS (ARIMA),** here the EU ETS price path is determined by the ARIMA(2,2,2) model;
6. **Tax+ETS (LR)**, here the carbon price is determined by a combination of the tax and EU ETS, where the tax serves as a minimum value that should always be paid even if the EU ETS price drops below this value and in case the EU ETS price exceeds the tax, then the price is set by the EU ETS. This price scenario is determined by combining the tax scenario and the EU ETS scenario using linear regression.

Table 26: Price paths until 2050 under different scenarios.

Carbon Price Paths						
Year	**No carbon price**	**Tax (cap in 2030)**	**EU ETS (GBM)**	**EU ETS (LR)**	**EU ETS (ARIMA)**	**Tax+ETS (LR)**
2023	€ -	€ 52.41	€ 83.57	€ 83.57	€ 83.57	€ 83.57
2024	€ -	€ 63.06	€ 83.85	€ 85.48	€ 94.76	€ 85.48
2025	€ -	€ 73.72	€ 83.68	€ 88.93	€ 106.12	€ 88.93
2026	€ -	€ 84.38	€ 82.91	€ 92.37	€ 118.79	€ 92.37
2027	€ -	€ 95.03	€ 83.38	€ 95.81	€ 132.97	€ 95.81
2028	€ -	€ 105.69	€ 83.75	€ 99.25	€ 148.84	€ 105.69
2029	€ -	€ 116.34	€ 83.02	€ 102.70	€ 166.54	€ 116.34
2030	€ -	€ 127.00	€ 82.43	€ 106.14	€ 186.42	€ 127.00
2031	€ -	€ 127.00	€ 82.73	€ 109.58	€ 208.67	€ 127.00
2032	€ -	€ 127.00	€ 83.00	€ 113.02	€ 233.58	€ 127.00
2033	€ -	€ 127.00	€ 82.69	€ 116.47	€ 261.58	€ 127.00
2034	€ -	€ 127.00	€ 81.84	€ 119.91	€ 292.68	€ 127.00
2035	€ -	€ 127.00	€ 81.82	€ 123.35	€ 327.48	€ 127.00
2036	€ -	€ 127.00	€ 82.57	€ 126.79	€ 366.57	€ 127.00
2037	€ -	€ 127.00	€ 84.19	€ 130.24	€ 410.51	€ 130.24
2038	€ -	€ 127.00	€ 85.32	€ 133.68	€ 459.51	€ 133.68
2039	€ -	€ 127.00	€ 83.58	€ 137.12	€ 514.38	€ 137.12
2040	€ -	€ 127.00	€ 84.68	€ 140.57	€ 575.53	€ 140.57
2041	€ -	€ 127.00	€ 83.24	€ 144.01	€ 644.23	€ 144.01
2042	€ -	€ 127.00	€ 84.94	€ 147.46	€ 721.14	€ 147.46
2043	€ -	€ 127.00	€ 85.27	€ 150.90	€ 807.23	€ 150.90
2044	€ -	€ 127.00	€ 85.60	€ 154.34	€ 903.61	€ 154.34
2045	€ -	€ 127.00	€ 86.09	€ 157.79	€1,011.47	€ 157.79
2046	€ -	€ 127.00	€ 87.00	€ 161.23	€1,131.72	€ 161.23
2047	€ -	€ 127.00	€ 87.28	€ 164.67	€1,266.84	€ 164.67
2048	€ -	€ 127.00	€ 87.05	€ 168.11	€1,418.06	€ 168.11
2049	€ -	€ 127.00	€ 85.70	€ 171.56	€1,588.03	€ 171.56
2050	€ -	€ 127.00	€ 86.29	€ 175.00	€1,776.84	€ 175.00

8.1.2.4 DCF

The final sheet of the DCF tool computes the NPV of a product investment. In this case, we display all the numbers from the actual case that is used in Section 8.3 but we explain the case in more detail in Section 8.3. Table 27 shows the sheet that computes the NPVs automatically by combining the previous three sheets. This sheet breaks down the computation of the NPV per year, which can mainly be subdivided into two parts: CAPEX and OPEX. The CAPEX describes the capital expenditures needed for the project including the time investments and sourcing of products themselves. Then OPEX comes into play which includes operational cost, maintenance cost, energy cost, and carbon cost. To determine the overall NPV, both the CAPEX and OPEX values are discounted using a predetermined discount factor of 12%. By employing this approach, the comprehensive NPV for the investment can be computed. Next to the DCF analysis sheet in Table 27, a second field is present to compute the NPV for the alternative product investment option. The final output, in terms of an NPV, of the DCF analysis is printed on this sheet as well for both the standard and alternative investment options, and the difference is calculated. In case the difference is positive then a business case for the alternative should be considered as it saves money when accounting for carbon costs.

Table 27: Discounted Cash Flow (DCF) analysis sheet.

Discounted Cash Flow - Aluminium

	Explanation	Totals	2023	2024
			1	2
Years		25	1	2
CO2 ton price			*83.57*	*85.48*
CAPEX				
Initial investment (CAPEX)	*i.e. price for Twinbelts*		€ 876.53	€ -
Carbon cost (before usage phase)	*i.e. embedded carbon (do note for some materials this is already included in the price)*		€ 562.41	€ -
Time investment			**€ -**	**€ -**
Total CAPEX			**€1,438.94**	**€ 0.00**
OPEX				
Carbon cost (use phase)	*(i.e. energy consumption calculated to CO_2 emissions, which is assumed to be uniformly distributed)*		€ -	€ -
Maintenance costs per year			€ -	€ -
Energy consumption costs per year			€ -	€ -
Carbon cost (end of life)			€ -	€ -
Total OPEX			€ -	€ -
Discount factor (per year)			1.00	1.12
NPV			€1,438.94	€ -
NPV cumulative			€1,438.94	€1,438.94
Total NPV		**€ 1,377.99**		

8.3 Case

This section describes the case in which the DCF tool is tested. In this case, we review two alternative product investment options for the materials of the Twin Belt's crossmember. We have selected this project due to the clear scope and the high market demand for the Twin Belt, resulting in significant potential implications from this analysis. Within this context, our specific attention is directed towards an airport project in Europe, primarily chosen due to the availability of relevant data. At present, the crossmember is manufactured using aluminium. However, this section undertakes an exploration of alternative materials, considering carbon pricing. Consequently, this section delves into this unique case, aiming to validate and verify the effectiveness of the DCF tool.

8.3.1 Case details

Firstly, the details of the case are shared which are relevant for building this case around the crossmembers present in the Twin Belt modules. A crossmember is an aluminium extrusion profile that connects and supports two sides of the Twin Belt module. Figure 41 shows the technical drawing of a Twin Belt with two crossmembers made from aluminium. For the airport project, the number of Twin Belt modules sold and their price are shown in Table 28.

Table 28: Total number of Twin Belt modules in the airport project per type and the price per part when made from aluminium.

Items	Part number	Total quantity	Price per part	Total price
Twin Belt module L=1600mm + guarding + LMS-V + PEC	001036-001-01602	51	€ 373.54	€ 19,050.42
Twin Belt module L=2000mm + guarding + LMS-V + PEC	001036-001-02002	20	€ 398.64	€ 7,972.72
Twin Belt module L=2400mm + guarding + LMS-V + PEC	001036-001-02402	12	€ 405.36	€ 4,864.37
Twin Belt module L=3600mm + guarding + LMS-V + PEC	001036-001-03602	3	€ 468.77	€ 1,406.32
Grand Total		**86**		**€ 33,293.84**

The total sales value of this project is more than 10 million Euros. From the total costs, the Twin Belt module contributes to €33,293.84, which is the case for the original product when made from aluminium. However, we are only looking at the crossmember and its costs. We assume that the price of a crossmember is determined by the cost of the materials only and that all other cost elements that make up the cost of a crossmember are negligible. From internal information within VI, we know that around 71-79% comes from the manufacturing of the extrusion profile, including the material cost to get to the extrusion profile. This assumption is supported as the rest of the cost components that make up the total cost of a crossmember are not altered in the alternative steel design and only the material and initial investment costs that come into play with a different material are different. The cost of the crossmember depends on the weight of the product and is shared in Section 8.4.2.1.

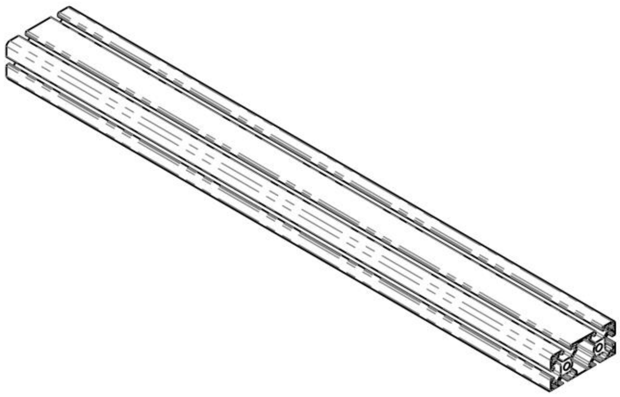

Figure 41: Technical drawing of the aluminium crossmember in SolidWorks. Source: From internal documentation at VI.

An alternative to the aluminium crossmember is a crossmember made from steel, which needed to be redesigned in SolidWorks to create a viable alternative together with product designers at VI. We chose steel as an alternative that should be investigated due to the fact that it has fewer emissions in the production of the material and that this seems valuable to research due to this reason. The crossmember made from steel needs less material due to the stiffness property of the material. Steel is more stiff compared to aluminium and therefore, fewer kilograms of steel is present in a crossmember compared to an aluminium crossmember. More information on the carbon emissions present in the different materials is provided later on in this chapter. A new design of the steel crossmember results in a crossmember which is displayed in Figure 42. More details on the crossmember made from steel and its volume and surface are provided in Table 38, which are all different based on the length of the crossmember. Appendix A.8 provides an overview of the details of different crossmembers per type of Twin Belt module.

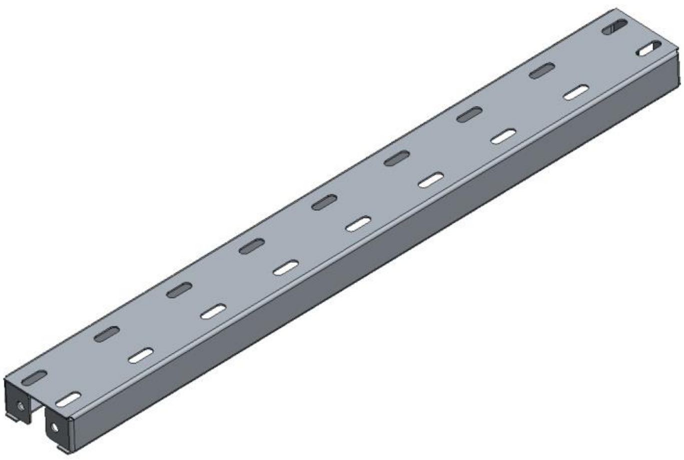

Figure 42: Technical drawing of alternative crossmember made from steel in SolidWorks.

8.3.2 Input values and assumptions of the case

This section discusses the different assumptions and inputs of the case and shows how we arrive at these assumptions and inputs. We use the LCA to determine the carbon emissions. This section is also structured according to the phases of the LCA as explained in Section 4.6 and the assumptions made are subdivided between these phases. All data on emission levels is retrieved from the IDEMAT database, which consists of carbon emission data which is a free open-source database from the University of Delft. The phases of the LCA are displayed in Figure 43. The computations made in this section are provided in the Excel file as explained in Appendix A.1. A general assumption in the case is that the project will go live in this year and the lifetime of a crossmember is 25 years.

