MASTER

The effect of price volatility on the LCC analysis of the electrical vehicle and its future costs

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Award date:
2023

THE EFFECT OF PRICE VOLATILITY ON THE LCC ANALYIS OF THE ELECTRICAL VEHICLE AND ITS FUTURE COSTS

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Master of Science in Sustainable Energy Technology
Master's in Environomical Pathways for Sustainable Energy Systems (SELECT) with the study load of 45 EC

Thesis Supervisor: Dr. Ir. Arjan Kirkels

June, 2023.
The Master thesis is public information.
This report was made in accordance with the TU/e Code of Scientific Conduct for the Master thesis.

Abstract

The current energy system is based on fossil fuel burning, contributing to 75% of global greenhouse gas emissions. Moreover, the automobile industry is becoming increasingly volatile as operational and strategic difficulties alternate. The automotive supplier sector faces some challenges with volatile volumes and significant uncertainty. It is apparent that there is a need for an accurate costing system for electrical vehicles.

The goal and contribution of this research are built on the idea of comprehending the price volatility surrounding the material costs of the electrical vehicles and how to have suitable forecast values for them in the face of uncertainty. The research compromises of empirical data analysis to identify the causes of price volatility of the selected materials and via using the materials, future material cost forecasts of the electrical vehicle is done.

Based on the methodology, three materials are selected that were the most prominent in the decomposition of electrical vehicles: steel, PP, and battery. It was found that for steel and PP, the main reason for the volatility is their cost components which are concluded as coal, coke, and iron ore for steel and natural gas, and crude oil for PP. On the other hand, for the battery, the main reason for volatility is the technological advancements of it. With the objective in mind, it is found that batteries have the most influence on the volatility regarding the material cost of the electrical vehicle.

Keywords: Electrical vehicle, life cycle costing, learning curve, regression analysis, price volatility, price forecasting.

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List of Abbreviations

Battery Electric Vehicle	BEV
Compulsory Third Party Insurance	CTP
Department of Energy	DOE
Electric Vehicle	EV
European Union	EU
Internal Combustion Engine Vehicle	ICEV
Life Cycle Costing	LCC
Lithium Ion Battery	LIB
Management Information System	MIS
Manufacturer's Suggested Retail Price	MSRP
Operating Profile	OP
Polypropylene	PP
United States	US

1. Introduction

The aim of this chapter is to have an overview of the problem and to give the goals that the study plans to achieve. In this chapter an introduction to the current situation regarding the pricing of electric vehicles (EVs) will be given. Moreover, problem is defined for the study and relevant research and sub-questions are formulated. Lastly, research design is constructed to give the reader a guide on what else is to come.

1.1. Background

The current energy system is based on fossil fuel burning, contributing to 75% of global greenhouse gas emissions. Moreover, this energy system is the main driver of climate change and greatly threatens human health, where at least 5 million people die due to air pollution created by our energy system (Ritchie et al., 2022). A significant increase in capital-intensive clean energy assets, which have relatively high upfront investment costs but lower operating and fuel expenses, is necessary to put the world on a path to achieve net zero emissions by 2050.

The cost of capital serves as an important benchmark to evaluate investors' preferences for risk and return as well as the price of money in the larger economy. It can also be used as a lever to affect prices and decision-making in the actual energy economy (Mogge et al., 2021). The lack of assumptions regarding the cost of capital may result in the mispricing of risk and the possibility of underinvesting or overinvesting in various markets and sectors.

Moreover, the automobile industry is becoming increasingly volatile as operational and strategic difficulties alternate. The automotive supplier sector faces some challenges with volatile volumes and significant uncertainty. For instance, the conflict in Ukraine had a direct impact on Europe, heightening consumer apprehension and resulting in reduced demand. Similarly, lithium prices are expected to soar due to the war. Another important reason for high uncertainty is COVID-19. Due to it, significant portions of the world's steel-making capacity were decreased, and the resumption of its production was delayed due to the recovery of demand happening more quickly than expected. As a result, steel prices began to rise sharply (Mogge et al., 2021). These events create a heavy load on the prediction and accurate pricing of electric vehicles.

The automotive industry, especially the electric vehicle manufacturers suffering due to many uncertainties that were not anticipated before. EU's dependency on Russia for critical raw materials such as palladium, nickel, and natural gas has been a crucial element in the increasing prices. Since nickel makes up between 15% to 20% of the cost of a battery pack, rising nickel prices will result in higher battery costs (Mogge et al., 2021). Moreover, palladium has a long lead time, and its scarcity will cause the production of automobiles to be delayed since it is an essential component needed to make catalytic converters. Below, the price change of critical raw materials needed to produce electrical vehicles (EVs) can be seen.

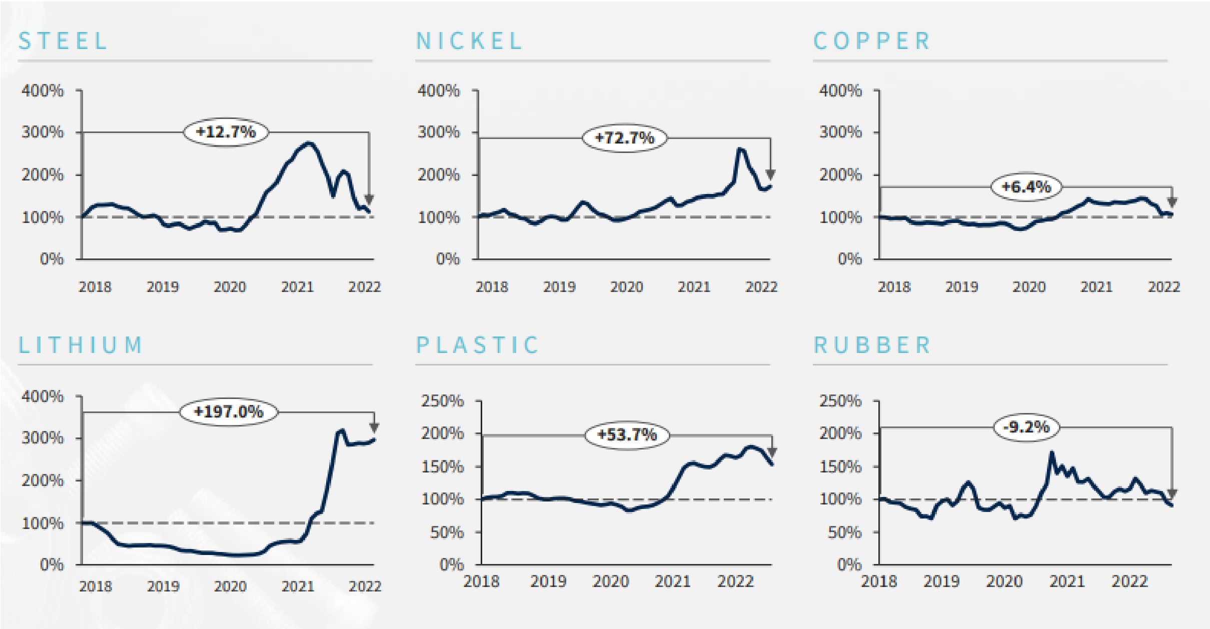


Figure 1: The price change of raw materials from 2018 to 2022 (Mogge et al., 2021).

As can be seen from the Figure 1, the price of raw materials is mostly unstable and especially lithium and nickel price have increased by more than 70%. Moreover, energy costs have increased significantly because of uncertainty and economic conflict. Due to the increased energy prices, unstable deliveries are happening. Prices are anticipated to stay at elevated levels, at least in the near mid-term, along with extremely high volatilities due to the geopolitical environment and the limited opportunities for a short-term extension of alternative energy sources. Energy prices are frequently not indexed in sales contracts; thus, many suppliers find it difficult to claim cost increases at original equipment manufacturers (Mogge et al., 2021). Energy price hikes are forcing increased factor prices on automotive companies.

After understanding the background of the problem, in the next section the problem is clearly defined and research goal is presented.

1.2. Problem Definition

The problem on which this research is based is the need for an accurate costing system for electrical vehicles. The need comes from the price volatilities existing within the costs of the materials and how to account for the future uncertainty regarding them. Additionally, the supply chain problems related to the import of raw materials, shortages in semiconductors, and high inflation rates cause global automotive production volumes to remain low. Hence, it is evident that there is a problem in defining the costs of the materials and realizing the true cause of price fluctuations which result in a declined production volume of passenger cars worldwide as can be seen from Figure 2.

Figure 2: Production volume of passenger cars (Mogge et al., 2021).

Specifically, the research goal is to find a way to incorporate price volatility into life cycle costing (LCC) analysis and accurately forecast the future prices of EVs. In this way, the rapidly changing costs will be incorporated into the production lifecycle of EVs, and vehicles will be priced more accurately.

1.3. Research Question

As discussed earlier, the main aim of the research is to understand the effect of price volatility and uncertainty of cost forecasts in the life cycle costing of electrical vehicles. For this reason, the research question proposed to meet the research goal is chosen as:

How do the price volatility and uncertainty in the cost forecasts affect the life cycle cost analysis of electrical vehicles?

To better elaborate on the topic, two sub-questions are determined:

Can the cause of price volatility and uncertainty in the cost forecasts of EVs be found?

Can those causes be included in the LCC of it?

1.4. Research Design

To answer the research and sub-questions, this study uses mixed methodologies, integrating qualitative and quantitative research. The empirical data found is supported by the qualitative findings from the literature to give a holistic view of the solution. Findings from this research provide insights to determine the cost components of the electrical vehicles and their effects on the manufacturing and future costs of it. In addition, this study provides an outlook to the future and gives further implications towards what needs to be done to make EVs cost-competitive via providing varied policy and government subsidy options.

The remainder of the research is structured as follows:

Chapter 2 provides a literature review to have a better outlook on price volatility, uncertainty, learning curves and life cycle costing in general. It emphasizes the terminology that is going to be used. Works of literature are offered to demonstrate how this research is interwoven with current scholarly discussions.

Chapter 3 provides the methodology that is going to be used for gathering empirical data and how to analyse that empirical data.

Chapter 4 provides the empirical chapter. Firstly, it discusses the empirical data gathered and finds out the main materials that affect the cost of EVs and their cost components, which are steel, PP, and battery. It is divided into three parts for the three main materials and decomposition of them, empirical data analysis using regression and other methods to determine how cost components affect the materials. Moreover the chapter provides an outlook on the future costs of the selected materials, and also the future manufacturing costs of the EV. For the forecasting costs of the materials, their cost components are used via the Monte Carlo analysis. It provides results for 2030 and 2050 since those are crucial dates for some EU policies. Additionally, the future cost of EV is discussed to combine the previous findings.

Chapter 5 wraps up the research by discussing the results and reflecting upon the research question. It also examines possible biases and ways to improve the research design. Lastly, it gives concluding remarks about the potential practical value of the results for different stakeholders.

2. Theory

In this section, the theory related to the sub-questions asked in the previous section will be provided. Based on the background research done, five key theoretical structures were investigated. For this section, life cycle costing, volatility, uncertainty, learning curves, and experience curves are chosen to be examined. The description of LCC was given to explain the reader the concept and to have a level of knowledge on what is to come next. Moreover, the procedure of LCC was conveyed with the elements of it. Similarly, the definition of volatility and uncertainty was given to have a base level of knowledge for all the readers. Learning and experience curves are explored due to the novelty of electric vehicles where there is an exponential maturity in technology that influences the cost of it.

The five structures chosen to be investigated corresponds to the research and sub-questions determined earlier where the main aim is to define the concept and the reasoning behind the chosen methodology in the following chapter.

LCC is chosen to explain the second half of the research question of how LCC is done and what are the key parameters regarding that. Moreover, uncertainty and volatility is explained to elaborate the first sub-question and to express the areas of them used in the automotive sector. Lastly, learning and experience curves are considered to cover the forecasting part of the EV costs.

2.1. Life Cycle Costing (LCC)

Life cycle cost is constructed by the comprehensive costs incurred throughout an item's existence, from its initial design and manufacturing phase to its operational stage and eventually the retirement (White and Ostwald, 1976). The life cycle cost of a physical asset encompasses its acquisition, operation, and disposal or redeployment, intending to optimize costs through the identification and quantification of all significant expenses using present value techniques. LCC evaluates various options to determine the optimal asset configuration and facilitates the study of the total LCC and trade-offs between cost elements during each phase of an asset's life cycle (Woodward and Demirag, 1989). Its application ensures informed decision-making for the selection of the most cost-effective asset configuration. Thus, LCC analysis enables an organization to maximize its investments by minimizing the overall costs associated with an asset throughout its useful life.

The LCC procedure is explained in Figure 3. The explanation of the procedure is done to give the reader background information on how it is done. However, this research will not execute an LCC from scratch. Contrary, it will use an LCC already done and work towards adding into it.

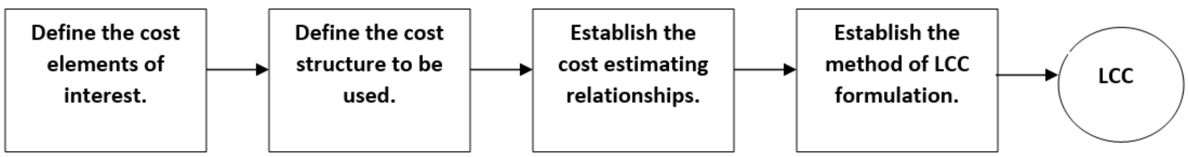


Figure 3 Harvey's (1976) life cycle costing procedure.

According to the procedure of LCC, the cost elements of interest are all the cash flows that occur during the life of the asset, including all expenditures from acquisition to disposal. The cost structure is defined by grouping costs to identify potential trade-offs and achieve optimum LCC.

The methodology for LCC developed by Kaufman (1970) involves establishing the operating profile and utilisation factors identifying all cost elements, determining critical cost parameters, calculating all costs at current prices, escalating current costs at assumed inflation rates, discounting all costs to the base period, and summing discounted costs to establish the net present value. The steps for Kaufman's method are provided in the following to give an overview of how it is done to the reader:

Step 1: The operating profile (OP) refers to the periodic cycle of the equipment, detailing when it will be operational or non-operational. It comprises the start-up, operating, and shut-down modes.

Step 2: While the OP specifies how much of the time the equipment will be used or not used, the utilisation factors specify how the equipment will be used in each mode of the OP. Hence, a machine may not be operating continually even though in the "operating" mode.

Step 3: It is necessary to identify each cost component.

Step 4: The critical cost parameters refer to the factors that control the costs incurred during the equipment's lifespan. According to Stevens (1976), the most significant factors are:

- Time between failures
- Time between overhauls
- Time for repairs
- Time for regular maintenance
- Energy use rate

Step 5: All costs are calculated using current exchange rates.

Step 6: All costs must be projected forward at suitable inflation rates. It is important to recognize the challenges involved in estimating such numbers since any lapse in accuracy could affect the accuracy of the computations that follow.

Step 7: Money has a time value which helps in assuring comparability. For this to happen, all cashflows should be discounted back to the base period.

Step 8: The LCC of the asset can be calculated by adding up all the cash flows involved. The misconception of choosing the asset with the lowest capital cost will then be revealed—the more expensive asset frequently has a lower total LCC—through comparisons between competing assets.

The steps for the LCC can be seen above. The procedure explains how LCC is done and in this paper, the main step that will be focused on is the identification of the cost part where price volatility will be included. After understanding the procedure of LCC, it is also important to understand the objectives of LCC to understand the value of the research. These are identified as follows (Flanagan and Norman, 1983):

- Improve the effectiveness of investment options.
- Consider the impact of all costs, not only initial capital costs
- Support the efficient management of finished structures and projects
- Make it easier to choose between competing options

The LCC approach evaluates all potential future costs and benefits and discounts them to their present value to determine the economic value of a project or set of project options. The following LCC components have been highlighted as being essential to achieving these goals (Woodward, 1997):

- Upfront capital expenses
- The asset's life expectancy
- The discount rate
- Costs of operation and maintenance
- Cost of disposal
- Information and feedback
- Sensitivity and uncertainty analysis

Those are the crucial LCC components. However, due to the nature of the research, the essential parts for this study are upfront capital expenses, asset life expectancy, and sensitivity and uncertainty analysis. Below, is a detailed look at each part of the LCC assessment.

Upfront capital expenses

The upfront capital expenses can be broken down into three sub-categories of expenses: Cost of purchase, cost of acquisition, and the cost of installation, commissioning, and training. Costs associated with the purchase include assessments for things like land, buildings, furniture, and equipment. The economic impact of various sources of funding and gearing are included in the acquisition costs, which can be evaluated by requesting quotes from suppliers and agents. The machine's installation fee and employee operating skills and training expenses are among the additional expenses (Woodward, 1980). To put it simply, the capital cost category comprises all expenses related to the purchase and operationalization of the physical asset. Based on these three expenses, the research will study the cost of purchase for the materials compromising the EV.

The asset's life expectancy
The forecast life of an asset is a crucial factor in conducting a life cycle analysis, as it has an exponential impact on the analysis. Five potential factors determine an asset's lifespan (Ferry and Flanagan, 1991):

1. Functional life: the time frame in which the asset will be needed
2. Physical life: the time frame over which the asset is expected to last physically until it needs to be replaced or undergo extensive rehabilitation
3. Technological life: the time frame until technical obsolescence forces replacement due to the creation of a more advanced substitute
4. Economic life: the time frame until economic depreciation forces replacement with a less extensive substitute
5. Social and legal life: the time frame until a replacement is required by human desire or law

Stone (1980) emphasized the significance of the impact of an asset's anticipated life on life cycle analysis since the asset's life is significantly shorter than the circumstances warrant, as opposed to when it is longer than is justified, the inaccuracies in estimated costs, and therefore design decisions, are likely to be bigger. In this research, the emphasis on the life of an asset is given to the functional life.

The discount rate
In the context of LCC analysis, the choice of an appropriate discount rate is a critical decision since all costs are discounted to their present value (Urien, 1975). Low discount rates will favour solutions with high recurrent expenses, low capital costs, and short lifespans. The effect of inflation may also be reflected in the discount rate, in addition to the real earning capacity of money invested over time (Woodward, 1997). Since the analysis is done for the current time, there will be no discount rates considered.

Cost of operation and maintenance
LCC focuses on maintaining physical assets for the lowest possible cost. Hence, estimating operating and maintenance costs is crucial to lowering the asset's overall LCC. Direct labour, direct materials, direct expenses, indirect labour, indirect materials, and establishment charges are all included in the running costs of an asset. The calculation of these costs is based on the performance of comparable assets, both as expected and as experienced (Bitros, 1976).

Direct labour, materials, gasoline, equipment, and purchased services are all included in maintenance costs. Regular planned maintenance; unplanned maintenance (responding to defects); and intermittent maintenance are common classifications for maintenance expenditures. Although resources are used in the form of maintenance charges, a regular, planned, preventative maintenance approach decreases the costs associated with downtime. On the other hand, the "run it until it breaks" strategy increases downtime loss while reducing maintenance costs (Tempest, 1976). For equipment with high downtime costs, it is crucial to maintain a regular, planned maintenance schedule, whereas for equipment with low downtime costs, repairs or replacements can be made as needed. To achieve the organization's goal of minimizing total cost, it is crucial to identify the ideal degree of maintenance service.

Cost of disposal
The cost of disposal is the price paid to dispose of an item at the end of its useful life. The cost of destruction, scrapping, or selling the asset would be included in the disposal cost, which would be adjusted for any take-home pay or resale tax. Such expenses would be subtracted from the asset's remaining value at the end of its useful life.

Information and feedback
LCC's effectiveness as a technique depends on the organization's ability to gather informational intelligence. As it has been said: "It's important to maintain a fair balance between the costs associated with information gathering and life cycle pricing. Whether the knowledge is merely "good to know" or necessary and useful is an issue that may be raised (Department of Industry, 1977)". Throughout the asset life cycle, data and subsequently information must be gathered to permit tracking of the asset's performance in use and serve as a source of intelligence on which to base subsequent choices.

Sensitivity and uncertainty analysis
The LCC heavily relies on the predictions and assumptions made during data collection. There is always some degree of uncertainty surrounding these estimates and assumptions, even while it is feasible to increase the accuracy of these estimates with the aid of historical data and statistical techniques.

Macedo et al. (1978) identified the following five main sources of uncertainty:

- The future operation and maintenance costs are affected by the differences between the actual and expected performance of the system
- Changes in operational assumptions resulting from changes in user activities
- Future technological advancements that could provide lower-cost alternatives and therefore shorten the economic life of any of the proposed systems
- Changes in the price levels of the system components.
- Inaccuracies in linkages between prices, price rates for resources, and the rate of inflation in total costs from the time of estimation to the asset's availability

The essential LCC components are explained above. It is important to note that although those elements are crucial parts of LCC, not all of them will be given a high importance in the continuum of this research. The focus of the research will be on the sensitivity and uncertainty analysis and upfront capital expenses parts. Uncertainty analysis will be the key area of research where I will be diving deep into that topic. To do that, I will mainly look at the upfront capital expenses, especially the material costs. Moreover, the asset's life expectancy is important in future estimations and forecasting. Hence, those three aspects will be given more importance.

Figure 4 summarizes the total consumer life cycle cost of an EV. The LCC is made up of the acquisition phase, operation phase, and disposal phase. The acquisition phase has been composed of three components: vehicle manufacturers suggested retail price (MSRP), the cost of the charge, and registration, compulsory third-party insurance (CTP) and stamp duty taxes (Kara et al., 2017). The operation phase compromises any cost related to the maintenance and operation of the electrical vehicle. Lastly, the disposal phase corresponds to any costs that might incur during the recycling and disposal of the vehicle.

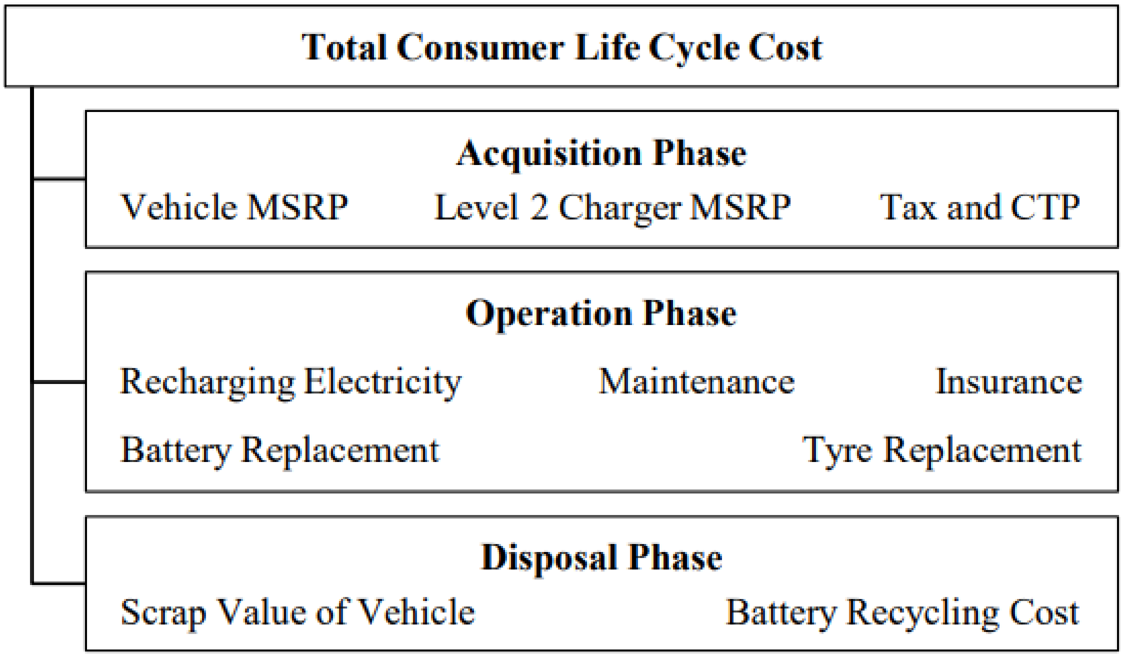


Figure 4 Consumer LCC framework of EV (Kara et al., 2017).