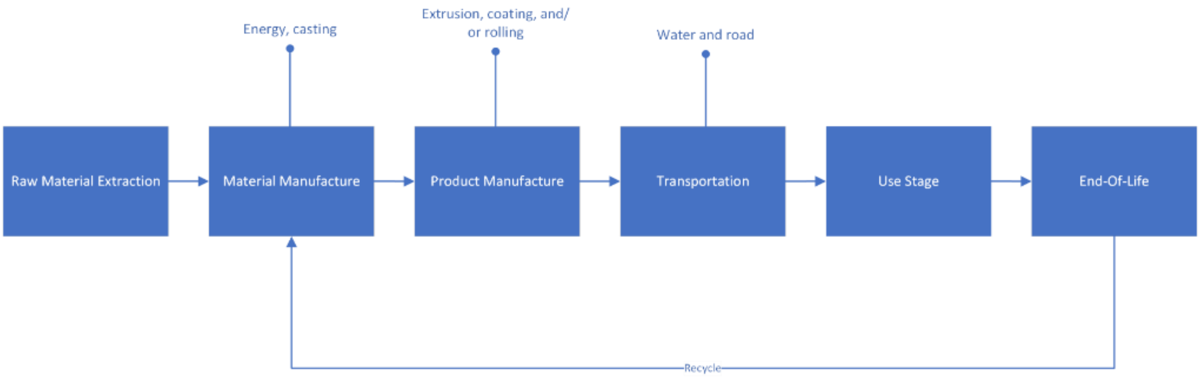

Figure 43: Different phases of life cycle assessment according to cradle-to-cradle.

8.3.2.1 Raw material extraction and manufacturing

We start our case by delving into the raw material extraction phase. To simplify the case we assume that the lifespan of aluminium and steel (type S235JR) is equal and both 25 years. We use the IDEMAT database, which consists of carbon emission data. It shows the emission data of getting the raw material itself and includes all emission steps to get to raw material. The raw materials have carbon emissions that were needed to produce them, this is called embedded carbon. The file used is called 'Idemat 2023RevA.xlsx' (IDEMAT, 2023). Currently, the crossmember is made of aluminium and some data is available regarding the volume, cost, and sales of the item within VI. This data is transformed to make it usable in the case as the cost per crossmember is needed, and the weight of a crossmember is differentiated per type of Twin Belt. Based on the total spent and the total ordered quantity of the Twin Belt modules a total average unit cost can be computed. These numbers are based on the sales of the previous three years, including 2020, 2021, and 2022. Additionally, we obtain the average number of crossmembers and weight using internal documentation in straitWeb, which is an online environment at VI where product-specific data is stored. With this information, we can calculate the weight and surface area per crossmember, as well as the total weight of crossmembers within a single Twin Belt module. Table 37 in Appendix A.9 shows this data for the aluminium crossmember, with sales divided between AP, which is Asia-Pacific, and EU, which resembles Europe. We incorporate the regionally averaged values for the rest of the case.

Table 38 also in Appendix A.9 shows similar information only for the steel (type: S235JR) crossmember, where the weight per crossmember is different and based on a new design from one of the employees of VI. The type of steel is assumed not to be stainless but needs a coating. The new design also leads to a new surface area, which is used to determine the carbon impact of coating. It is important to note that due to the more efficient new design of the steel crossmember, the volume and surface area of the steel design is smaller than the original aluminium crossmember. The aluminium and steel design in SolidWorks only provide the data on the volume and surface area of the design and therefore, the weight needs to be calculated using the density of the two materials which are 2755 kg/m^3, and 7850 kg/m^3 respectively (Tosec, n.d.). Table 37 and Table 38 show the weight of a crossmember using this density.

Moreover, the cost price of aluminium and steel are retrieved by consulting cost engineers within VI and these resulted in a cost price of 1.10 Euros per kilogram of aluminium and 0.54 Euros per kilogram of steel (LME, n.d.; MEPS, n.d.). Combining these prices with the data in Table 28, Table 37, and Table 38 provides us with the total weight (kg) of material in the European airport project from crossmembers as well as the total price. The computations are provided in Appendix A.9.

The total weight per material that comes from crossmembers in the European airport project is 796.19 kilograms for aluminium and 610.66 kilograms for steel. Multiplying the weight with the price per kilogram provides us with the total price of a crossmember. The total price of crossmembers from the raw materials in the Twin Belt modules is 876.53 Euros for aluminium, and 326.78 Euros for steel. This is seen as part of the CAPEX of this DCF analysis tool.

Additionally, the raw materials also have carbon emissions that were needed to produce them, this is called embedded carbon. The IDEMAT database has information on what the carbon equivalent emissions are for the two materials and their weight. The impact factor of 1 kilogram of aluminium is 7.30 kg CO_2/kg. For steel, this is 0.93 kg CO_2/kg. Combining these numbers with the total number of kilograms of both materials results in total emission levels from raw materials of 5815.39 kg CO_2 for aluminium and 56.53 kg CO_2 for steel. Therefore, we can conclude that the crossmember from steel is better in terms of emissions when looking at the raw material extraction and manufacturing phase compared to the one from aluminium.

8.3.2.2 Product production

The second phase in the LCA concerns product production and in this case, it consists of two elements, which are the production and coating phases of the two materials. The production process of the aluminium and steel to the final product is different and therefore, this production phase has different emission levels as well. In this phase, we do not consider the potential difference in the cost of the coating and production method.

For aluminium, the production process that is currently used is extrusion, which has an impact factor of 0.792 kg CO_2/kg. Additionally, anodising aluminium has an impact factor of 2.188 kg CO_2/m^2. Multiplying the production process with the total number of kilograms of aluminium gives total production emissions of 630.58 kg CO_2, and for the anodising, the surface and impact factor combined give 152.09 kg CO_2 as the total emission level.

For steel, the production method is rolling as sheet steel is used to produce the product alternative, which has an impact factor of 0.887 kg CO_2/kg. Powder coating is the coating method for steel, which has an impact factor of 3.956 kg CO_2/m^2. The total production and coating emission levels are 541.66 and 128.70 kg CO_2 respectively.

Concluding, the total emissions for the aluminium crossmember in the product production phase are higher than those from the steel crossmember. This can be partially explained because of the surface area difference as the surface area of the aluminium product is much higher, $69.51\mathrm{m}^2 > 32.53\ \mathrm{m}^2$. Therefore, the total emission levels from coating are higher from aluminium compared to steel even though the impact factor of powder coating steel is higher than anodising aluminium.

8.3.2.3 Transportation

The fourth phase of the LCA is transportation, which is assumed to be over land and water. Both products are transported from China by VI, due to confidentiality reasons the exact supplier locations are not mentioned. However, we can state that the aluminium extrusion profile is sourced from the Shandong province, and the sheet steel is from Wuhan. The shipping routes over land are slightly different within China, 811 and 907 kilometres respectively. The shipping routes over the sea are identical as both products are shipped from Shanghai South Port to Rotterdam Port, which is 19,462 kilometres following the route as shown in Figure 44.

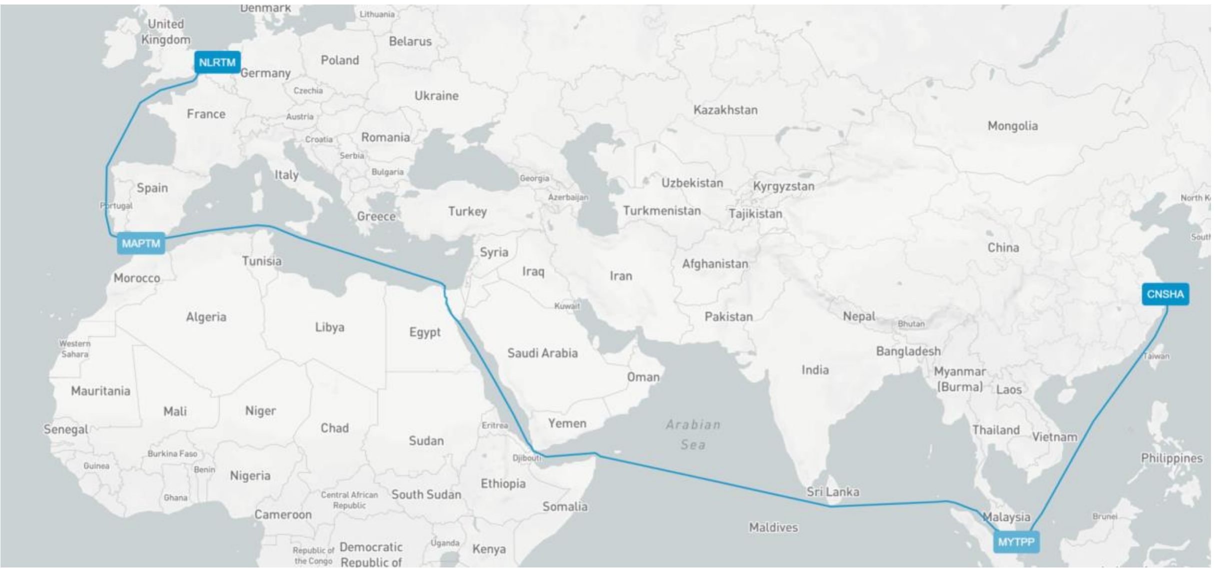

Figure 44: Shipping route over water from Shanghai South Port to Rotterdam Port.

The last part of the route consists of 85 kilometres from Rotterdam Port. The impact factors over the road and on the water are computed using the weight of the product as well as the unit is kg CO_2/tkm. The unit tkm can best be explained using a small example, for example, 10 tons that travelled 1,000 km equal 10,000 tkm. In this computation, the emissions for possibly needing an additional container due to weight or volume restrictions being violated are not taken into consideration. As steel has a higher density compared to aluminium, weight can become a limiting factor and the reason why a container cannot be maximally loaded (Tosec, n.d.). However, due to the different design, the steel crossmember weighs less than the aluminium crossmember, and thus in this project this weight restriction does not influence the emission levels due to the need for an extra container.

The impact factor on the road is 0.076 kg CO_2/tkm and 0.005 kg CO_2/tkm on water. Multiplying the distance with the impact factors respectively results in total transport emission levels of 105.46 kg CO_2 for steel and 131.70 kg CO_2 for aluminium. Therefore, we conclude that when looking at the transportation emission only we would prefer the crossmember from steel over the one from aluminium.

8.3.2.4 Use Phase

In this case, the use phase does not produce any emissions as we only look at materials and not at the usage of an entire system. Therefore, the total use phase emissions are 0 kg of CO_2. Possible elements that can be included in a business case are maintenance cost energy cost and additionally carbon cost.

8.3.2.5 End-of-Life

At the end of the lifespan of both materials, they can be recycled and then reused again. This results in a negative carbon impact and thus reduces the total carbon emissions. Due to a lack of data, the possible end-of-life emissions of removing coating and the energy that is needed to do so are not accounted for. We assume that the coating material itself is 100% waste and cannot be reused. Aluminium can be recycled better than steel and therefore the impact factor is -7.056 compared to -0.16 kg of CO_2. Multiplying this with the total weight results in carbon emissions at the end of life of –5,617.94 and -97.71 kg of CO_2 for aluminium and steel respectively. Thus, we can conclude that the crossmember made from aluminium is preferred when only looking at the emissions won back at the end-of-life phase.

8.3.2.6 Conclusion

To conclude and summarize this chapter the total emission levels are summarized and these results are used in the DCF analysis tool to compute the carbon cost per year. Since money and cost should be discounted it is valuable to have the carbon emissions split out per year or phase. Table 29 shows the total emissions of a crossmember made from either steel or aluminium, which is split out per phase of the LCA. The total emissions for a crossmember made from steel are 1,246.64 kg CO_2 and 1,111.82 kg CO_2 for aluminium. Therefore, when only looking at the carbon emissions we would prefer to use the crossmember made from aluminium. However, we do not only look at the carbon emissions but also at financial incentives like the investment costs. The NPVs of both the aluminium and steel crossmember under different carbon prices are computed in Section 8.3.3.

Table 29: Total emission levels in kg of CO2 per LCA phase of steel and aluminium showing that the aluminium crossmember has fewer emissions when looking at the entire life cycle .

		Steel	Aluminium
Raw Material	Total weight	610.66	796.19
	Impact Factor (kg Co2/kg)	0.93	7.30
	Total Raw Materials	**568.53**	**5,815.39**
Production	Process	Rolling	Extrusion
	Impact Factor (kg Co2/kg)	0.89	0.79
	Total Production	**541.66**	**630.58**
Coating	Part surface (m2)	32.53	69.51
	Impact Factor (kg Co2/m2)	3.96	2.19
	Total Coating	**128.70**	**152.09**
Transport	Kilometers by road	992.00	896.00
	Kilometers by water	19,462.00	19,462.00
	Ton Kilometers by road	605.78	713.39
	Impact Factor Road (kg Co2/tkm)	0.08	0.08
	Ton Kilometers by water	11,884.68	15,495.51
	Impact Factor Water (kg Co2/tkm)	0.01	0.01
	Total Transportation	**105.46**	**131.70**
Sub-total			
	Sub-total	**1,344.34**	**6,729.76**
Use			
	Total Use phase		
EOL	Impact Factor Recycling (kg CO2/kg)	-0.16	-7.06
	Total End of Life	**-97.71**	**-5,617.94**
Total			
	Total Carbon emissions	**1,246.64**	**1,111.82**

8.3.3 Results from DCF analysis

In this section, we present the results of the DCF analysis, utilizing the data derived from Sections 8.1, 8.2, 8.3, 8.4.1, and 8.4.2. The purpose of this analysis is twofold: it provides recommendations to VI regarding the case and also serves as a validation and verification of the DCF methodology employed.

Table 30 shows the results of the DCF analysis in terms of the NPV values of both the aluminium and steel crossmember and the difference between the NPVs. We do this for different pricing scenarios and this provides an insight into what the impact would be if there is no carbon pricing and also in case there is carbon pricing under different price paths. From the results in Table 30, it is evident that the steel crossmember exhibits a more favorable NPV when compared to the aluminium counterpart. This divergence can be attributed to the lower material cost of steel per kilogram (€0.54) compared to aluminium (€1.10). Additionally, the steel crossmember design, despite having a higher density than aluminium, manages to maintain a lower weight, resulting in a reduced overall investment cost. Consequently, in scenarios where carbon pricing is absent, the steel crossmember emerges as the preferred choice.

When introducing carbon pricing into our analysis, we delve into the carbon emissions aspect. Aluminium initially exhibits higher carbon emissions, particularly before the use phase. However, the ability to recycle a significant portion of aluminium at the end of its life cycle results in lower total carbon emissions for aluminium compared to steel. It is worth noting that the carbon credits earned by VI through aluminium recycling are only realized at the end of the product's 25-year lifespan. Due to the time value of money, these future earnings are less valuable in present terms. Our analysis reveals that the carbon emissions offset gained at the end of the product's life cycle does not significantly impact the total NPV, rendering aluminium crossmembers less attractive. The financial benefit accrued from carbon pricing does not outweigh the inherent economic advantages of steel crossmembers.

Furthermore, we observe that for the ARIMA forecast in which the price rises the most until 2050, the price difference between aluminium and steel is the lowest, namely 539.08 Euros. This can be explained due to the fact that aluminium can be recycled for a large part and thus earns back much of the carbon cost at the end-of-life phase when the carbon price is highest, while steel recovers almost nothing back at the end. The largest disparity can be found for the linear regression forecast, where the difference is 968.34 Euros.

Even when the discount rate is set to 0%, in the EU ETS (LR) scenario, we see that there is still a positive difference and thus the steel product is still preferred. Only when we alter the WACC to a negative value we get an NPV for the crossmember from aluminium that is lower than the one from the steel crossmember. So, in this case, we would prefer to invest in the crossmember made from aluminium in the EU ETS (LR) scenario. With a 0% WACC and the ARIMA(2,2,2) price path, we see that the NPV for alumnium becomes negative, -5,678.09 Euros, and the NPV for steel is 315.35 Euros. So this is a scenario in which the aluminium crossmember is preferred as the future recycled steel creates a returning cashflow that does not have to be discounted due to the 0% discount rate. Additionally, the ARIMA price path is also the one that has the highest price in 2050 and therefore values carbon the most in the future.

Table 30: Results of DCF analysis in terms of NPV and the difference in NPVs under different scenarios showing that the crossmember from steel is preferred in every carbon price scenario.

Scenario	NPV Aluminium (€)	NPV Steel (€)	Difference (€)
No carbon price	876.53	326.78	549.75
Tax	1,182.23	396.42	785.81
EU ETS (GBM)	1,406.91	438.57	968.34
EU ETS (Linear regression)	1,317.83	437.02	880.81
EU ETS (ARIMA)	970.05	430.98	539.08
Tax+ETS	1,377.99	438.07	939.92

8.4 Sensitivity analysis

In this section, we perform a sensitivity analysis to determine how different values of an independent variable and their uncertainty affect a particular dependent variable under a given set of assumptions (Kenton, 2023). In the case of this thesis, we determine how the NPV is impacted by alternations of the discount rate.

A discount rate is an important number that influences the result of the DCF analysis in terms of the NPV. Therefore, we conduct a sensitivity analysis to see how sensitive the NPV is to changing the discount rate. We alter the discount rate between -2% and 13% and show the results of the NPV of steel, aluminium, and their difference in Table 31. The price path that is used is the one from linear regression, as discussed in Section 7.2.

Table 31: Results of sensitivity analysis for the discount rate displaying that the crossmember from aluminium only becomes more attractive for negative discount rates.

Discount rate (%)	NPV aluminium (€)	NPV steel (€)	Difference between NPVs (€)
-2	-63.36	413.00	-476.37
-1	261.50	418.65	-157.15
0	513.85	423.04	90.81
1	710.37	426.46	283.91
2	863.79	429.13	434.66
3	983.85	431.22	552.64
4	1078.04	432.85	645.19
5	1152.10	434.14	717.95
6	1210.46	435.16	775.30
7	1,256.56	435.96	820.60
8	1,293.05	436.59	856.46
9	1,322.00	437.10	884.90
10	1,345.02	437.50	907.52
11	1,363.35	437.82	925.54
12	1,377.99	438.07	939.92
13	1,389.70	438.27	951.42

We observe that the higher the discount rate the larger the difference between the NPV of steel and aluminium. A higher discount rate results in future cashflows being valued at less than if a lower discount is used. Thus it makes sense that the difference between NPVs becomes larger as the amount of money that VI gets back through recycling is valued less. For aluminium, this creates a high increase in the NPV while for the NPV of steel, it results in only a very small difference in the NPV. We explain this as the aluminium cost is high at the start and money is retrieved back at the end of the lifetime of the product. However, with a higher discount rate this money is valued less. Table 31 confirms this conclusion and Figure 45 shows the results of the sensitivity analysis in a line graph. We can also see that when the discount rate becomes negative, at around -0.5%, the NPV values cross and the aluminium crossmember becomes more attractive to invest in compared to the one from steel. Therefore, we can conclude that even though there are changes in the NPV of aluminium and steel the conclusion and outcome of the business case do not change when altering the discount rate on a positive scale. However, when introducing a negative discount rate we do see that the investment decision changes.

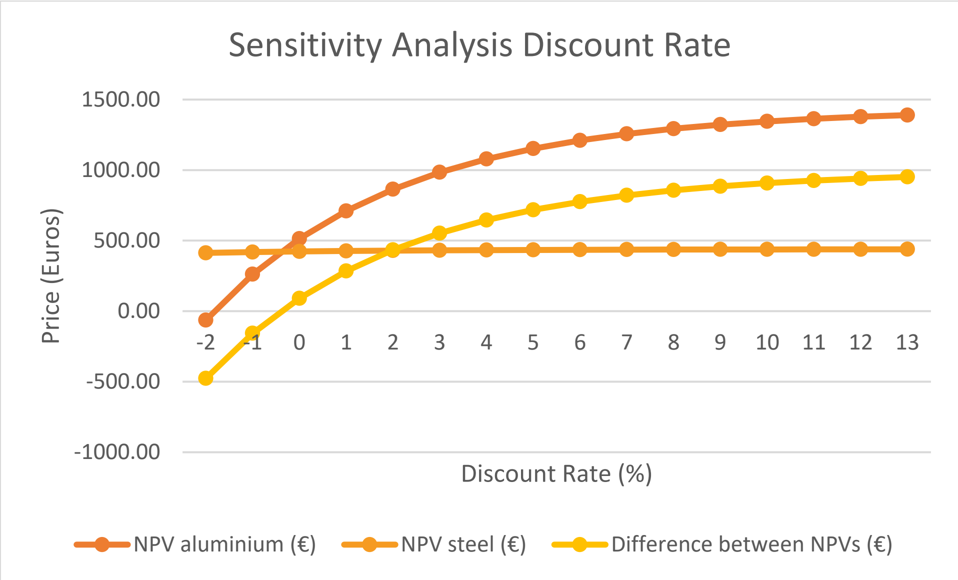

Figure 45: Line graph showing the results of the sensitivity analysis for the discount rate and the break-even point at around -0.5% where the aluminium alternative becomes more attractive than the steel crossmember.

In the sensitivity analysis, we did observe that the NPV of steel exceeded that of aluminium. We observe a change in the difference between the two NPVs under different discount factors and also saw that a negative discount rate led to the aluminium crossmember being more attractive when accounting for carbon pricing. Thus, in this specific business case, the set discount rate can result in a different recommendation of where to invest in for VI as the result remains to invest in a crossmember made from steel.

8.5 Final Conclusions

In this chapter, we delved into the decision between steel and aluminium crossmembers, considering both the environment and financial impact. We started by looking at how much carbon each material emits throughout its life. We first demonstrated the DCF tool and the different assumptions and price paths within this tool. These price paths are retrieved from literature and from the three different forecasts in Chapter 7. Together these different price paths help to provide more insights into what different carbon prices will mean for the NPV values of the steel and aluminium crossmember and ultimately show whether different decisions are made under different carbon prices. In Section 8.3.3 we conclude that even though each carbon price leads to a very different NPV this does not influence the decision made as the crossmember made from steel is preferable in every carbon pricing scenario. The difference between the two NPVs ranges from 549.75 Euros to 939.92 Euros and it favors the steel crossmember in every scenario and thus answering sub-questions 8 and 9 (RQ8 + RQ9). These two sub-questions concerned what the influence is of the expected carbon price path on the NPV of a product and how the different carbon price paths influence the decision made. Lastly, we researched what the sensitivity is of the discount rate and how this impacts the decision-making. In Section 8.4 we conclude that the discount rate can impact the investment decision, however, in the case used in this thesis, this only happens for a negative discount rate when dropping below -0.5%. Due to the change in time value for money, we see that the aluminium crossmember is preferred for more negative discount rates. However, for positive discount rates or a discount rate equal to 0% we only see smaller impacts and no change in the decision-making.

8.6 Discussion and limitations

In this section, we discuss the results of this thesis including all results until and including Chapter 8 and we share the limitations of this research.

While this research acknowledges the limitation of assuming normality in the context of the EU ETS time series, the diagnostic tests, including the Jarque-Bera test, played a critical role in the decision-making process. In our case, the assumption of normality was a simplifying assumption that allowed us to leverage the well-established ARIMA model, which is widely used in time series forecasting. The almost bell-shaped graph, although not a definitive indicator of normality, provided an initial indication of the log returns' distribution. However, the Jarque-Bera test demonstrated that the data deviated from a normal distribution. This result, rather than being a limitation, can be seen as a valuable insight into the characteristics of the EU ETS time series data. In practical forecasting, it is often necessary to make certain assumptions to facilitate the selection of an appropriate model. In this case, while normality assumptions did not hold entirely, they were made with the intent to apply a well-understood model that could provide useful forecasts. However, we acknowledge the need for future research to explore forecasting methods that do not rely on strict normality assumptions, particularly when dealing with financial time series data such as the EU ETS. This limitation challenges the validity of tests and computations dependent on normality assumptions, such as the student-t test and the Geometric Brownian Motion (GBM). Therefore, future research may consider alternative methods that can accommodate the specific characteristics of the EU ETS data more effectively, ensuring the robustness of forecasting and analysis.