Overall, LCC is an important tool to understand a products cost throughout its whole life cycle. For this research, the relevant life cycle will be taken as the manufacturing of electrical vehicles. Based on this framework, this research will focus on the vehicle MSRP in the acquisition phase, specifically the costs of the materials that are needed for the manufacturing of the electrical vehicle.

2.2. Uncertainty

The term uncertainty is used a lot in this study and is therefore important to understand what it means and in which ways it is used. In this way, a common knowledge about uncertainty will be earned and the reasoning for the types of uncertainties used will become clear.

The word "uncertainty" is meant to imply two linked concepts: chance and data. Neither is a mathematical issue, yet both phenomena can be studied mathematically. The mathematical disciplines that, respectively, deal with data and chance are statistics and probability (Moore, 1990). Many of the urgent policy concerns that we currently have demand that we face the unknown and make difficult decisions in the face of incomplete information (Farber, 2010). Given the potential for catastrophic effects and the inadequacy of traditional decision-making methods, uncertainty is especially harmful in these circumstances.

In essence, uncertainty is the lack of information, which may or may not be available. Various kinds of uncertainty have been identified to better comprehend and address the uncertainties to which we are constantly exposed (Rowe, 1994). Understanding the nature of uncertainty and how to get the most useful information out of uncertain situations can be gained by breaking uncertain situations down into four components: temporal (present and past), structural, metrical, and translational (Rowe, 1994). By this way, it would be easier to comprehend which ones to use in this research.

Depending on the situation, one or more types of uncertainty may be more prevalent. These classes are quite distinct, even though they aren't necessarily autonomous. Before examining their interactions, each class can be taken into account alone (Rowe, 1994). In Table 1, the leftmost column lists a few class features. The first set of parameters on the right display specific information that is unknowable and uncertain. Different levels of uncertainty are distinguished using the second parameter on the right. This parameter is frequently defined in reverse or in terms of the information to lessen ambiguity. The next set of parameters shows how well uncertainty has been managed, and the last set shows the primary strategies applied.

Table 1 Parameters of the classes of uncertainty.

Uncertainty Class	Unknown Information	Discriminator Parameter	Valuation Parameter	Method
Temporal	Future	Probability	Luck	Prediction
Temporal	Past	Historical data	Correctness	Retrodiction
Structural	Complexity	Usefulness	Confidence	Models
Metrical	Measurement	Precision	Accuracy	Statistics
Translational	Perspective	Goals and values	Understanding	Communication

Information about the past is open to different interpretations. The past is not necessarily an accurate predictor. Complexity-related structural uncertainty depends on the number of factors used to characterise a scenario, how they interact, and how useful the models of the complex situation are. They tend to be more useful if the models used also accurately reflect reality.

Classes of Uncertainty

Temporal – Future

The best-known type of uncertainty is uncertainty about the future. Future events are unpredictable, and as they approach, people worry about how they will turn out. The goal of traditional decision-making under uncertainty is to maximise payoffs when different states of nature occur. This is done by dealing with future states of nature without considering the probability of their occurrence. The payoffs are expressed as value or utility functions, and if these functions contain uncertainty, they can make the decision difficult. As can be seen from Table 1, probability serves as a discriminative measure of the likelihood of future states. All probability models are based on the idea that the future will behave similarly to the past.

Temporal – Past

There is no temporal ambiguity in the past if one knows all the historical data necessary for a particular objective. Of course, there may be errors of measurement or complexity. Failure to measure past circumstances when they occurred in a way that can be recalled when needed, or failure to record history, is the fundamental cause of past temporal ambiguity. Measurement uncertainty is present in reconstructing incomplete or unrecorded history from secondary sources and other sources.

Time regression cannot be used to reconstruct stochastic discontinuous systems. A collapsed probability function cannot be reconstructed. It is necessary to have historical data on the relative frequency of occurrence as it was thought to be at the time of the event. Probability did not exist in the past. If an event is discontinuous, hindsight only tells us whether it happened or not; it doesn't tell us anything about how past probability functions worked. Historical data is used as a discriminating parameter and is valued according to its accuracy. When documented for the current purpose, historical facts were accurate. Measurement uncertainty implies a lack of accuracy. Retrodiction is a term occasionally used to describe the reconstruction of time by regression.

Metrical – Uncertainty in Measurement

Gaining knowledge about the world as we perceive it through measurement. Nominal, ordinal, cardinal or ratio scales are used when making observations about the real world. In each case, we make a distinction based on the accuracy of each type of scale, or the smallest unit of measurement for which it is possible to distinguish one unit from another using the available measurement tools.

How accurately we have measured and interpreted scale value measurements are referred to as accuracy. The measurement process involves making multiple observations of scale values and describing the results using statistical models. Because statistical models must always take multiple data into account, a single observation has minimal significance. Our confidence in the model of the underlying process by which the data are generated determines the value of statistical models. A larger sample size increases the accuracy of modelling the process. A "frequency distribution" is the term used to describe the process model. The relative frequency of previous measurements is systematically listed.

Structural – Uncertainty Due to Complexity

The number of degrees of freedom in a system and the interactions between the parameters that express those degrees of freedom are both indicators of complexity. Complex systems can be addressed using linear and non-linear single and multiple objective optimisation theory. Simplification of one or more parameters is important when systems become too complex to deal with directly. The result is a model, which is an abstraction of the system under study.

The usefulness of the model serves as a discriminating parameter for models. Regardless of how well they capture reality, some models are more useful than others. For example, a model that successfully elicits agreement and disagreement between parties with differing opinions will have high utility, even though it may have little to do with reality and is instead abstract. The degree of confidence one has that the modelled system is accurately represented is the parameter for evaluating models. The confidence in the validity of a model increases with the degree of conviction that it accurately captures the complicated system. If the system being modelled is a real system, the accuracy of the model is evaluated empirically.

It's been said that understanding simplicity comes before understanding complexity. Perhaps simplicity is nothing more than a highly condensed and practical picture of reality, retaining only those elements that are essential to the task at hand.

Translational – Uncertainty Due to Communication

When an analysis is complete, the results need to be presented to decision-makers, experts, stakeholders and the public. They all have different levels of training and understanding of the results. They all have conflicting interests and ideals, and each looks at the analysis from a different angle. Many professional practitioners have different views on how to approach uncertainty. These are all respectable points of view. They serve different functions. Practitioners from different backgrounds can be misinterpreted and unable to communicate without a translator. When people with different viewpoints try to talk to each other about uncertainty, it is important to acknowledge these differences in perspective.

Each type of practitioner makes a different effort to reduce uncertainty. The scientist minimises uncertainty by making more and better measurements to increase model confidence and improve prediction or retrodiction. The regulator uses margins of safety to ensure that the actual level of risk is less than the estimate, recognising that neither improved measurement nor empirical validation of risk models will eliminate uncertainty in the short time required for regulatory action. As more such characteristics are calculated for use in risk models, these margins of safety increase. The result is extremely high levels of conservatism. Reducing redundant margins of safety without sacrificing high confidence that the actual risk is less than the estimate is a solution in the absence of reliable measurements.

Engineers ignore risk and uncertainty. They consider structural complexity as they try to combine subsystem designs to meet a larger design requirement. They discuss cost-effective design and express confidence that designs that have been tested and standardised contain acceptable margins of safety. It is desirable to have less uncertainty in system complexity.

As mentioned earlier, engineers deal with certainty rather than risk or uncertainty. For managers of technical systems, it's a way of life to deal with uncertainty and take calculated risks to achieve system performance. In all three dimensions, managers want to reduce uncertainty, but they want to do so in a targeted and economical way. Translational ambiguity also arises when dealing indiscriminately with regional, national, international and local institutions. Another example is when the diversity of values leads to unjustified polarisation of issues. These kinds of uncertainties are different from the uncertainties in the problems addressed and are caused by social activity. Nevertheless, these uncertainties are real and often predominate.

After understanding the types of uncertainty and the reasons for it, it is important to note which of them will be relative to this research. The temporal future uncertainty is the main uncertainty about the future, which is also included in the research question about the cost of EVs. Moreover, the temporal past uncertainty is the type of uncertainty used in the data analysis, where by looking at the cost components of the materials, the behaviour of the cost curve was tried to be explained. Similarly, checking the outliers of the data sets and trying to understand the reasons for it falls under metrical uncertainty. Moreover, regarding the decrease in the cost of batteries which has an exponential learning curve, different views are present. Depending on the literature checked, researchers come up with varied models that represent the prospective cost curve of an EV battery. Similarly, some researchers look at the industrial data and base their models on that. This difference in views creates a translational uncertainty concerning the future costs of the batteries. Uncertainty is a key element in this research where it is apparent in different areas as discussed above. Hence, it was important to understand what uncertainty is and which types of uncertainty are used in this study.

2.3. Volatility

Volatility and uncertainty are used interchangeably in our daily lives. However, they do not necessarily mean the same thing. Because of this, a definition of volatility is provided. Volatility, as used in daily speech, refers to changes in a phenomenon over time. It is more explicitly used in economics to express the variability of the random or unexpected component of a time series without specifying any associated metrics (Andersen et al., 2006). Volatility is essentially latent and changes stochastically over time. Volatility models can be cast in discrete time or continuous time, depending on the data accessibility, and intended application of the model estimates and accompanying projections (Dupire, 1994). Both theoretical advancements and real-world financial applications depend heavily on volatility (Andersen and Bollerslev, 1998). For a variety of markets and data sets, reduced-form models for realized volatility have been taken into consideration.

Prices and their volatility are largely dictated by shifting demand patterns (Renner and Wellmer, 2020). Innovative businesses are minimizing their financial and delivery risks by streamlining their raw material purchases in the face of unprecedented volatility. Important commodities, including semiconductors, resins, and steel, were severely disrupted by the developments caused by digitalization, deglobalisation, and geopolitical shifts on top of the COVID-19 pandemic. The main causes range from a lack of comprehensive demand planning to tariff changes. However, it is anticipated that these changes won't merely represent a brief uptick in volatility but rather a first indication of what the future of the global economy will include (Kromoser et al., 2021). As a result, it will be vital for every organization to be better prepared when another period of significant upheaval eventually occurs.

Volatility is a key factor in establishing the fair value of an option or any derivative instrument containing option features, according to modern option pricing theory, which dates to Black and Scholes (1973), the desire to determine market-implied volatility has remained constant over time, particularly among traders and those who assert to have some ability to foresee future volatility. For instance, Bandi and Perron (2006) state that "our results mainly support a notion of long-run unbiasedness of implied volatility as a predictor of realized volatility," even though "nothing can be stated about short-term unbiasedness." Although volatility and rising input costs are difficult to associate, they offer a chance to institutionalize best practices and enhance pricing (Abdelnour et al., 2021). Nonetheless, margins will suffer if these actions are not taken strategically.

Price changes of a commodity are referred to as "price volatility". The percentage difference in the commodity price from day to day is used to calculate volatility. A market is volatile if there is significant volatility, not if prices are high or low. Given that supply and demand determine price, volatility must be a product of the market's fundamental supply and demand dynamics. Therefore, extreme qualities of supply and/or demand are reflected in high degrees of volatility (U.S Energy Information Administration, 2003). The tangible properties of the commodity, the market structure, production elasticity, and the accessibility of replacements are all factors that affect price volatility (Regnier, 2007). When price changes have an impact on the contract's underlying assumptions, price volatility can be economically hazardous (Weidman et al., 2011). Hence, it is important to address the reasons for the price volatility.

For the materials, due to the inherent uncertainty that exists in the operating environment, volatility is a naturally occurring phenomenon in every stage of material procurement, manufacturing, material planning, and distribution (Moheb-Alizadeh and Handfield, 2018). The prices of raw materials are rising quickly, primarily going upward across categories, as supply chains adjust to the new normal (Abdelnour et al., 2021).. Manufacturers and distributors need to modify their pricing strategies to account for this change in input costs. However, a lot of business executives have been reluctant to raise their product pricing to reflect the impact of rising input costs. This reluctance may be primarily motivated by the worry that being the "first mover" in their market could harm customer relationships in a way that would only be made worse by the pandemic, like significant volume loss. However, there are not many options besides passing on input cost hikes.