In Chapter 7 we use the ARIMA model to forecast the price path of the EU ETS until 2050. Then we forecast or show different price paths under three different models, the ARIMA model and two benchmark models, linear regression and Geometric Brownian Motion. While GBM is a common choice for modeling asset price dynamics, it is important to acknowledge its limitations. This model primarily generates sample paths and does not provide explicit forecasts. Consequently, the performance of GBM is determined on the average sample path. The inclusion of GBM as a benchmark is aimed at highlighting the challenges and assumptions associated with this stochastic process and contrasting its performance with our ARIMA model.

Another remark that should be discussed in light of the forecast is the fact that we chose to use the forecasted price path of the ARIMA model based on the training data set instead of the entire dataset. We made this choice because of the fact that we do not want to let the ARIMA model use the extreme trend that is present in the last years of the EU ETS. The way in which the ARIMA model is built up the return behaviour of the last years is included, while it is evident that there is a jump in behaviour around 2021. Due to the fact that possible future jumps are challenging to predict and that the ARIMA model is not made to make these forecasts with jumps we decided to exclude the test data for the forecast until 2050. In this way, we can provide a more reliable basis for forecasting under normal conditions, which is preferred on the long time horizon. Another limitation of this research is that we compare the GBM, linear regression, and ARIMA models in performance. However, to execute the forecast using linear regression we needed a method called forward filling. This does influence the forecast as it uses slightly different train and test data. There is unfortunately no way to overcome this challenge.

In determining the split ratio between the training and test datasets, we chose a 90/10 division. This choice was made with careful consideration of several factors that impact the reliability of our forecasting model. One key consideration was the observed shift in the behavior of the EU ETS price in recent years, especially after 2020. During this period, the price dynamics deviated significantly from the patterns seen in previous years. To address this transition, we decided to allocate a substantial portion of the dataset (90%) to the training set. This allows our model to learn and adapt to the changing price behavior, which is critical for accurately capturing evolving market dynamics. Simultaneously, we are aware of the potential vulnerability of smaller test sets to the influence of outliers or unique data points. While a more conventional 80/20 split might offer greater resistance to outliers in the test set, we chose the 90/10 split to maintain a balanced representation of the recent price dynamics in both the training and test sets. It is important to emphasize that, given the shift in price behavior, this split is a trade-off and it is valuable to research the impact of the split more extensively. By exposing the model to a substantial portion of recent data in the training set, we aim to balance the need for model adaptability with robust performance evaluation.

A limitation of these forecasts and price paths until 2050 is that the long horizon poses a lot of uncertainty. The amount of uncertainty is so high that making a forecast model that covers this time span is almost certaintly not correct. Linear regression is a method that matches well with this long time span as it assumes a constant trend over time. However, it is important to emphasize on this high degree of uncertainty until 2050.

The cradle-to-cradle perspective, which looks at the entire lifecycle of a product, is very valuable due to the holistic overview this provides. Another limitation of this research is the data availability in the case. In this case, numerous assumptions are made due to the lack of data for example the exact location where the aluminium crossmember comes from. Therefore, in this example, the assumption is made that it is from China. We also assume in this thesis that carbon pricing is in place for VI on all elements that emit carbon in the case, including the material, production, transportation, and end-of-life phase. If some of these elements were to be excluded from carbon pricing in the future it would alter the business case and the price of carbon emissions for that specific element should be excluded.

Lastly, we reflect on the fact that the scope of this thesis is based in the Dutch jurisdiction and thus this impacts the generalizability of the DCF tool. The DCF tool is generalizable for all industries and companies in the Netherlands that want to compute future carbon costs. However, in other countries, we should adjust the carbon price paths based on the country in which the model is applied. For countries within the EU, the forecast on the EU ETS can remain the same, however, a carbon tax should sometimes be excluded as some countries do not have a carbon tax.

9 Conclusion, contributions, and future research

In this chapter, we conclude this research and provide recommendations and directions for future research. Section 9.1 provides the conclusion of the research. In the conclusion, the main research question is answered. Section 9.2 highlights the relevance of the research and the contributions to theory and practice. Lastly, the recommendations are given for both VI and future research in Section 9.3.

9.1 Conclusion

We first briefly recap the goal of this master thesis. In this thesis, we aim to give insights into how the carbon price may develop in the future and how companies can use carbon pricing to make more well-informed decisions for product investments. This master thesis explores and answers the main research question:

How can VI incorporate carbon pricing scenarios into their decision-making process for product investments?

Shortly summarized the DCF tool created can help with providing the right tooling to monetize carbon emissions and include them in a business case. We recommend to use the price paths as created in this master thesis to show the impact of different carbon prices on the decision making. However, the price path recommended to VI on the long horizon is the one resulting from linear regression which increases to 175 Euros per ton of CO_2 in 2050. The results of this research provide significant insights and recommendations that can serve as a valuable guide for VI in addressing carbon pricing. This is particularly relevant given the existing influence of carbon pricing on VI, especially in relation to the sourcing of energy and raw materials.

Results of different price paths

This research performed three different methods to generate price paths of the EU ETS and one price path based on the Dutch carbon tax as found in literature. The three methods to generate price paths are the ARIMA(2,2,2) model, GBM, and linear regression. Based on all methods and literature we conclude that it is likely that the carbon price will increase over time. However, the rate at which the price will increase differs very much as the GBM rises to 86.29 Euros per ton of CO_2 by 2050 and the ARIMA(2,2,2) model to 1,776.84 Euros per ton of CO_2. The price path that is generated using linear regression rises until 175 Euros by 2050 and the Dutch carbon tax only rises until 127 Euros per ton of CO_2 according to the Dutch government.

Long and short-term recommended carbon price path method

Another key takeaway from this study is the recognition of the differing time horizons involved in VI's decision-making processes. For short-term forecasts spanning 2-3 years, the ARIMA(2,2,2) model has demonstrated superior performance based on various performance metrics. This model, when applied with a sufficient amount of data, provides a reliable short to medium-term carbon price forecast, which is vital for immediate investment decisions that have an impact on the short to medium-term only. This is also in line with the time span in which VI currently makes forecasts.

In contrast, for long-term price paths used in business cases and the DCF analysis, the linear regression model emerged as the recommended choice. This model performs best in terms of R^2 and it also aligns closely with forecasts found in literature, offering a stable price path for long-term planning. Furthermore, the consistent trend across all forecasting methods in this thesis, indicating future carbon price increases, aligns with existing literature and underscores the importance of considering carbon pricing in investment decisions.

Changing legislation

Looking ahead, as changing legislation and the Carbon Border Adjustment Mechanism (CBAM) come into effect in 2026, along with the inclusion of new sectors, the integration of carbon pricing into business cases becomes increasingly vital. Carbon pricing and the created DCF tool enable the quantification of carbon emissions and sustainability, aligning VI with evolving industry standards and environmental responsibilities.

Practicality of the DCF tool

The DCF tool as created in this thesis proves to be a robust and practical approach for incorporating carbon pricing and scenarios into the decision-making process for product investments at VI. Its compatibility with existing VI methodologies and its simplicity makes it a versatile tool suitable for both smaller and larger projects, ensuring that the organization can effectively navigate through the evolving landscape of carbon pricing and sustainability. The practical use and validity of the DCF tool is proven using a case that compared a crossmember made from aluminium versus steel. This case shows that the crossmember made from steel is preferred in terms of the NPV when considering both a carbon price and general financial elements like the investment. Moreover, the case also proves that the DCF tool is valuable when wanting to make a decision for a product investment, which also includes different carbon pricing scenarios.

Conclusion

In conclusion, this research provides VI with a comprehensive understanding of how to incorporate carbon pricing scenarios effectively, taking into account both short-term and long-term perspectives. We do so by providing a DCF tool, which helps to answer the main research question on how VI can incorporate carbon pricing scenarios into their decision-making process for product investments. By quantifying the financial and environmental implications, this methodology offers valuable insights into how different carbon pricing policies may influence investment decisions between multiple alternatives. These recommendations will empower VI to make informed, sustainable, and economically sound investment decisions in an ever-changing environmental and regulatory context.

9.2 Contributions to theory and practice

This research has both a theoretical and practical contribution. These contributions are discussed in Sections 9.2.1 and 9.2.2.

9.2.1 Contributions to theory

This section highlights the various theoretical contributions made by this thesis.

Integration of finance, econometrics, and sustainability research fields

The theoretical contribution lies in the integration of carbon pricing within the DCF methodology. This combines the fields of finance, econometrics, and sustainability research by combining carbon pricing, (econometric) forecasting methods, and the DCF analysis tool. While the DCF tool is well-established in the field of finance, the integration of carbon pricing is a novel addition to the existing body of knowledge as well as a forecast of carbon prices based on econometric and mathematical models. This combination of concepts represents a significant contribution to current body of knowledge.

Specifically, the DCF tool developed in this study incorporates a carbon price trajectory extending until the year 2050. In the existing literature, no comparable tool exists that integrates the DCF framework with a long-term carbon price trajectory based on a forecast up to 2050. Therefore, this is a novel tool, which helps to make informed product investment decisions in light of evolving carbon pricing dynamics.

Application of different forecasting techniques on the EU ETS

Furthermore, the carbon price trajectories utilized in this study are computed through the application of forecasting techniques not previously employed within the context of the EU ETS market. These techniques encompass ARIMA, GBM, and linear regression, thereby expanding the body of knowledge in the field of carbon pricing analysis.

Generalizability and adaptability

In addition to its uniqueness, the developed model exhibits a high degree of generalizability. While initially tailored to the Dutch jurisdiction, it can readily be adapted for application in other industries and companies. The only adjustment that needs to be made is plugging in and computing the carbon price path of the country in which the DCF tool is used as the carbon prices may differ per country.

Conclusion

In summary, the contribution of this thesis mainly lies in the integration of the fields of finance, econometrics, and sustainability. It contributes significantly to the theoretical landscape by introducing a pioneering approach that computes carbon price paths using the ARIMA model, GBM, and linear regression and integrates these carbon price paths into the DCF tool. Together this helps companies to make product investment decisions.

9.2.2 Contributions to practice

In addition to its scientific contributions, this thesis holds substantial practical implications for VI, providing valuable tools and insights that can shape the organization's decision-making processes and sustainability efforts. The practical contributions can be summarized into five areas, which are creating awareness, making well-informed financial decisions, guiding decision-making, integration with existing models, and decision-making based on the case.

Creating awareness

This research has a practical contribution by raising awareness about the critical concept of carbon pricing. Through an extensive literature review and the presentation of the findings within the organization, we have shed light on the importance and implications of carbon pricing and on upcoming legislative changes likes CBAM. Moreover, we also created more awareness by having the opportunity to have discussions with the CEO and COO of VI, facilitating a direct exchange of ideas and information, which further underscores the practical impact of this research.

Making well-informed financial decisions

The first area concerns the contribution of the development of the DCF tool. A key contribution of this research is the creation of a DCF tool. This method equips stakeholders within VI with a robust framework to compare the NPV of various products over their projected lifetimes, accounting for the potential implementation of a carbon pricing system and enabling them to make well-informed decisions. This innovation is particularly valuable as, at present, no carbon pricing mechanism is in place within VI. By failing to consider the future implications of evolving legislative landscapes and potential carbon pricing, the company could face unforeseen financial risks. The DCF tool also addresses the challenge of 'valuing' carbon emissions, offering VI a structured methodology and a practical Excel-based tool for internal carbon pricing decisions.