After understanding the meaning of volatility, it is also important to understand the concept in the context of this research. Manufacturing enterprises are being severely impacted by the supply and price volatility of raw materials. For instance, compared to the most recent pre-pandemic low, US steel prices have increased by 250% as a result of disruptions brought on by the pandemic and followed by a strong comeback in demand. The price of natural gas increased by about 50%, one of the several supply shocks brought on by the war (Juliano et al., 2022). Although the recent effects have been severe, firms have dealt with market disruptions before.

The studies suggest that market disruptions brought on by extreme events, such as natural catastrophes, geopolitical unrest, and other global crises, are increasing in frequency and severity. However, reacting to a price increase reactively, frequently results in last-minute, generic, broad-brush price increases that reduce consumer satisfaction and deteriorate whatever systematic pricing or margin plans businesses may have in place (Abdelnour et al., 2021). Hence, companies can create a set of risk indicators for their most important raw materials using knowledge from previous instances of volatility, even while the present crises appear to be abating. They can prioritize materials for closer monitoring and take the necessary steps to reduce the risks of supply disruptions by routinely evaluating these signs (Juliano et al., 2022). Although those processes seem intuitively correct and straightforward, the true problem businesses face is their capacity to carry them out quickly, precisely, and with enough granularity to be useful (Abdelnour et al., 2021). Firms may put off taking action because they believe they don't have enough data or analytical skills to advance. The majority of firms have enough data in their current systems to perform simple analyses and quick actions.

Market volatility for raw materials typically arises from supply disruptions, sluggish demand, or substantial price peaks and troughs. Examples of temporary and persistent supply disruptions that resulted in considerable price rises can be seen during the last 20 years. For instance, the world's largest producer of rubber, Thailand, experienced severe flooding in 2010, which drove up the price of the product by 57% year over year (Juliano et al., 2022). Similarly to this, the sole plant in the world that creates the speciality pigments used in car paint was temporarily shut down by the 2011 Tohoku earthquake and tsunami in Japan. Major automakers were compelled to postpone the production of vehicles in a few hues as they rushed to switch out the pigments for different chemicals (Juliano et al., 2022). Since the start of the epidemic, supply chain disruptions have rocked the industry, leading to shortages and higher pricing. In some cases, the bullwhip effect has occurred, creating considerable variations in availability and pricing when changes in demand are amplified as they advance further upstream in supply chains.

Natural gas, electricity, and heating oil prices are some examples of basic energy prices that tend to fluctuate more often than those of other commodities. One factor contributing to the erratic nature of energy prices is the extremely limited options available to many consumers when the price of one fuel, such as natural gas, fluctuates (U.S Energy Information Administration, 2003). As a result, whereas customers can easily switch between food products when the relative costs of different foods vary, the majority do not have that choice when it comes to heating their houses.

As described above, volatility is present in a lot of different sectors. In this research, its effect on the prices of EVs is investigated since the shortages of raw materials affect heavily the costs of the vehicle. For instance, a lot of automakers were unprepared for the shortage of semiconductors brought on by the rise in demand for consumer electronics and technological infrastructure induced by the epidemic. One of the things that made it difficult for automakers to meet the high demand in their industry was the supply problems with semiconductors. In 2021, it is predicted that the market imbalances will cost the industry 10 to 12 million units (Juliano et al., 2022). Similarly to the semiconductors, it is important to investigate the effects of raw materials such as steel and plastics and energy costs, natural gas and coal, on the importance of determining EV costs. For this reason, volatility and its practical usage cases are presented in this section.

2.4. Learning Curves

Many industries, including electronics, automotive, construction, software and chemicals, have studied how competence increases as a manual operation is repeated (Nadeau et al., 2010). A learning curve is a quantitative representation of how well workers perform monotonous tasks. Workers tend to take less time to complete tasks as they are repeated because they become more familiar with the operation and tools and because they discover shortcuts to completing the task.

The time required to produce a unit, the quantity produced per time interval, the cost to produce a unit and the percentage of non-conforming units is all performance indicators used as dependent variables in learning curve models (Sturm, 1999). When creating a product family, most of the work is focused on optimising the commonality of the parts, but when the product is to be built, the product structure plays an important role. Therefore, it is preferable to create product models that require the same manufacturing capabilities in addition to those that share components. The platform construction problem was first introduced by Fujita et al. (1998). The objective function of the authors' proposed total profit model for product variety design optimization is a total cost to be minimized. The cost of production is calculated using a learning curve parameter, so models that require complicated worker setup are likely to be removed from the platform. The result is a group of models that share many elements and are similar in terms of the production skills required (Anzanello and Fogliatto, 2011). An example from the aircraft manufacturing sector is used as a case study to illustrate the results. Wright (1936) designed learning curves empirically after observing how the cost of building aeroplanes fell as repetitions were completed. As the number of aeroplanes built increased, this reduction continued at a steady rate, leading to the creation of the "80% learning curve" rule of thumb, which was then widely used in the aviation industry. According to this formula, as the number of units increases, the total assembly cost is reduced by an average of 20%.

A non-linear optimisation procedure aimed at reducing the sum of squares error can be used to determine the learning curve parameters. When working with non-linear regression, convergence is often not achieved, so one option is to change the initial values of the parameters. The coefficient of determination, the sum of squares error or the model's adherence to a validation sample can be used to determine the goodness of fit of a model (Heimerl and Kolisch, 2010). Univariate and multivariate models of varying complexity have been produced by the wide range of learning curve applications, allowing the mathematical representation of the learning process across different economic sectors. The most common univariate models are log-linear, exponential and hyperbolic (Chen et al., 2008). Moreover, the learning curves can be categorized into four as (O'Connor, 2016):

Research and development: This process can have long time horizons, unclear outcomes and large spill over effects on other industries.

Learning by doing: This results from the production and deployment processes. Firms make, often incremental, improvements to their manufacturing processes, installation methods, and distribution and financing systems.

Economies of scale: These arise as companies or industries grow in size, spreading some relatively fixed costs over a larger volume of product sales. Increased specialisation, where firms specialise in a single element of the product or supply chain rather than all firms being forced to be generalists, is one way that economies of scale can reduce costs at the industry level.

Learning by waiting: This involves taking advantage of spill overs from other sectors, countries or technologies. This is primarily the result of innovation taking place elsewhere rather than accelerated early technology adoption.

After understanding the types of learning curves, it is also important to understand the benefits of it. New technologies are first introduced in small, generally cost-insensitive sectors where their performance is valued (O'Conner, 2016). The benefits of learning allow cost savings and a wider range of successful applications for the technology. Cost savings from wider use lead to even wider use. For instance, early applications for electric lighting included theatres and mills where gas lighting was unsuitable for safety reasons. Satellites valued solar power for its ability to generate electricity without burning fuel. Off-grid homes were an application that saw success as the technology advanced and costs fell. This pattern is repeated across many different types of technologies and the trend is often an "S-shaped" curve defined by a logistic function (O'Conner, 2016). However, learning curves have the drawback of complacency since cost decreases over time, and it is not clear when to enter the market. However, costs often don't come down over time. The fourth point, learning by waiting, really depends on someone else doing the R&D, deployment and learning by doing. It means using the labour of others for free. The fact that 1980 turned into 2016 didn't make solar more affordable; rather, millions of people around the world installed solar during that time, even though it wasn't the most economical choice. And now, thanks to those pioneers who helped the industry mature, solar energy is often cheaper than grid electricity. A similar outcome is expected for electric vehicles as well.

As discussed above, the learning curve theory can be implemented for electrical vehicles as well. Especially, this theory is applied to forecasting the costs of the EV and battery which is still a novel technology having the research and development category of learning curve.

2.5. Experience Curves

The experience curve was first formally used in strategy formation in 1966 during a presentation by the Boston Consulting Group to the General Instrument Corporation regarding the likely cost behaviour of the management information system (MIS) technology, which was still in its infancy at the time. Even though understanding of the experience curve phenomena itself was at an early stage at the time, the fundamentals of the experience curve as they were stated have held up well (Reeves et al., 2013). The client's long-term successful cost-reduction efforts had only allowed it to survive as a minor competitor. It was obvious that competitive profitability and market share were correlated. An appealing first explanation for this was the shape of the learning curve. The customer was trying to catch up to its more powerful rivals on the cost curve. Later, cost of television component research revealed considerable variations in the pace of cost improvement between monochrome and colour components (Henderson, 1984). Given that the same plant, the same workers, and the same processes were all utilized at the same time, this was challenging to explain. Once more, the notion of moving down a cost curve offered a supportable premise.

For a long time, it has been recognized that repetitive jobs result in a reduction in labour hours and cost per unit. This influence was especially clear to see in the construction of aeroplanes during warfare. Per doubling of experience, the rate of labour decline was typically between 10 and 15 per cent. Military contracting has traditionally included this requirement (Henderson, 2012). The link between a technology's specific costs represented in real terms as the dependent variable and the technology's experience as the independent variable is often described by an experience curve. In a two-dimensional coordinate system, a technology's experience is represented on the horizontal axis, while its related costs are shown on the vertical axis (Samadi, 2018). For a given increase in production, technological costs often decline earlier in the deployment process than they do later. Thus, experience curves tend to have a linear shape when expenses are represented on a double-logarithmic scale. Either the learning rate or the progress ratio that an experience curve represents can be used to characterize it.

The supporting data for the experience curve notion itself was provided by semiconductors. The large range of semiconductors gave researchers the possibility to examine various growth and price reduction rates in a comparable setting. The Electronic Industries Association's price information was matched to the total volume of the industry (Anzanelllo and Fogliatto, 2010). There arose two different patterns. In one trend, prices in constant dollars remained stable for extended periods before starting a somewhat steep and protracted decrease. The opposite pattern saw a steady drop in pricing, measured in constant dollars, at a consistent rate of around 25% every time the total experience doubled (Wene, 2000). The experience curve relationships' universality has been demonstrated through work with customers since 1966.

The experience curve has shown that, when represented in constant value money, practically every product will follow a relatively predictable pattern of cost drop in terms of value added. In most of the wealthy nations of the world, output per capita has increased on trend by several per cent each year when gross national product is divided by population and deflated to calculate constant dollars. This is the same as arguing that productivity has increased steadily and continuously over time.

The experience curve effect is primarily caused by scale, learning, adaptability, and investment. Technology is frequently used as an explanation for cost reduction. Technology, however, is a by-product of investment, education, and adaptation. Predicting things that have never been done is difficult (Kahouli-Brahmi, 2008). Yet, once it is understood that it is possible, it just remains a matter of time, money, and study until it can be repeated by others.

Growth is a derivative, much like technology. Every change slows down or stops the growth of the items it replaces. The growth of products that are getting more cost-effective is also accelerated. The experience curve effect can lead to rapid growth to become self-reinforcing and vice versa. If scale is not necessary for expansion, it might not be a source of cost savings. A decrease in operating cost must be used to offset a cost reduction that does not increase total output. The decrease in operating costs that arises must exceed the cost of the capital involved (Kahouli-Brahmi, 2008). If not, there won't be cost savings.

After the explanation of experience curves, how it is used in the EV market is investigated. Lithium-ion batteries have a well-established experience curve, with a learning rate of around 20% from 1992 to 2016. For every doubling of the total capacity produced, the cost decreases by a certain percentage, known as the learning rate or if the learning rate is 80%, manufacturing costs will remain 80% the same even if cumulative production doubles (O'Connor, 2021). If the 50 kWh battery pack in Tesla's Model 3 costs $187 per kWh, for a total price of $9,350, then doubling the total production of battery packs would result in a cost reduction of $1,870.