Guiding decision-making using internal carbon pricing

The second practical contribution regards the fact that the deliverables help to guide decision-making for VI. The developed DCF Excel tool empowers VI to make informed decisions regarding internal carbon pricing. This tool serves multiple purposes: 1) Gain Internal Insights: VI can use it to gain deeper insights into the potential financial impact of future carbon pricing scenarios on product investments, 2) Create Internal Investment Funds for Sustainability: The system can help in the allocation of internal funds dedicated to sustainability initiatives, ensuring that the company remains competitive in an evolving regulatory landscape, and 3) External Communication and Customer Engagement: VI can utilize the tool to provide insights into the carbon emissions and costs of their systems to customers, showing VI’s commitment to environmental responsibility. Additionally, it can be used to quantify and communicate the value of carbon emissions reductions to external stakeholders, enhancing the company's position in the market.

Integration with existing methods

The third practical contribution can be found in the integration with existing models. The DCF tool created in this research can integrate with VI's current business case calculation models. This integration improves the versatility of the tool, enabling its application in complex business scenarios. Thereby it streamlines the decision-making process while also including carbon emissions. For VI this is valuable as it aligns with well-established financial evaluation metrics like NPV, ensuring consistency with VI’s standards. The alignment of the tool with VI makes it easier to integrate the tool with VI’s current workflow and it is also beneficial as employees are already familiar and need less training. This further facilitates a more sustainable approach to decision-making.

Decision-making based on insights from the case

The validation through a case is the fourth practical contribution of this thesis. The case presented in this thesis serves a dual purpose. Firstly, it aids ongoing decision-making within a project by providing insights into carbon emissions considerations. This shows that for the crossmember the steel construction is preferred compared to the one made from aluminium when looking at the entire lifecycle. Secondly, it serves as a practical validation of the developed methodology, affirming its usability and relevance in real-world scenarios.

Conclusion

In summary, the practical contributions of this thesis extend beyond theoretical frameworks, offering VI a tangible means to navigate the dynamic landscape of carbon pricing and sustainability. By providing the DCF tool for internal carbon pricing, aiding sustainability initiatives, and integrating with existing models, this research provides VI with a comprehensive approach to making informed, environmentally responsible, and financially sound decisions in an evolving regulatory environment. Lastly, a large practical contribution can also be found in the fact that this research creates more attention and awareness on the topic of carbon pricing within VI.

9.3 Recommendations

In the previous chapters, we explored how carbon pricing affects VI's choices. As we finish this thesis, we move on to giving advice. This section provides recommendations, split into two parts: suggestions for VI and recommendations for future research.

9.3.1 Recommendations VI

VI can leverage the findings of this research to shape its approach to carbon pricing and sustainable decision-making. Here are some recommendations for VI. As there are numerous recommendations we will mention the larger ones first and then end with a few smaller ones found in the research.

Integrate carbon pricing into VI's strategy

Firstly, carbon pricing should become an integral part of VI. The DCF analysis tool, developed within this thesis, provides a valuable tool for quantifying carbon emissions and incorporating them into business cases. This is especially crucial considering the rapidly evolving landscape of carbon emissions regulations, with significant changes expected in 2026. Given that many of VI's projects have a lifespan of over two years, factoring in potential future carbon costs is essential. Neglecting this aspect could prove detrimental to the company's financial health. To initiate this fundamental change within the organization, it is advisable to view the inclusion of carbon pricing as a strategic shift that permeates the entire company culture. Moreover, it is also important to see the DCF tool as a first version and to use it more often and update and adjust it when new features are needed.

Selecting appropriate forecasting models

Selecting the appropriate forecasting model is important for reliable carbon pricing projections. For short to mid-term forecasts, we recommend using the ARIMA(2,2,2) model due to the fact this performs best and is most accurate. When conducting comprehensive business case assessments and looking at a longer time horizon, the linear regression model, representing the general price path, is advisable. However, we do recommend reviewing these forecasts every year due to possible changes in legislation that create structural breaks and thus different price behaviour. Forecasting a price on a horizon until 2050 brings much uncertainty and the best way to handle the uncertainty is to review the model once every year.

Practical testing for larger cases

In this research we applied the DCF tool for a small product investment trade-off. However, to assess the model's financial impact in real-world scenarios, VI should consider applying the model to larger cases, such as the innovation project into wooden supports. Other valuable larger cases are investigating energy efficient motors or material decisions for platforms. This practical testing not only validates the methodology but also offers tangible insights into the financial implications of emission reduction initiatives.

Additional recommendations

Then some general recommendations to VI that were found during the research period but which were excluded from the scope are:

- Create awareness within the company, customers, and suppliers on carbon pricing and CBAM;
- Map VI's customers according to a sustainability maturity scale and to see where their customers are and how much they value sustainability. This is a key element in the process for VI as carbon pricing is not fully taking effect for all carbon emissions of VI. Therefore, the carbon pricing set today is similar to an internal carbon price and thus the ambition level of a customer determines how much of the carbon cost can be added to the bill of the customer;
- Get more knowledge about the suppliers' emission levels and demand transparency;

- Work on data availability as we observed that much data is unstructured or just simply not available. Data availability is fundamental for accurate LCAs and the calculation of carbon costs. VI should prioritize efforts to improve data collection, organization, and accessibility. This will facilitate informed decision-making by enabling a comprehensive assessment of carbon emissions associated with alternative product investment options;
- Use front-running customers to do innovative sustainable projects with that can serve as a showcase for others;
- Find a proper place to include carbon emission data, we recommend doing this in the CAP8 system, which is a system that contains the cost of all items of VI;
- Research which factors have the largest impact on the carbon emissions in a project using a regression model. Using this information VI can distinguish whether the raw materials, transportation, energy usage, or any other factor have the largest impact. This helps give direction to VI in where to make the largest impact in terms of emission reduction;
- VI should investigate to start working with carbon budgets in a project which may help to guide the project in the right direction of reducing emission levels. However, more data maturity is needed for this. A final goal for VI is to make sure that for every project VI works on, they deliver an indication of the carbon emissions of that project. In this way, VI can also work with carbon budgets and check them. This is important for legislative reasons, CSRD, as well as valuation reasons. Because the tool can be used using the carbon emissions as input and then calculating their worth over time.
- Research how carbon pricing influences the globalization strategy of VI as carbon prices may differ per country. This impacts the supplier decision and guides the decision on whether to supply locally or not;
- Investigate which impact carbon pricing will have on fixed capital for VI and see how this impacts the balance sheet. Possible more service-based business model can also help to overcome this.

9.3.2 Recommendations for future research

While this thesis represents a significant advancement in the comprehension of the relationship between carbon pricing, investment decisions, and sustainability, it also shows areas that should be explored further. In this section, we present the recommended areas for future research.

Explore different forecasting models

Firstly, other more complex forecasting models may be valuable to research to provide more accurate forecasts. A valuable model to explore are machine learning models like Long-Short Term Memory (LSTM). These models are less explainable compared to the ARIMA model but they are better at capturing patterns based on the findings in literature. A limitation of the ARIMA model is that it is not able to handle non-linearities of the drift term in a time series which may not provide accurate results. A proper alternative is a machine learning algorithm like neural networks, random forests, and gradient boosting machines which can capture nonlinearities effectively. Models that can forecast structural jumps and nonlinear relations may be valuable in the context of this thesis and these are recommended to be explored for a more accurate forecast in both the short and long term. Moreover, external factors influencing the carbon price are also not included in this research while they might pose valuable insights. Another, valuable field to research regards large language models. These can be used by for example, scanning the internet on developments or news announcements and translating these into the carbon price forecast. However, in the scope of this research, a general price path is already very valuable. We do note that there is still a high level of uncertainty when forecasting on a horizon until 2050 as much can change in the future of which we do not even know the existence and complex machine learning methods are still subject to this enormous level of uncertainty.

Align scenario analyses with international standards

A promising direction for future research entails aligning scenario analyses with those outlined by the Network for Greening the Financial System. This approach could enhance the value and relevance of scenario-based assessments by ensuring they are in harmony with internationally recognized standards and practices, thereby facilitating cross-sectoral and cross-border comparisons.

Efficient methods for carbon emission assessment

Lastly, another interesting research direction is to find better and faster methods to know the carbon emissions of VI and their products, such as regression models. This is valuable to research as currently gaining insights into the amount of carbon emissions is very time-consuming. However, with the CSRD it becomes mandatory and also when wanting to use the DCF tool it is necessary to know the carbon emissions. Therefore, having a faster way of getting to these carbon emissions can be valuable.

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Appendix

Appendix A.0: Carbon pricing per key account of VI

Table 32: Carbon pricing per key account of VI, which are the largest customers of VI.

Company name	Segment	Carbon pricing (yes/no/N.A.)	Internal carbon price (EUR/ton CO_2)	Source (if available)
VI	Warehousing	No	-	
LPP	Warehousing	N.A.		
Schwarz Gruppe	Warehousing	N.A.		
Zalando	Warehousing	N.A.		
Ahold Delhaize	Warehousing	Yes	150	(Ahold Delhaize, 2022)
Hilton Food Group	Warehousing	N.A.		
Walmart	Warehousing	No	-	(Walmart, 2020) (Walmart, 2022)
Woolworths	Warehousing	No	-	(Woolworths, 2021) (Woolworths, 2022)
Amazon	Warehousing	N.A.		
Nike	Warehousing	Yes/No*	Unknown	(Nike, 2020) (Nike, 2022)
Deutsche Post DHL group	Parcel	No	-	(DHL, 2022)
UPS	Parcel	No	-	(UPS, 2022)
FedEx	Parcel	No	-	(FedEx, 2022)
Alibaba	Parcel	N.A.		
Sichuan Provence-Chengdu-Shuangliu (CTU)- and Tianfu (TFU)	Airports	N.A.		
Chicago Department of Aviation (ORD)	Airports	N.A.		
Vancouver (YVR)	Airports	N.A.		
Singapore Changi (SIN)	Airports	N.A.		
Hong Kong (HKG)	Airports	N.A.		
Los Angeles World Airports (LAX)	Airports	N.A.		
AVINEX Shanghai Pudong (PVG)	Airports	N.A.		

and Hongqiao (SHA)				
Shenzhen Airport Group (SZX)	Airports	N.A.		
Jedco Jeddah Airports (JED)	Airports	N.A.		
Delta Airlines (Delta)	Airports	Yes	Unknown	(Delta Air Lines, 2022)
Orlando (MCO)	Airports	N.A.		
AENA – Spain	Airports	No	-	(AENA, 2022)
Schiphol Group Amsterdam (AMS)	Airports	N.A.		
New York (JFK)	Airports	N.A.		
London Heathrow (LHR)	Airports	N.A.		
Istanbul IGA (IST)	Airports	N.A.		
Oslo Avinor (OSL)	Airports	N.A.		

*Yes/No due to the fact that they use an internal carbon price only for some parts of the business, but not in general

Appendix A.1: Programming files in Python and Excel

This thesis included programming different steps in Python and using Excel. In this appendix we provide an overview of which code can be found in which file.

To prepare the data and do some basic analysis we use the 'Prep_Test_Returns.py' file.

The exact Python code of how the ARIMA model is programmed without manual differencing is in the 'NewARIMA_WithoutManualDifferencing.py' file. It is important to note that this is the code that looks at the train data and not all data.

The file 'NewARIMA_WithoutManualDifferencing_All_Data.py' contains the code for the ARIMA model when used for forecasting until 2050 using all available data.

The 'GeometricBrownianMotion.py' file contains the code for the Geometric Brownian Motion, which results in different price paths until 2050.

We perform linear regression in Excel using built-in forecasting functions and we manually prepared the data and used forward filling.

The computations made in the case are provided in the Excel file 'DCF analysis tool' in the sheets 'Case', 'Avg crossmembers', and 'Carbon emissions'.

Appendix A.2: Seasonality decomposition

In this appendix we prove that seasonality is insignificant in this time series and therefore, it is left out of the forecasting model. To determine whether the data is seasonal or not a seasonal decomposition plot is made in Python.

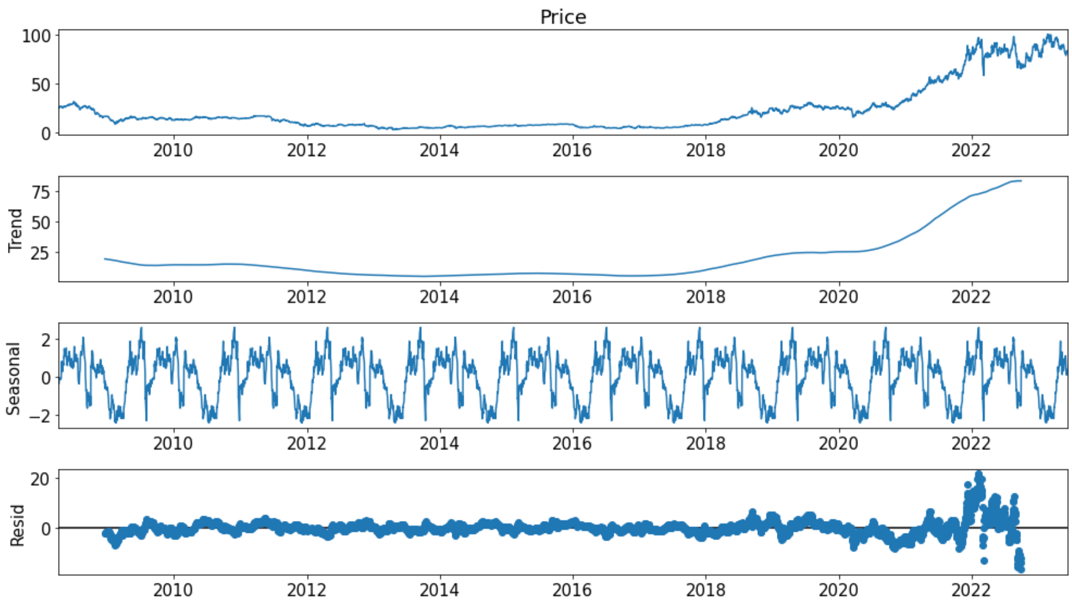

Figure 46: Seasonal decomposition plot for the original EU ETS price series.

Figure 46 shows a seasonal pattern in the original time series of the EU ETS with a nearly annual cycle. The cycles seem to be slightly longer than one year and these plots also show that there is a trend in the data and the residual plot confirms heteroskedasticity. In the seasonal plot, third plot, the range in which the price fluctuates is -2 to +2. However, this range is small compared to the order of magnitude of the price itself thus it seems that this seasonality only has a minor impact on the daily prices. Therefore, a seasonal decomposition graph is also created on the log returns, resulting in Figure 47.

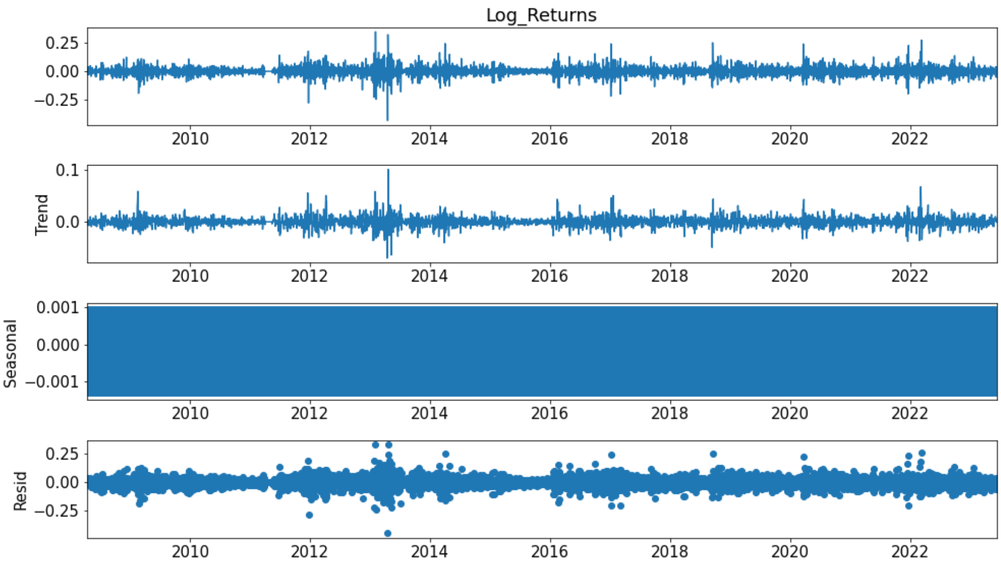

Figure 47: Seasonal decomposition plot for the log return EU ETS series.

This plot shows that there is no trend anymore and the residual plot is also more stable compared to the original time series. The seasonal graph shows a blue rectangle indicating that the seasonal fluctuations change rapidly around the value of 0, as the range is only -0.001 to 0.001. This can be the case due to rounding as well as prices are rounded to two decimals. This is a minor range that seems to be insignificant. This claim is confirmed when conducting a student t-test on the log returns. The student t-test is used to determine whether the mean of a single sample is significantly different from a known or hypothesized population mean. It consists of a null hypothesis and alternative hypothesis:

- Null hypothesis (H0): The sample mean is equal to the hypothesized population mean.
- Alternative hypothesis (H1): The sample mean is not equal to the hypothesized population mean.

Assumptions: The data is approximately normally distributed and the observations are independent.

We provide a general outline of how the t-test works:

1. Calculate the t-statistic: The t-statistic measures the difference between the sample means and takes into account the variability within the samples.
2. Calculate the degrees of freedom: This value depends on the sample sizes and is used to determine the critical t-value from the t-distribution.
3. Calculate the p-value: The p-value is the probability of observing a t-statistic as extreme as the one calculated, assuming that the null hypothesis is true.
4. Compare the p-value with the chosen significance level (alpha): If the p-value is less than alpha, one rejects the null hypothesis in favour of the alternative hypothesis.
5. Make a decision: If one rejects the null hypothesis, we conclude that there is a statistically significant difference between the means. If we fail to reject the null hypothesis, we do not have enough evidence to conclude a significant difference.

The results of the t-test give a t-statistic of -0.03 and p-value of 0.98 (> 0.05) and therefore, we fail to reject the null hypothesis and state that seasonality is not statistically significant. Thus seasonality is not accounted for in forecasting this time series as the impact of seasonality is proven to be insignificant in this log return time series, which is forecasted in this thesis.

Appendix A.3: Jarque-Bera (JB) test

To conduct the Jarque-Bera test, however, it is important to keep in mind certain characteristics of the data with autocorrelation being an important one. As seen in Section 6.4 the data is slightly auto-correlated and therefore some adjustments are made.

A normal distribution has a skewness of 0 and a kurtosis of 3. When performing a Jarque-Bera test this skewness and kurtosis can be tested to see whether they match the ones of a normal distribution (Jarque & Bera, 1987). The skewness of the logarithmic returns is -0.82 and the kurtosis is 14.35. These clearly deviate from the normal distribution. The Jarque-Bera test statistic JB is given by:

$$JB = \frac{n}{6}\left(Skewness^2 + \frac{1}{4}(Kurtosis - 3)^2\right) \tag{18}$$

Where,

$$Kurtosis = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^{4}}{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2\right)^2} \tag{19}$$

$$Skewness = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^{3}}{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2\right)^{3/2}} \tag{20}$$

In the JB test, the null hypothesis states that the skewness is 0 and the excess kurtosis, deviation from 3, is as well. The test statistic has a Chi-squared distribution. In case the test statistic exceeds the critical value, we reject the null hypothesis. Thus, the normality assumption is rejected based on skewness and kurtosis.

However, from previous tests, we know that there is autocorrelation. In that case the estimated standard errors of the skewness and kurtosis, which are $\sqrt{6/n}$ and $\sqrt{24/n}$ respectively, are invalid. Therefore, this autocorrelation should be accounted for, which can be done by 1) removing autocorrelation from the series and then applying the JB test on the new series, or 2) adjusting the estimated variance of skewness and kurtosis for autocorrelation. The second option is chosen due to the complexity and modelling techniques needed for the first option, which are seen as too complex for the aim of this thesis.

The approach of Lobato and Velasco is chosen to modify the Jarque-Bera test statistic to account for the variance that comes from correlation (Lobato & Velasco, 2004). The first step in this approach is computing the autocovariance (ACV) for all $n-1$ possible lags h. The formula for ACV is:

$$ACV(h) = \frac{1}{n}\sum_{t=1}^{n-|h|}(x_t - \bar{x})(x_{t+|h|} - \bar{x}) \tag{21}$$

To compute the skewness and kurtosis the ACVs are taken to the power of 3 or 4 respectively.

$$Skewness: ACVF^{(3)} = \sum_{h=1-n}^{n-1} ACF(h)^3 \tag{22}$$

$$Kurtosis: ACVF^{(4)} = \sum_{h=1-n}^{n-1} ACF(h)^4 \tag{22}$$

In this method the second, third, and fourth central moments of the series are also required, these are given by:

$$m_j = \frac{1}{n}\sum_{t=1}^{n}(x_t - x)^j \tag{23}$$

For $j = 2,3,4$.

The adjusted test statistic of the Jarque-Bera becomes:

$$JB_{adj} = \frac{n * m_3^2}{6 * ACVF^{(3)}} + \frac{n * (m_4 - 3m_2^2)^2}{24 * ACVF^{(4)}} \tag{24}$$

In this adjusted test the test statistic is also compared to the critical value from the chi-squared distribution. Normality is rejected when the test statistic exceeds the critical value. The result of the JB test is only valid if autocorrelation is successfully removed (Heeswijk, 2012).

When running the adjusted Jarque-Bera test we can conclude that the log returns do not follow a normal distribution. The critical value, at a significance level of 5%, is 5.99, while the adjusted Jarque-Bera statistic is 268,819.64. This value exceeds the critical value, thus it can be concluded that the log return time series is not normally distributed.

The student t-test used to test seasonality in Section 6.1 assumes that the data is normally distributed. It is proven that this is not true in this section, however, due to the Central Limit Theorem and the large sample size we can state that the distribution becomes normal and therefore, the conclusion on seasonality remains the same. It is however, good to gain insights into the actual distribution of the data.

Appendix A.4: ARIMA(1,1,1) forecast results

This appendix shows the results for the ARIMA(1,1,1) model. We observe that the forecast is a flat line until 2050 in Figure 48 and Figure 49.

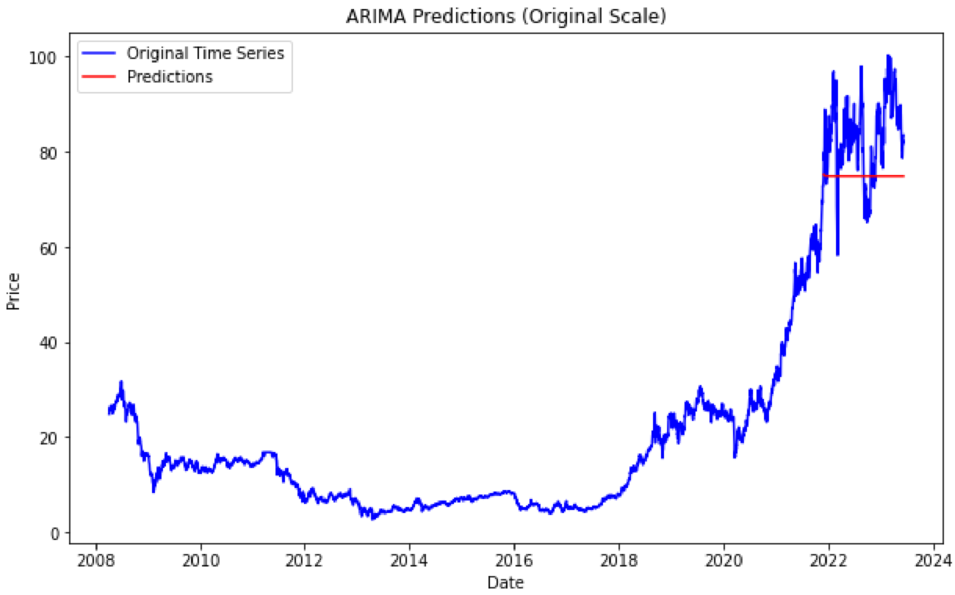

Figure 48: Out-of-sample log predictions of ARIMA (1,1,1) model from 1st of December 2021 until 9th of June 2023 compared to original data.