Let's say the overall learning rate for the Tesla Model 3 is 10%. At the current cumulative production level of 1 million units, a manufacturing cost of $30,000 would experience a $3,000 reduction to $27,000 once cumulative sales reach 2 million (O'Connor, 2021). The Model 3's manufacturing cost could then fall by a further $2,700 to $24,300 when total production doubles again to 4 million units, perhaps in 2025. Benefits can extend across product lines, as demonstrated by Tesla's $100,000 Roadster from 2007, which enabled the $70,000 Model S in 2012 and the $40,000 Model 3 in 2018. Costs have risen due to short-term component supply shortages, but as companies scale up production, costs typically fall (O'Connor, 2021). Hence, enabling cheaper EVs in 2025 is the most important result of EV penetration in 2021.

As can be understood from this example, experience curves exist in different parts of the manufacturing line of the electrical vehicle. Moreover, the rate at which learning occurs will modify the prospective prices and change the penetration of EVs into the automotive market. For this reason, experience curves are an important part of this research. It should be noted that only the experience curves in the manufacturing of materials are considered and other aspects are disregarded in this study.

2.6. Concluding Remarks

To conclude, many theories are investigated in this chapter in detail. As discussed previously, the level of detail in each theory varies. Therefore, this section aims to provide an overview of what will be used further in the continuum of this research. The concepts of LCC, uncertainty, volatility, learning curve and experience curve are explored due to their relevance to the research and sub-questions.

The theory part for LCC is mainly done to understand the concept as it is present in the research question. For the LCC analysis of electric vehicles, only the production cost of materials is considered, as most of the cost of an electric vehicle is due to its materials. Also, from the LCC components, only the life expectancy of the asset, the upfront investment and the sensitivity and uncertainty analysis will be in focus. Regarding the steps of the LCC, the main step that will be targeted is the identification of the costs.

Uncertainty theory is used for the first sub-question. The temporal future uncertainty will be the main type of uncertainty that will be used for forecasting the EV costs. Furthermore, temporal past uncertainty is used to understand the past uncertainty in the material costs and it is used to understand the reasons for the past costs. Finally, translational uncertainty is also part of understanding the differences between learning and experience curve models. Therefore, these types of uncertainty are used in the rest of the research.

Volatility is mainly expressed in the theory chapter to have an understanding of what it means in the automotive industry. In this research its effect on the prices of EVs is investigated.

The learning curve theory is used to forecast the material costs of EVs, especially the cost of the battery. The type of learning curve used is the research and development model.

The experience curve is included in the theory section to provide practical examples of how it is used and how it affects the materials of EV.

The following chapter aims to translate the theory into empirical research. Data collection and analysis are carried out to quantify the uncertainty and volatility associated with EV materials. In addition, the future costs of the selected materials are projected using a learning curve, and finally the chapter concludes with the expected material costs of EVs for 2030 and 2050.

3. Methodology

This chapter dives deep in the methodology used to answer the research question. It does so by using various types of methodology. For each part, a literature review is done to better comprehend the topic. Moreover, afterwards, data is gathered from online resources and analysed according to the methods found in literature review. Lastly, forecasting of prices are done. These different types of methodology will be detailly explained in this chapter.

3.1. Literature Review

The first method to answer the research question was doing an explorative literature review. I have used literature review to explain the key concepts, and clearly define the problems stated in Section 1. Literature review was done primarily to define the main concepts and investigate possible ways to tackle the problem. For the first sub-question, terms like volatility, uncertainty, and how they manifest themselves in electrical vehicles and costing systems are investigated. For this reason, scientific and grey literature are chosen to be investigated.

For scientific papers, Scopus was used as the main source of information. It was used to check how other academics deal with price volatility and uncertainty in the cost forecasting. The search queries selected were “price AND volatility” which yielded 22,616 publications, to narrow the search result the subject areas are selected to be “Energy” and “Material Science”. With this new query the results have been narrowed down to 3,211. Afterwards, the abstracts are skimmed and the ones relative for the research are selected to be used. For the second part of the question, “uncertainty AND forecast” are chosen to be selected for the search in the same subject areas, this yielded in a number of 4,326 publications. Similarly, after reading the abstracts the relative articles are used for further evaluation. Moreover, for the understanding of the life cycle costing topic, “life cycle costing AND electric vehicle” was searched in “Energy” and “Material Science” subject areas that yielded in 1019 search results. “Material Science” subject area was selected since the focus of this study is to understand how the materials and their costs affect the life cycle costing of the electrical vehicle. Moreover, due to the inseparable nature of the electrical vehicles to energy systems, “Energy” was selected in the subject area. Also, different combinations of these terms are utilized to obtain relevant literature.

Since academic literature did not provide enough information about the current and over time relevant price information regarding the materials associated with electrical vehicles, grey literature was chosen to obtain those missing information from the academic literature. The grey literature studied includes reports from EV manufacturer’s costing information of materials, and price prediction texts from European Union and United States. In addition, the literature was developed using the snowballing technique.

3.2. Gathering Empirical Data and Empirical Data Analysis

In order to answer the first sub-question, empirical data is gathered and analysed. This analysis is done through the Bill of Materials provided by TNO, the amount of each material used in the EV was collected. With the materials gathered, a cost analysis was done where the current cost for manufacturing each material was found via various grey literature. This was done to understand which of the materials impact the weight and cost of the EV. With the information of each of the materials about the weight needed to produce an EV and the total cost associated with each material, the most crucial materials are determined. This determination was done via checking the materials that constitutes at least 80% of the total weight and 80% of the total cost (Cinelli et al., 2020). The decided materials are used for further investigation. For the determined materials, the costs are checked.

The research was done by checking financial reports and trading websites to come up with a monthly 10-year cost curve for the selected materials. The time duration was selected to be from 2010 to 2020. The ten-year time frame was selected due to two main reasons. Firstly, for most of the materials the most recent cost information could not be found after December 2020. The second reason for the selection was because of the highly unexpected events happening in the last three years like the pandemic (Mandel and Veetil, 2020) and war in Ukraine (Khudaykulova et al., 2022). If I have included those values, then the forecasting and data analysis would give me highly uncertain and unreliable results since the costs were highly volatile. Moreover, for the next years, those types of unexpected events are not thought to be happening again. Hence, the time interval selected only covers from 2010 to 2020.

Finally, for the selected materials, its cost components are investigated. The cost components are analysed since those are believed to be the reasons for the price volatility and uncertainty. The investigation was done using reports and articles on the cost components. Similarly to the materials, for the found cost components, their costs from 2010 to 2020 are checked. Their cost curves are then used in the data analysis part to further explain their relationship within each other.

It should be noted that the data found for the cost of the materials and its cost components comes mainly from reports from the US. However, the Bill of Materials and the reports used in the analysis of the cost components comes primarily from resources within EU. Hence, it was necessary to acknowledge that there might be differences for the costs of the materials. To overcome this issue, all the costs found in USD are changed to EUR according to the exchange rate at their time. Also, the cost data found are cross compared with the European data for all the time periods that could be found.

An outlier analysis was done for the material cost curves and their cost components' cost curves. An outlier was defined as an observation that differs significantly from other observations that it raises questions about whether it was produced by a separate mechanism (Hawkins, 1980). From the analyst's point of view, the interpretability of an outlier detection model is crucial. Finding out why a particular data point should be regarded as an outlier is frequently useful because it gives the analyst more information about the diagnostic needed in an application-specific circumstance (Aggarwal and Aggarwal, 2017). This approach is also known as outlier detection and description (Akoglu et al., 2013) or as learning the deliberate knowledge about the outliers (Knorr and Ng, 1999). The interpretability of different models varies. Models that use the original features and apply less data transformations typically have superior interpretability. Data modifications frequently increase the contrast between outliers and regular data points at the expense of interpretability, which is the trade-off. As a result, it is crucial to bear these things in mind when selecting a particular model for outlier analysis.

It is important to study outliers since they can provide meaningful information. The outliers are detected via checking if the data point is within the range of lower quartile and upper quartile or not (Walfish, 2006). Firstly, each cost component was checked against the material with a scatter graph to understand if there are any outliers visually. Afterwards, the lower quartile, upper quartile and inter quartile range are found. These values are found by calculating the 25th percentile, 75th percentile, and the difference between 75th percentile and 25th percentile respectively. Then, the inter quartile range is multiplied by 1.5 and that value is added to the upper quartile and subtracted from the lower quartile. Any value that is not within the range of the last calculated two numbers is considered as an outlier (Glen, 2023). After the determination of outliers, each of them is investigated to understand if it is due to measuring errors or if a special event happened during that time and removed from the main data set.

For each of the crucial materials determined a trend analysis is done for its time series. In this trend analysis, R software is used to check if the cost curves have a seasonality, or specific trend within each year. Firstly the time series is decided if it is multiplicative or additive time series. Time series data decomposition distinguishes the general seasonality in activity and the underlying trend. There are three main components of a time series called trend, seasonality, and error or residuals. Trend corresponds to how things are changing in the long term. Seasonality means how things are changing within a given period, in this analysis every month. Lastly, the error suggests an activity that cannot be explained by the trend or seasonality (Radecic, 2021). Additive and multiplicative time series (y_t) is composed of trend (T_t), seasonality (S_t) and random (R_t).

The time series decomposition in R decomposes the time series into three parts: seasonal, trend-cycle, and remainder or irregularity or error component. The decomposition is a method that deconstructs a time series (Tang, 2019). The first step is to estimate the trend. To do that, R software obtains moving averages covering one season, in my case one year of 12 months. Then, the trend component is eliminated from the original time series. Thirdly, the seasonal component is estimated for a given time period where the average of the remainder is taken for that period. Afterwards, it is adjusted to seasonal indexes to ensure that it adds to zero. Lastly, the remainder is calculated by subtracting the estimated seasonal and trend-cycle components.

Below is the formula for additive time series:

$$y_t = T_t + S_t + R_t$$

For the multiplicative time series, the trend, seasonality, and random components are multiplied as follows:

$$y_t = T_t \times S_t \times R_t$$

The way those three components interact determines the difference between a multiplicative and additive time series. In the multiplicative case, the components multiply together to make up the time series. If the trend is increasing, then the amplitude of seasonality increases (Radecic, 2021). In the additive case, the components add together to make up the time series. If the trend is increasing, there will be similar-sized peaks and troughs throughout the time series (Radecic, 2021). Hence, in order to determine if a time series is additive or multiplicative, I have first decomposed the time series into both additive and multiplicative ways. After taking out the trend and seasonality, I checked the auto-correlation factor within the residuals and decided on the lowest sum of squares correlation values to name if the time series is additive or multiplicative.

After the trend analysis is done for the crucial elements, an analysis is constructed for their cost components. This analysis is done using SPSS software. In that software, regression analysis is done for the materials and its cost components. The regression model is done both individually and as paired for the cost components to each of the crucial material. As discussed in the theory section, the cost relationships can be explained in linear, parabolic, and hyperbolic ways (Woodward, 1997). Hence those types of regression models are employed.

Regression analysis is a tool to investigate statistical relationships between variables. The causal effect of one variable upon another is determined. With regression analysis, the quantitate effect of the causal variables upon the variable they influence is estimated (Sykes, 1993). The statistical significance is found by looking at the metric R-squared, which is the degree of confidence that the true relationship is close to the estimated relationship.

The different type of regression analysis is checked within three different intervals, monthly, six-monthly, and annually. The main statistical value checked is the coefficient of determination (R-squared) value. It is selected to be used as the primary indicator of if two data sets have a relation within each other because it is found that compared to the mean square error (MSE), mean absolute error (MAE), and symmetric mean absolute percentage error (SMAPE), R-squared is more informative and truthful. Therefore, it is suggested that R-squared should be used as the standard metric to evaluate regression analysis (Chicco et al., 2021). Hence the conclusions are drawn from the value of R-squared.

The values are analysed monthly, 6-monthly, and annually. The reason for varied time frames is for some of the cost components it is not possible to see the reaction of the cost of the material instantly. Hence there is a need to check for the lags between the action and reaction by using different intervals.

With the simple regression analysis where only one cost component's effect is investigated, it is possible to find the relationship as:

$$Y = \alpha + \beta x + \varepsilon$$

Where Y is the cost of the material selected from data selection and x is the cost of its cost component, α is the constant, β, which is referred as coefficient, is the effect of the cost component, which is expected to be positive, and ε is the noise term suggesting the other factors influencing the price of the material. Y is the dependent variable and x is the independent variable (Sykes, 1993). What regression analysis do is, it produces an estimated of the parameters α and β, using the information given in the data set.

With multiple regression analysis where more than one cost component's effect is analysed at the same time, the model can be found as:

$$Y = \alpha + \beta x_1 + \gamma x_2 + \varepsilon$$

Similarly, Y is the cost of the material selected from data selection and x_1 and x_2 are the costs of its cost components, α is the constant, β and γ, are the coefficients, which are expected to be positive, and ε is the noise term(Sykes, 1993). In this case the estimate is produced for the parameters α, β and γ, using the information given in the data set.

After the regression analysis, the coefficient of each model is checked. For the models with negative coefficients, the graph of the cost component and the material is investigated for any dips or unexpected lows are checked. Moreover, any significant events that happened around the dip value is analysed using articles and reports. If before and after that time there is a similar positive trend between the material and its cost component, the most recent trend is considered, and the regression analysis is done again to eliminate the negative coefficient.

Moreover, if the R-squared results are not higher than 80%, the decomposed data sets are analysed under trend, seasonality, and random components. For this analysis, the trend of the selected material and the trend for the cost components are put under linear regression for 12-month and 6-month time frames. A one-year time frame is not considered in this analysis since there are no seasonality components in that one. Similarly, the same thing is done for the seasonality and random components as well.

Also, if the R-square is still lower than 80%, lagged methods are analysed to check whether or not there is a lag in the reaction of the price. In this lag analysis, R software is used to understand the relationship between two time series where y_t denotes the material and x_t denotes the cost components of it. The aim is to understand if the series y_t is related to past lags of the x_t. The auto corelation function (ACF) is used. Auto corelation function is a measurement that keeps track of how two time series data sets move in relation to one another. It is used to objectively assess how well different time series match one another and, in particular, when the best match takes place. Hence, based on the data on time series, varying lags are created between y_t and x_t and the ACF values are crated for lags between 12 periods before and after (Penn State, 2023). With the ACF values, the highest ones are chosen to check the correlation between the lagged time series of x_t and y_t. This analysis is done via checking the R-square result in linear regression of the lagged time series.

3.3. Forecasting

After materials are analysed using various techniques, in order to cover the second part of the research question, forecasting methods are used. Depending on the maturity of the manufacturing process, either Monte Carlo analysis or experience curves are used. The forecasting is done for the years 2030 and 2050. Those two years are selected to be forecasted since the EU has set some serious climate targets. For 2030, they aim to reduce greenhouse gas emissions by 55% below 1990 levels and for 2050, the EU aims to be climate neutral (International Energy Agency, 2016). EU reports regarding the future conditions of the cost components are used to estimate the prices.

In order to estimate mathematical functions and simulate the functioning of complicated systems, Monte Carlo simulation combines random sampling and statistical modelling. The objective behind the Monte Carlo approach is to repeatedly execute the experiment or utilize a sufficiently lengthy simulation run to acquire a large number quantities of interest using the Law of Large Numbers and other statistical inference techniques (Kroese et al., 2014). The Monte Carlo method is used to estimate the future value of the selected materials based on their cost components. The number of iterations is selected to be 1000, which means that with the found time curves of the materials a thousand samples are created and checked whether or not the numbers are converging to a certain value. If there is no convergence, the number of iterations is increased to 10,000 (AWS, 2023). Since the result accuracy is proportional to the number of simulations, having more iterations is beneficial for the precision of the forecast.

For the Monte Carlo analysis, firstly I have created thousand random values between 0 and 1. Then, I have used the coefficients from the linear regression lines that I have obtained using the materials and their individual cost components. I have then used the constant and coefficients adding the future costs of the cost component and gained thousand replicas of the future result. Lastly, I have put all the results into a histogram to better understand the range and frequency of the values.

For the materials, I have already done the linear regression and have an equation for it similar to the following:

$$y = ax + b$$

Where y is the material selected and x is the cost component of the material and a is the coefficient for the cost component and b is the constant for the material. Then, I have created two random probabilities of 1000 iterations for the coefficient and constant to be used later. From the linear regression, I also have the standard error for a and b.

$$\sigma_{\bar{x}} \times \sqrt{n} = \sigma$$

By using the standard error terms ($\sigma_{\bar{x}}$) and the number of total cases ($\sqrt{n}$), which is 132 for a monthly analysis of 10 years, I have found the standard deviation (σ) of the coefficient and the constant values. Via using the standard deviations found for the coefficient and constant, I have used NORM.INV function in Excel to get the inverse of the normal cumulative distribution for the specified mean and standard deviation. This function has three arguments. The first one is the probability corresponding to the normal distribution, which I have used the probabilities I have created for the coefficient and the constant. The second argument is the mean of the distribution which corresponds to a and b values respectively. The last argument is the standard deviation of the distribution which is found using the formulas above. For the found values of NORM.INV function for coefficient and constant, I have put the future price of the cost component in the equation for x and gained the possible future value for the material cost (Johansen et al., 2010). Lastly, I have repeated the results for all the iterations and put them into a histogram to better assess the situation and decide on the range and most probable value for the future cost of the material.

After the iterations, Monte Carlo outputs the most probable cost result for the material selected. Moreover, Monte Carlo method is mainly used to assess the range of future probable cost for the materials. By this way, I will have results for the minimum and maximum values for 2030 and 2050 prices of the materials via using the regression coefficients found earlier.

For the materials that are found to be not mature enough, experience and learning curves are used to understand the future cost behaviour. The learning curve equations are found via literature review and implemented towards the material's cost curve for future conditions. The learning curve equation used is as follows:

$$Y = aX^b$$

Where Y represents cumulative average cost per unit, a represents the cost it takes to produce the initial quality, X represents the cumulative units of production, and finally b represents the learning curve coefficient. The experience curve rate will be b, which is the determinant of how fast the cost decrease will be.

After obtaining the future forecasts of the material costs, the future cost of the EV is analysed. The material cost of EV is done to answer the second sub-question to include the price volatility into the prospective LCC of EV for 2030 and 2050. The forecasted values for the materials are added to find the overall material cost of EV. It is important to note that only the selected materials' costs are forecasted and the rest is thought to be remaining stable.

The next chapter will show the results of the methodology defined above. With this methodology, it is possible to investigate the volatile relationship between the materials of EV and their cost components and how their prices influence the prospective prices of the electric vehicles.

4. Results

In this chapter the current situation in the pricing of the electric vehicle is considered. After understanding the current situation, the bill of materials provided by TNO which is based on Ford's C- and D-segment cars, is analysed. The critical materials for the electric vehicle are determined using the appropriate methodology discussed in the previous chapter. Once selected, each material is further investigated for its own cost components and regression analysis is carried out to find out the effects of its cost components, and finally the costs of the selected materials are forecast to determine the trajectory of the costs of the EV. The aim of this chapter is to understand the causes of price volatility and uncertainty in electric vehicles and to provide forecasting results for the future material costs of EVs, thus answering the research question quantitatively.

4.1. Determination of Crucial Materials

The analysis of the materials was done using the Bill of Materials supplied by TNO. In Table 2 the list of the materials used for the manufacturing of an EV can be found.

Table 2 Bill of materials.

Material	Number of parts it is needed	Amount (kg)
Steel	20	679.00
Battery	1	648.00
Plastics	18	101.00
Traction motor material	1	76.70
Inverter material	1	67.60
Tire	1	40.80
Laminated glass	1	39.20
Brake rotor material	1	41.00
Cable	1	30.00
Antifreeze	1	16.00
Aluminium sheet	4	15.80
Paint	1	11.80
Cast iron	1	11.30
Exterior lightening	1	10.00
Polyacrylamide	1	10.00
Copper	2	3.50
Brake fluid	2	2.90
Windshield wiper fluid	1	2.70
Magnesium	1	0.20
Zinc	1	0.10

For the materials listed below, a time-cost curve is checked for a period of 10 years from 2010 to 2020. The materials with the highest percentage of weight are analysed. They are polypropylene (PP) plastic, hot dipped galvanized steel, NMC 111 battery, traction motor material, inverter, tire, glass, brake rotor material, cable, cast iron, and copper. The current prices for those materials can be seen below in Table 3.

Table 3 Current prices of EV materials.

Material	Amount (kg)	Price (€/kg)	Total Price for the EV (€)
Battery (Frith, 2021)	648.00	34.40	22,200.00
Brake rotor material (Alnaqi et al., 2018)	41.00	2.60	69.60
Cable (US Bureau of Labor Statistics, 2020a)	30.00	0.50	15.00
Cast iron (Index Mundi, 2023)	11.30	0.00106	0.0121
Copper (Macro Trends, 2023a)	3.50	9.33	32.60
Glass (US Bureau of Labor Statistics, 2020b)	39.20	3.98	40.11
Inverter material (Fakhfakh, 2016)	67.60	1.48	100.00
PP (US Bureau of Labor Statistics, 2020c)	101.00	0.82	82.80
Steel (Trading Economics, 2023)	679.00	0.60	407.00
Tire material (US Bureau of Labor Statistics, 2020d)	40.80	0.45	18.30
Traction motor material (Precedence Research, 2022)	76.70	7.93	608.00

After, finding the current costs of the materials with the highest weight, the percentage graphs for the weight and cost is created respectively in Figure 5 and Figure 6. Those graphs are used to determine the materials that have the highest contribution for the weight and material price of EV.

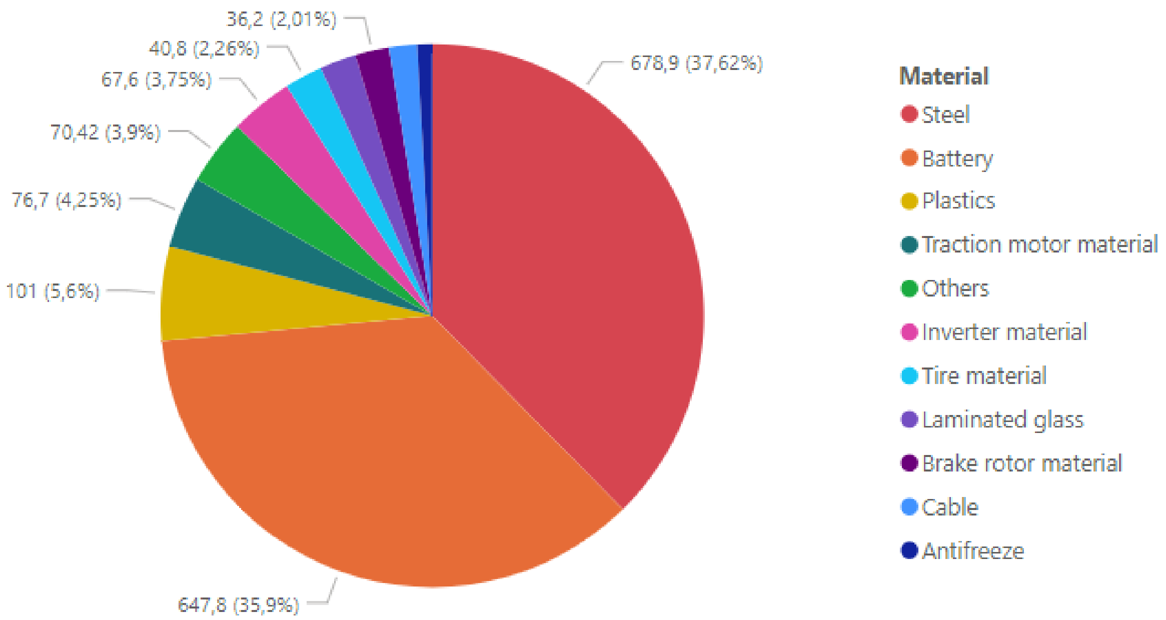


Figure 5 Percentage graph for the weight of the materials.