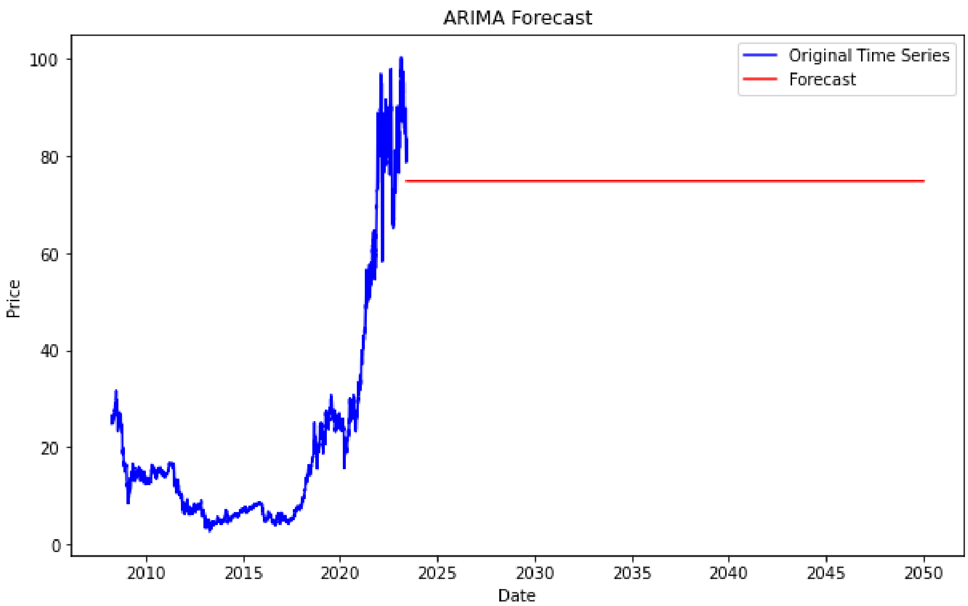

Figure 49: ARIMA(1,1,1) model forecast until 2050 and original EU ETS time series.

Appendix A.5: AIC and BIC results

This section presents the AIC and BIC results of different configurations of the ARIMA model. Table 33 shows the AIC and BIC values for different configurations. The general rule of thumb is that the lower the values the better the performance of the model.

Table 33: AIC and BIC results of using the Hyndman-Khandakar algorithm to optimally tune the ARIMA model based on the train data.

Performance of different ARIMA models	**AIC**	**BIC**
Initial models fitted (step a)		
(1,1,1)	-14,083	-14,065
(0,2,0)	-11,677	-11,671
(0,1,0)	-14,085	-14,079
(2,1,2)	-14,114	-14,083
(2,2,2)	-14,064	-14,034
(1,1,0)	-14,083	-14,071
(1,2,0)	-12,578	-12,566
(0,1,1)	-14,083	-14,071
(0,2,1)	-14,083	-14,064
Variations of current model fitted (step c)		
(1,2,1)	-14,071	-14,052
(2,1,1)	-14,087	-14,063
(1,1,2)	-14,085	-14,060
(0,1,2)	-14,088	-14,069
(1,2,2)	-14,066	-14,042

Appendix A.6: ARIMA(0,2,0) and ARIMA(1,2,0) forecast results

This section shows the forecasts until 2050 of the two best performing ARIMA configurations in terms of AIC and BIC. In Figure 50 and Figure 51 we do observe that for both the (0,2,0) and (1,2,0) configuration the price increases drastically as time moves on. Therefore, we decided to research other configurations.

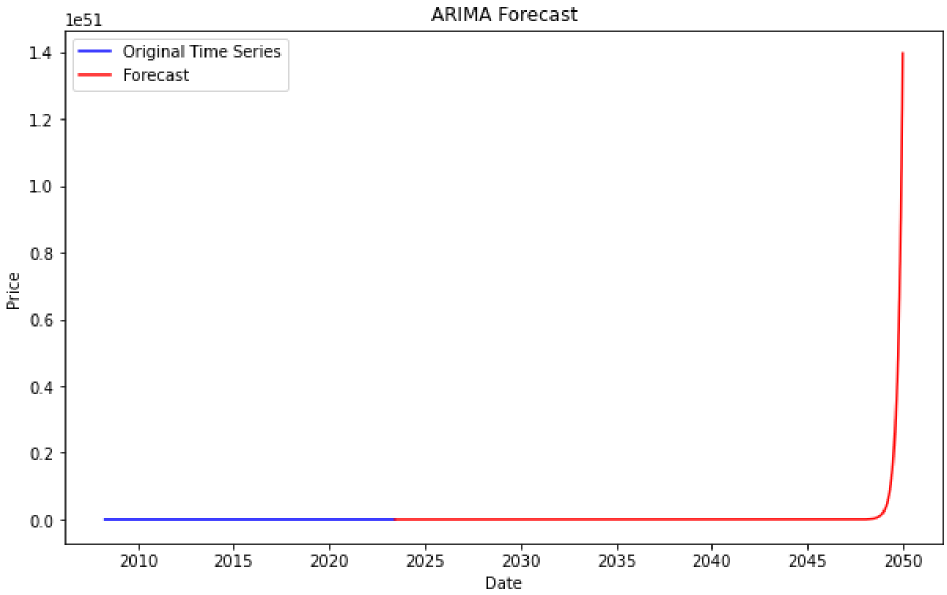

Figure 50: ARIMA(0,2,0) model forecast until 2050 and original EU ETS time series.

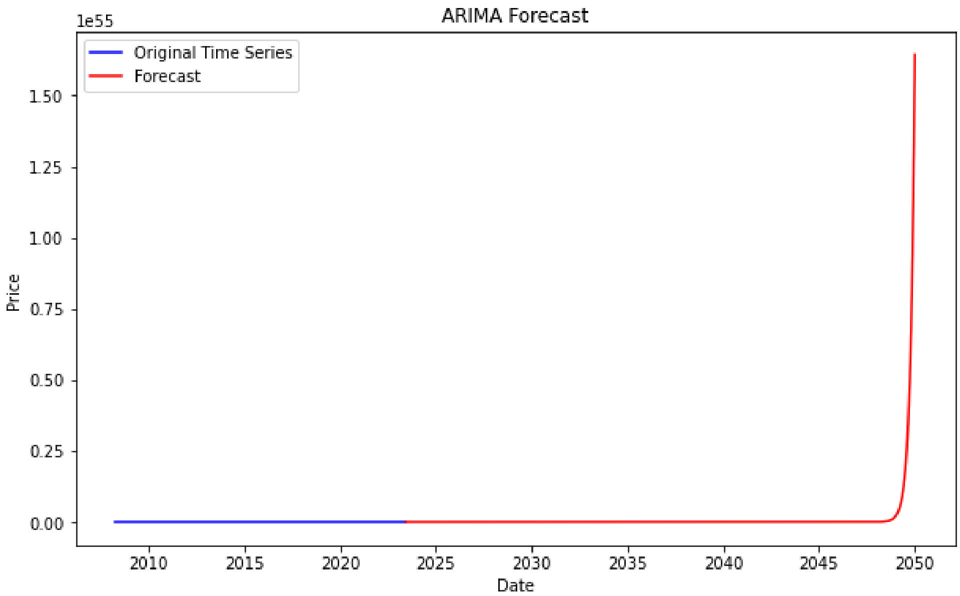

Figure 51: ARIMA(1,2,0) model forecast until 2050 and original EU ETS time series.

Appendix A.7: First version of DCF

This appendix discusses and shows the first version of the DCF. It also elaborates on the different elements present in the first version of the DCF.

Creating the first version of the DCF is an iterative process between the DCF analysis approach and the case chosen. The first step consists of creating a DCF tool that is able to include all the elements that come into play for the case. Consecutively, the DCF is generalized more so that it can be used on all kinds of product investment decisions. Firstly, the decision on the discount rate should be made.

Firstly, the first version of the DCF is shown. Here the price paths and probability per price path are integrated into a DCF tool, which can be used to make investment analysis. The probabilities per price paths were determined using balance equations, however, these are not present in this thesis anymore. The DCF consists of multiple sheets. In this section each sheet is explained.

The first sheet is the input sheet, which can be seen as a dashboard in which manual adjustments can be made to make it fit the specific problem. The general input elements present in this sheet are:

- Current year
- Discount rate
- Time period (years), which refers to the life time of a product
- Project duration, which refers to the number of years until the operation starts
- Cost per employee per hour, which is set to 59 EUR
- Cost per employee per hour, is calculated from the monthly salary
- Hours needed for investment

After filling in the general input variables the carbon related variables should be filled in. Firstly the carbon price scenario can be chosen from a dropdown menu. Each scenario has a different price path. If the future scenario is unknown and VI wants to handle it as such, then the dropdown menu option ‘Unknown scenario’ can be chosen which computes the weighted average carbon price based on the price paths of all scenarios. Then the carbon price that matches the current year is displayed in the cell below the scenario selection. Additionally, the carbon emissions before the use phase, during the use phase, and end-of-life can be filled in to use for calculating the carbon costs. These carbon emissions should be retrieved by filling in the Simplified LCA tool of VI or another LCA tool.

In Figure 52 the ‘Input 1 – DCF’ sheet is shown, the output is shown on this sheet as well which is the NPV of a product investment.

Input DCF		
Current year	2023	*Fill in*
Discount rate	9%	
Time period (years)	30	*Fill in*
Project duration (years till start operation)	0	*Fill in*
Cost per employee per month	2.750	*Assume that this is 40*4=160 hours per month*
Cost per employee per hour	17	
Hours needed for investment	40	*Fill in*
Carbon costs		
Carbon price scenario	Tax (cap in 2030)	*Dropdown menu*
Current carbon price under scenario	€ 52,41	
Carbon emissions (before use phase)		*Fill in*
Carbon emissions (use phase, annually return)		*Fill in*
Carbon emissions (End of Life)		*Fill in*
NPV	**€ 409.684,04**	

Figure 52: DCF sheet 'Input 1 - DCF' for DCF analysis.

Secondly as seen in the input sheet above the carbon price paths are all different scenarios. Figure 53 shows the different carbon price scenarios and their price paths. The following price scenarios are included:

7. **No carbon price**, here the carbon price is set equal to zero at all times;
8. **Tax (cap in 2030)**, here the current tax is 51.41 EUR and this increases until 127 EUR by 2030 and then it is assumed to remain constant until 2050;
9. **EU ETS (low)**, here the scenario is described by the EU ETS market for a low price scenario. This value still needs to be computed and thus the column is still empty;
10. **EU ETS (medium),** here the price path is determined by a medium EU ETS scenario;
11. **EU ETS (high),** here the price path is described by a high EU ETS scenario;
12. **Tax+ETS (low)**, here the carbon price is determined by a combination of the tax and ETS, where the tax serves as a minimum value that should always be paid even if the EU ETS price drops below this value and in case the EU ETS price exceeds the tax, then the price is set by the EU ETS. This price scenario is determined by combining the capped tax scenario and low EU ETS scenario.
13. **Tax+ETS (medium),** this scenario combines the capped tax scenario and medium EU ETS scenario;
14. **Tax+ETS (high)**, this scenario combines the capped tax scenario and high EU ETS scenario;
15. **Unknown scenario**, in case that no information is known on what the future beholds this scenario can be used. It computes a price based on the weighted average using the probabilities as calculated with the steady-state probabilities. The scenarios that are used are the no carbon price, capped tax, EU ETS (medium), and Tax+ETS (medium). This scenario is later deleted and therefore no further explanation on steady-state probabilities can be found in this thesis.

Carbon Price Paths										
Year	No carbon price	Tax (cap in 2030)	Tax (no cap)	EU ETS (low)	EU ETS (medium)	EU ETS (high)	Tax+ETS (low)	Tax+ETS (medium)	Tax+ETS (high)	Unknown scenario
2023	€ -	€ 52,41	€ 52,41				€ 52,41	€ 52,41	€ 52,41	€ 46,85
2024	€ -	€ 63,06	€ 63,06				€ 63,06	€ 63,06	€ 63,06	€ 56,38
2025	€ -	€ 73,72	€ 73,72				€ 73,72	€ 73,72	€ 73,72	€ 65,90
2026	€ -	€ 84,38	€ 84,38				€ 84,38	€ 84,38	€ 84,38	€ 75,43
2027	€ -	€ 95,03	€ 95,03				€ 95,03	€ 95,03	€ 95,03	€ 84,96
2028	€ -	€ 105,69	€ 105,69				€ 105,69	€ 105,69	€ 105,69	€ 94,48
2029	€ -	€ 116,34	€ 116,34				€ 116,34	€ 116,34	€ 116,34	€ 104,01
2030	€ -	€ 127,00	€ 127,00				€ 127,00	€ 127,00	€ 127,00	€ 113,54
2031	€ -	€ 127,00	€ 137,66				€ 127,00	€ 127,00	€ 127,00	€ 113,54
2032	€ -	€ 127,00	€ 148,31				€ 127,00	€ 127,00	€ 127,00	€ 113,54
2033	€ -	€ 127,00	€ 158,97				€ 127,00	€ 127,00	€ 127,00	€ 113,54
2034	€ -	€ 127,00	€ 169,63				€ 127,00	€ 127,00	€ 127,00	€ 113,54
2035	€ -	€ 127,00	€ 180,28				€ 127,00	€ 127,00	€ 127,00	€ 113,54
2036	€ -	€ 127,00	€ 190,94				€ 127,00	€ 127,00	€ 127,00	€ 113,54
2037	€ -	€ 127,00	€ 201,59				€ 127,00	€ 127,00	€ 127,00	€ 113,54
2038	€ -	€ 127,00	€ 212,25				€ 127,00	€ 127,00	€ 127,00	€ 113,54
2039	€ -	€ 127,00	€ 222,91				€ 127,00	€ 127,00	€ 127,00	€ 113,54
2040	€ -	€ 127,00	€ 233,56				€ 127,00	€ 127,00	€ 127,00	€ 113,54
2041	€ -	€ 127,00	€ 244,22				€ 127,00	€ 127,00	€ 127,00	€ 113,54
2042	€ -	€ 127,00	€ 254,88				€ 127,00	€ 127,00	€ 127,00	€ 113,54
2043	€ -	€ 127,00	€ 265,53				€ 127,00	€ 127,00	€ 127,00	€ 113,54
2044	€ -	€ 127,00	€ 276,19				€ 127,00	€ 127,00	€ 127,00	€ 113,54
2045	€ -	€ 127,00	€ 286,84				€ 127,00	€ 127,00	€ 127,00	€ 113,54
2046	€ -	€ 127,00	€ 297,50				€ 127,00	€ 127,00	€ 127,00	€ 113,54
2047	€ -	€ 127,00	€ 308,16				€ 127,00	€ 127,00	€ 127,00	€ 113,54
2048	€ -	€ 127,00	€ 318,81				€ 127,00	€ 127,00	€ 127,00	€ 113,54
2049	€ -	€ 127,00	€ 329,47				€ 127,00	€ 127,00	€ 127,00	€ 113,54
2050	€ -	€ 127,00	€ 340,13				€ 127,00	€ 127,00	€ 127,00	€ 113,54

Figure 53: Carbon price paths per year from 2023 until 2050.

The final sheet present in the first version of the DCF is called 'DCF' as it computes the NPV of a product investment. This sheet is shown in Figure 54 and consists of numerous elements, which can mainly be subdivided into two parts: CAPEX and OPEX.

The CAPEX describes the capital expenditures needed for the project including the time investments and sourcing of products themselves. Then the operational expenditures, also abbreviated to OPEX, come into play which include operational cost, maintenance cost, energy cost, and also carbon cost.

To determine the overall NPV, both the CAPEX and OPEX values are discounted using a predetermined discount factor of 12%. By employing this approach, the comprehensive NPV for the investment can be computed.

Discounted Cash Flow					
	This format can be copy-pasted to be below each other for comparisson		2023	2024	2025
[TITLE ALTERNATIVE]	***Explanation***	**Totals**	1	2	3
Years		28	1	2	3
CO2 tonne price			*52,41*	*63,06*	*73,72*
CAPEX					
Number of items/parts in project	*(i.e. number of avg. parts of Twinbelt in Schiphol AMS)*	500			
Initial investment (CAPEX)	*i.e. price for Twinbelts*		**€ 408.996,54**		
Carbon cost (before usage phase)	*i.e. embedded carbon (do note for some materials this is already included in the price)*				
Time investment			**€ 687,50**		
Total CAPEX			**€ 409.684,04**	**€ 0,00**	**€ 0,00**
OPEX					
Carbon cost (use phase)	*(i.e. energy consumption calculated to CO2e emissions)*				
Maintenance costs per year					
Energy consumption costs per year					
Carbon cost (end of life)					
Total OPEX			-	-	-
Discount factor (per year)			1,00	1,09	1,19
NPV			€ 409.684,04	€ -	€ -
NPV cumulative			€ 409.684,04	€ 409.684,04	€ 409.684,04
Total NPV		**€ 409.684,04**			

Figure 54: Discounted Cash Flow (DCF) analysis sheet.

Appendix A.8: Details aluminium and steel (S235JR) crossmember

This appendix shows the details of the aluminium and steel crossmember in Table 34 and Table 35.

Table 34: Details of the aluminium crossmember in terms of volume, length and surface area.

Part number	Volume crossmember (mm^3)	Length crossmember (mm)	Surface area (mm^2)
001036-001-01602	1,376,187.1	844	808,249.1
001036-001-02002	1,376,187.1	844	808,249.1
001036-001-02402	1,376,187.1	844	808,249.1
001036-001-03602	1,376,187.1	844	808,249.1
001036-001-11602	1,947,554.2	1,194	1,142,450.6

Table 35: Details of the steel crossmember in terms of volume, length and surface area.

Part number	Volume crossmember (mm^3)	Length crossmember (mm)	Surface area (mm^2)
001036-001-01602	370,434.2	844	378,292.8
001036-001-02002	370,434.2	844	378,292.8
001036-001-02402	370,434.2	844	378,292.8
001036-001-03602	370,434.2	844	378,292.8
001036-001-11602	522,515.3	1,194	532,364

Appendix A.9: Case computation of total weight from crossmembers in Twin Belt and product specific input

The following information is retrieved when combining Table 36, Table 37, and Table 38. Once we know the total weight of crossmmebers from both types of material per type of Twin Belt module we can compute the total weight of crossmmebers in the entire European airport project when made from either aluminium or steel. This can be done by multiplying the total quantity of a module type time the total weight from crossmembers and adding these together. Table 36 shows the results.

Table 36: Computation of total weight of steel crossmember within Twinbelt of European airport system.

Items	Total quantity	Price per part	Total price	Total weight of crossmembers in 1 part TB from alu (kg)	Total weight of crossmembers in 1 part TB from steel (kg)
Twin Belt module L=1600mm + guarding + LMS-V + PEC (001036-001-01602)	51	€ 373.54	€ 19,050.42	7.58	5.82
Twin Belt module L=2000mm + guarding + LMS-V + PEC (001036-001-02002)	20	€ 398.64	€ 7,972.72	11.37	8.72
Twin Belt module L=2400mm + guarding + LMS-V + PEC (001036-001-02402)	12	€ 405.36	€ 4,864.37	11.37	8.72
Twin Belt module L=3600mm + guarding + LMS-V + PEC (001036-001-03602)	3	€ 468.77	€ 1,406.32	15.17	11.63
Grand Total	**86**		**€ 33,293.84**		

The total weight is computed according to the following equations:

$$Total\ weight\ Aluminium\ (kg) = 51 * 7.58 + 20 * 11.37 + 12 * 11.37 + 3 * 11.37 = 796.19\ kg$$

$$Total\ weight\ Steel\ (kg) = 51 * 5.82 + 20 * 8.72 + 12 * 8.72 + 3 * 11.63 = 610.66\ kg$$

Table 37: Product-specific information on order quantity, spent/expenditure, crossmembers, weight, and surface area derived from VI for the aluminium crossmember.

	Total Avg Unit Cost EUR	Total Spent EUR	Total Ordered Quantity	# Crossmemembers per part	Weight per crossmember- (kg)	Total weight of crossmembers (kg)	Surface area crossmember (mm^2)	Surface area crossmember (m^2)
Part number								
SCC-AP								
001036-001								
001036-001-01602	€ 373.54	€ 559,559	1,498	2	3.79	7.58	808,249.1	0.81
001036-001-02002	€ 398.64	€ 576,029	1,445	3	3.79	11.37	808,249.1	0.81
001036-001-02402	€ 405.36	€ 1,604,025	3,957	3	3.79	11.37	808,249.1	0.81
001036-001-03602	€ 468.77	€ 642,689	1,371	4	3.79	15.17	808,249.1	0.81
SCC-EU								
001036-001								
001036-001-01602	€ 366.10	€ 366	1	2	3.79	7.58	808,249.1	0.81
001036-001-02402	€ 440.83	€ 1,322	3	3	3.79	11.37	808,249.1	0.81
001036-001-03602	€ 656.83	€ 657	1	4	3.79	15.17	808,249.1	0.81
Grand Total	€ 409.00	€ 3,385,673	8,278					
Weighted average price Twin Belt (made of ALU)	€ 409.00			**Weighted average ALU weight of the crossmembers per part (kg)**	11.32			

Table 38: Product-specific information on order quantity, spent, crossmembers, weight, and surface area derived from VI for the steel (S235JR) crossmember.

	Total Avg Unit Cost EUR	Total Spent EUR	Total Ordered Quantity	# Crossmemembers per part	Weight per crossmember- (kg)	Total weight of crossmembers (kg)	Surface area crossmember (mm^2)	Surface area crossmember (m^2)
Part number								
SCC-AP								
001036-001								
001036-001-01602	€ 373.54	€ 559,559	1,498	2	2.91	5.82	378,292.8	0.38
001036-001-02002	€ 398.64	€ 576,029	1,445	3	2.91	8.72	378,292.8	0.38
001036-001-02402	€ 405.36	€ 1,604,025	3,957	3	2.91	8.72	378,292.8	0.38
001036-001-03602	€ 468.77	€ 642,689	1,371	4	2.91	11.63	378,292.8	0.38
SCC-EU								
001036-001								
001036-001-01602	€ 366.10	€ 366	1	2	2.91	5.82	378,292.8	0.38
001036-001-02402	€ 440.83	€ 1,322	3	3	2.91	8.72	378,292.8	0.38
001036-001-03602	€ 656.83	€ 657	1	4	2.91	11.63	378,292.8	0.38
001036-001-11602	€ 409.00	€ 3,385,673	8,278	2	4.10	8.20	532,364	0.53
Grand Total								
	€ 409.00							
Weighted average price				**Weighted average STEEL weight of the crossmembers per part (kg)**	8.68			