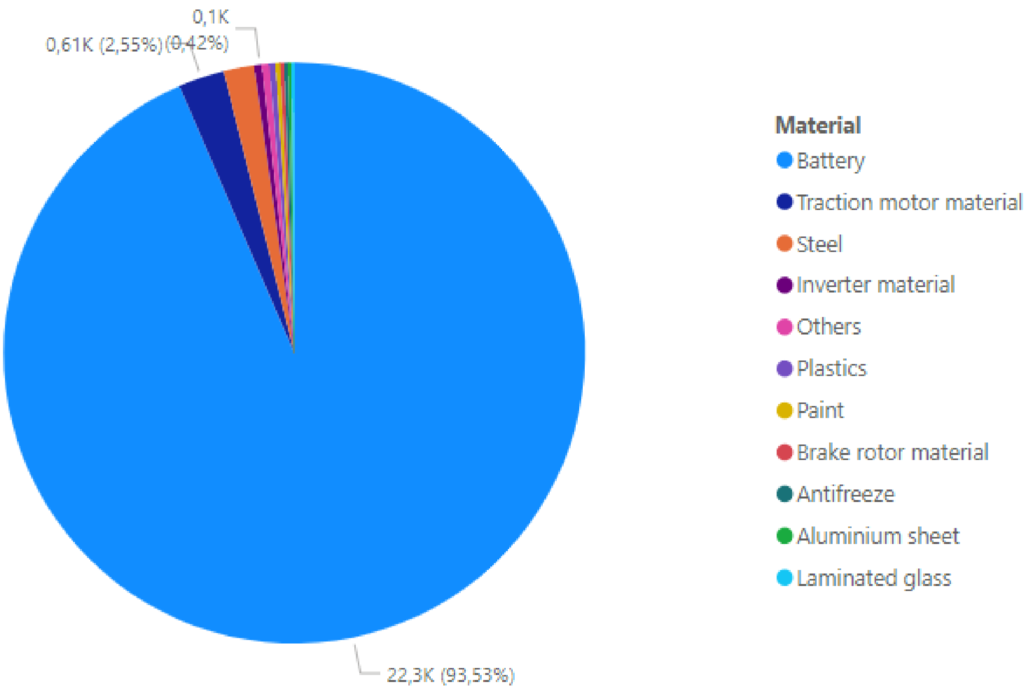


Figure 6 Percentage graph for the prices of the materials.

Steel, plastics, and battery are found to be the most used materials with a weight percentage of 37.60%, 5.59%, and 35.90% respectively. Moreover, regarding their total prices, battery, steel, and plastics makes up more than 95% of all the material price of EVs which can be seen in Figure 6. Based on this examination, the materials that make up 80% of the total weight and cost are identified as steel, plastics (PP), and battery. Hence, those three materials are selected to be used for a more detailed analysis of the behaviours of their costs and reasons for uncertainty within them. Moreover, regression analysis is used to understand the trends and volatility of the electrical vehicle in the following section.

4.2. Material and Cost Component Analysis

As mentioned in the previous part, steel, PP, and battery are selected for the discovery of their affects in the price volatility of the electrical vehicles. Firstly, the costs for those materials are investigated in a ten year time frame from 2010 to 2020. For steel and PP a decomposition analysis is done using R software. Since the technology of producing batteries is relatively new compared to PP and steel production, the cost of the battery is primarily determined by the technology advancements and the learning curve models (Penisa et al., 2020). Hence a learning curve analysis is done for the battery.

4.2.1. Steel

Firstly an outlier analysis is done for steel. The upper and lower range for the outliers is done by adding and subtracting 1.5 times interquartile range from the third and first quartile respectively. For steel, the lowest possible value is found to be 0.336 €/kg and the highest possible value is found to be 0.671 €/kg. The ten identified outliers based on the range and the reasons for being outside the range can be seen in Table 4.

Table 4 Outlier analysis for steel.

Date for the Outlier	Value (€/kg)	Reason for it
1-12-2015	0.333	The increase in the supply of steel has led to significant price declines in all regions of the world (OECD, 2016).
1-4-2018	0.685	Steel prices increase due to the increased yearly growth of 2.4%. moreover, the speculations in trading in futures markets has impacted the steel stop prices to increase (OECD, 2019).
1-5-2018	0.752	
1-6-2018	0.785	
1-7-2018	0.784	
1-8-2018	0.785	
1-9-2018	0.745	
1-10-2018	0.724	
1-11-2018	0.714	
1-12-2018	0.675	

After taking out the outliers, the cost data is checked whether it is a multiplicative or additive time series as explained in the previous chapter. Based on the investigation, steel's cost curve is found to be a multiplicative time series since it had a lower sum of squares correlation values when checked as multiplicative time series. The decomposition of steel can be found in Figure 7.

The horizontal axis for the decomposition analysis represents the time from 2010 to 2020. The vertical axis is divided into four sections as observed, trend, seasonal, and random. Observed means the price of the material obtained monthly over a ten-year period, and values are in €/kg. The second row suggests the observed trend over the data set. It is divided from the observed data set. Afterwards, the seasonal row is found by dividing the trend from the observed data set. Similarly, for the last row, from the observed data set trend and seasonality is divided to get the random part (Gordon, 2019). Trend, seasonal, and random components in the end multiplied together makes up the observed data set.

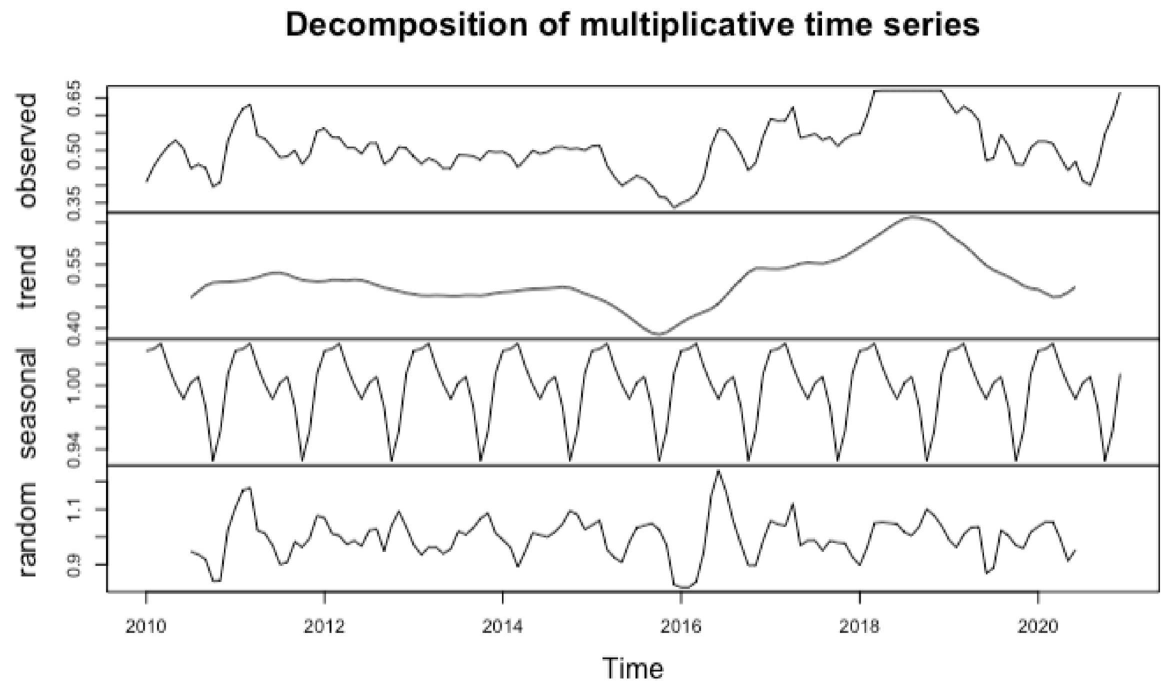


Figure 7 Decomposition of steel.

For steel, there is a clear seasonality where throughout the year, the prices go down and the volatility of seasonality in steel varies 6%,suggesting that throughout the year, steel's seasonality is mostly stable due to the contracts for manufacturing of steel having done yearly, not creating price variations throughout the year. Moreover, no clear trend can be identified using steel's cost curve, which suggests that the price of steel shows significant variability over both the long term as well as short term.

Figure 7 represents the variability of the data points and the reasons for that apart from the cost components of it. After the analysis of the variability in the cost of steel, its cost components are checked.

Cost Component Analysis

Utilising the literature review, the cost components of steel are found. For the steel's production costs, raw materials are found to be the major cost component with more than 60% cost contribution in the selected EU countries (Lu et al., 2022), the other cost components can be seen in Figure 8.

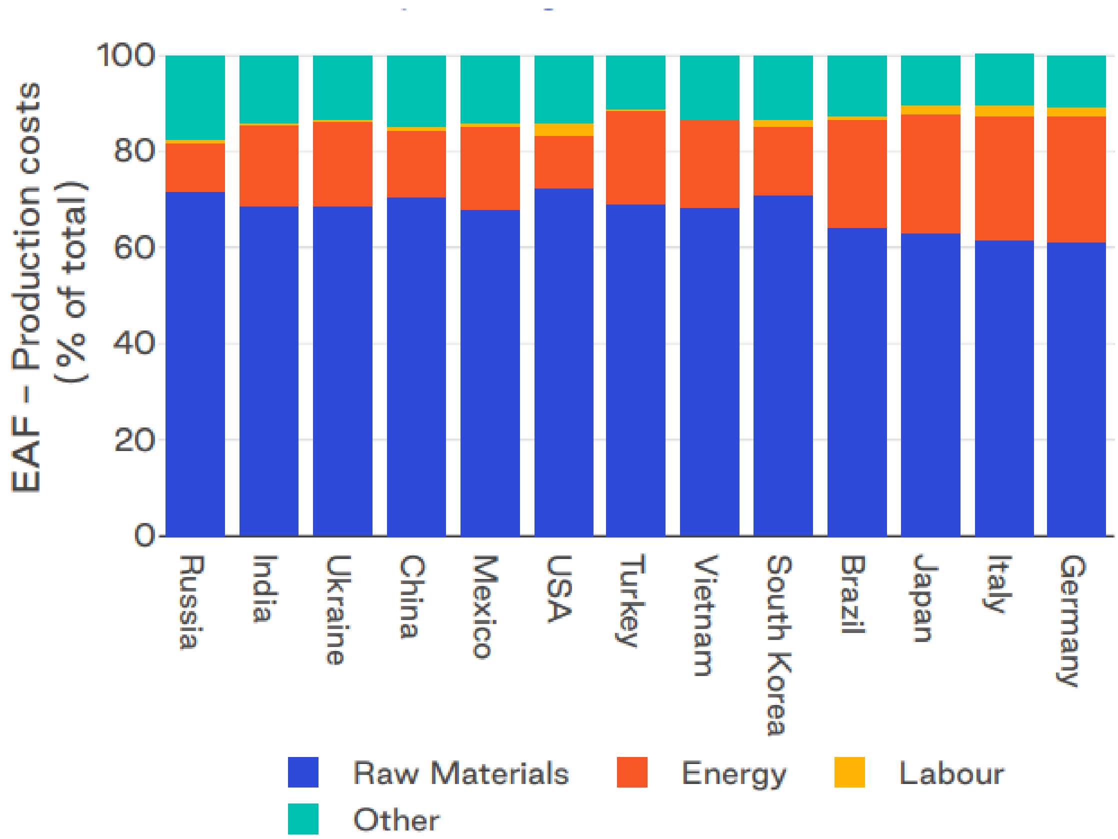


Figure 8 Share of different cost components in steel production costs in different countries for 2021 (Lu et al., 2022).

According to Medarac et al. (2020), raw materials needed for the production of steel are iron ore, coal, oxygen, and limestone. The second biggest cost contributor for manufacturing steel is energy. The energy needed to produce steel comes from coke and coal (Medarac et al., 2020). Hence, coal, coke, and iron ore are selected to be used for the regression analysis for steel to understand their effects on the volatility of the price of steel and how they influence the future costs of steel. The cost curves of iron ore, coal, and coke compared to steel can be seen in Figure 9.

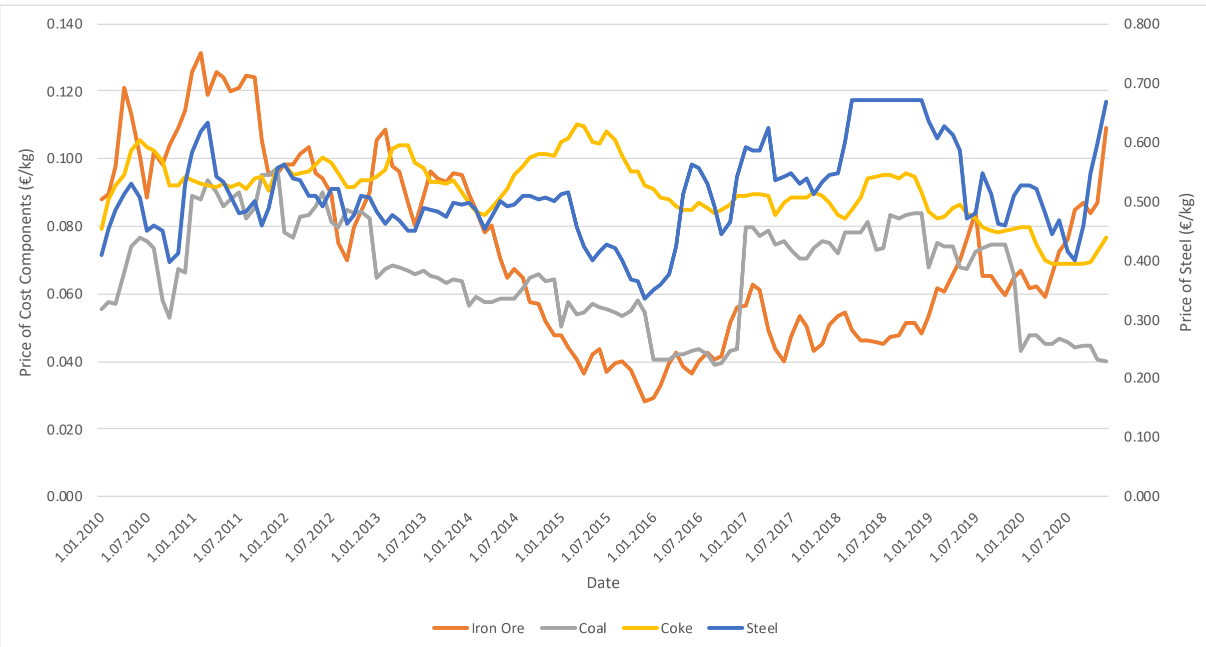


Figure 9 Cost curves of steel and it's cost components.

For the selected cost components, the same outlier analysis and time series decomposition is done to understand the trend and seasonality patters of them. When steel's cost components are checked, only outliers are found for coke. The lower and upper most acceptable values are found to be 0.0689 €/kg and 0.1126 €/kg. With this range, five outliers are identified. The values and the reasons for that can be seen in Appendix A.

Via utilizing the same method, all the cost components are found to be multiplicative time series. Next, the multiplicative time series are decomposed as seen in Appendix B. Based on the decomposition, for the iron ore, there is a declining trend and the seasonality suggests that throughout the year, the seasonality affect seems to change a lot. This is due to the market structure of iron ore. The iron ore industry could be considered oligopolistic, meaning that its market structure consists of a small number of firms, who together have substantial influence over the industry. The majority of the market is controlled by four significant competitors. Hence, they determine the price and demand through their supply decisions, leaving the prevailing market variables to determine both at any particular time (Garg, 2014). For this reason there is a great volatility in the seasonality of iron ore. For the coal, similar to iron ore, there is a declining trend until 2016 and afterwards it is varied. Moreover, the seasonality suggests that in the winter months, the cost of coal increases since it is used for heating purposes. On the other hand, coke seems to be stable throughout the assessed period, with an apparent seasonality in the middle of the year. Regarding the seasonality of coke, there is a high volatility especially in the middle of the year. This is due to the contractual arrangements in the coke market, where most of the agreements regarding the cost of coke is done in six-month intervals, creating a high variability for the midyear.

For steel, since the cost of it is determined by its raw materials and energy carriers, regression analysis is done to understand what type of relation each has within each other. The regression analysis is done using SPSS Software and R programming (Radecic, 2021). The effect of each component is checked for each month, 12 data points per year (monthly), once a year (annually), averaging 12 months of the year to obtain one data point per year, and twice a year, averaging the first six months of the year and then the second six months of the year to obtain two data points per year (bi-annually). These, three different types of time frames are selected in order to capture different types of sensitivity and for some of the cost components, the contracts are done bi-annually or annually, hence the costs react accordingly to those times not change the behaviour according to months. Moreover, three different types of regression curves are checked, which are linear, parabolic (quadratic), and hyperbolic (cubic) since those are the types of cost relationships that can exist according to Woodward (1997).

For the analysis, the output used to determine the correlation is R-square. The R-square value shows the correlation between the price of the cost component to the price of the material. It is mainly used as an indicator to understand if the price volatility of the material can be explained by its cost components. The R-square results for the regression analysis can be seen in Table 5. As can be seen from Table 5, the highest R-square found is for iron ore regressed through the annual data set of steel. The graph of it can be seen in Figure 10.

Table 5 Regression results for steel's cost components.

Iron Ore			
Regression Type	**Monthly**	**Bi-Annually**	**Annually**
Linear	0.001	0.002	0.006
Parabolic	0.004	0.015	0.024
Hyperbolic	0.260	0.435	0.458
Coal			
Regression Type	**Monthly**	**Bi-Annually**	**Annually**
Linear	0.197	0.268	0.320
Parabolic	0.200	0.276	0.326
Hyperbolic	0.202	0.276	0.329
Coke			
Regression Type	**Monthly**	**Bi-Annually**	**Annually**
Linear	0.010	0.054	0.096
Parabolic	0.091	0.174	0.359
Hyperbolic	0.091	0.173	0.364

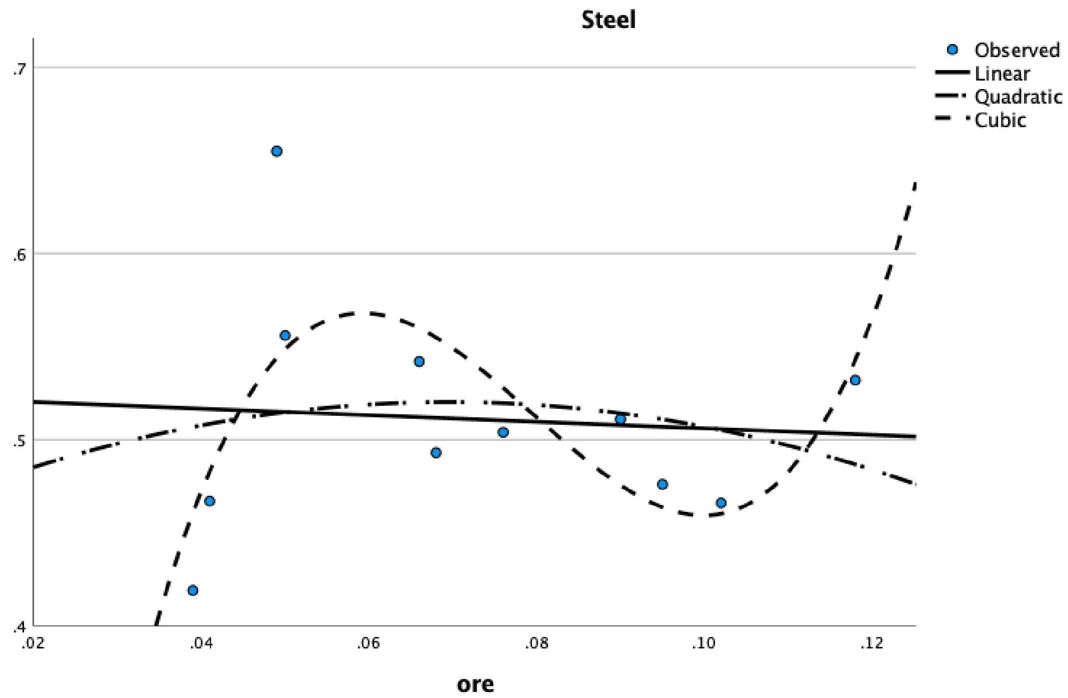


Figure 10 Regression curves for steel and iron ore annually data set.

The rest of the graphs of each regression can be seen in Appendix C. Since there are other factors influencing the price of steel, explained previously, R-square value is not expected to be higher than 0.5. However, this does not necessarily mean that the analysis could not be broadened. To understand the influence of price volatility of materials considering their cost components, another investigation is done using the decomposed data sets.

For the second investigation, the decomposed data sets for steel and its cost components are checked under linear regression to analyse if there is a correlation between the trend and seasonality components of the data sets. Based on this investigation, the highest R-square value found for steel is the bi-annual trend analysis including all components with a result of 0.9634.

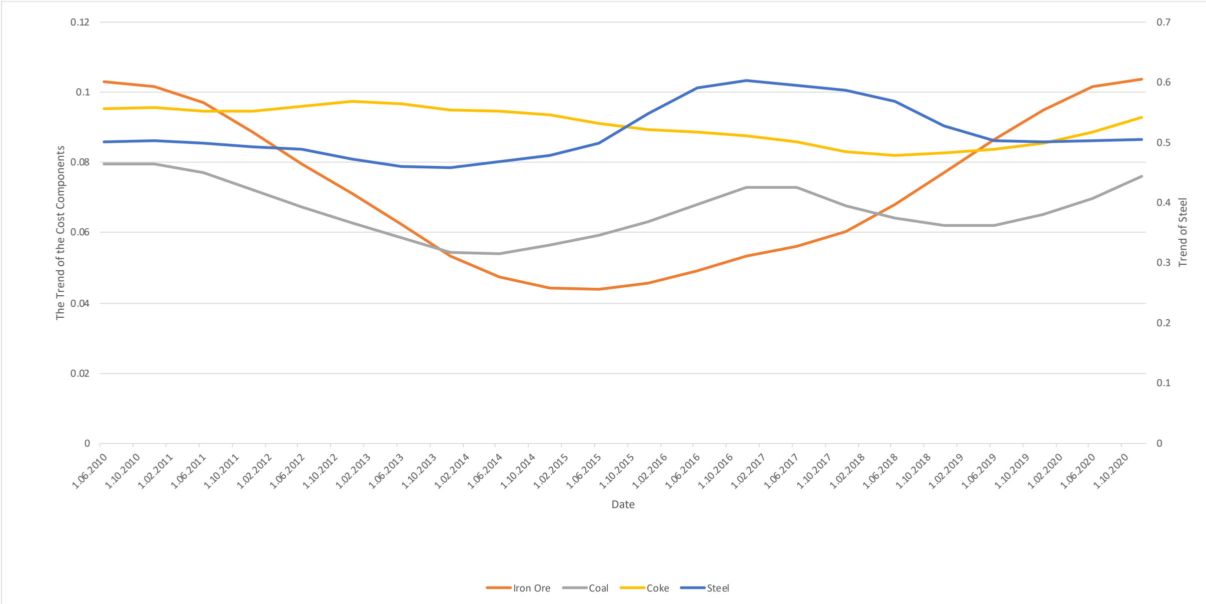


Figure 11 Bi-annual trend curve for steel and its cost components.

This result shows that there is a high correlation between the trend of the steel and the trends of iron ore, coal, and coke. As can be seen from Figure 11, the bi-annual trend for steel and its cost components follow a similar curvature. Especially, coal's trend curve is nearly the same as the steel's one. Also, the trend of iron ore seems to have higher dips and reacts relatively slower to the changes in the trend of steel's price. This is mostly due to iron ore being used in steel manufacturing. Moreover, Figure 11 suggests that although there are other factors affecting the price of steel, like its own seasonality, the trend of how the cost changes throughout the years depends on the trends of its cost components. Moreover, the second highest R-square value from the regression analysis is 0.8058 with the seasonality components checked.

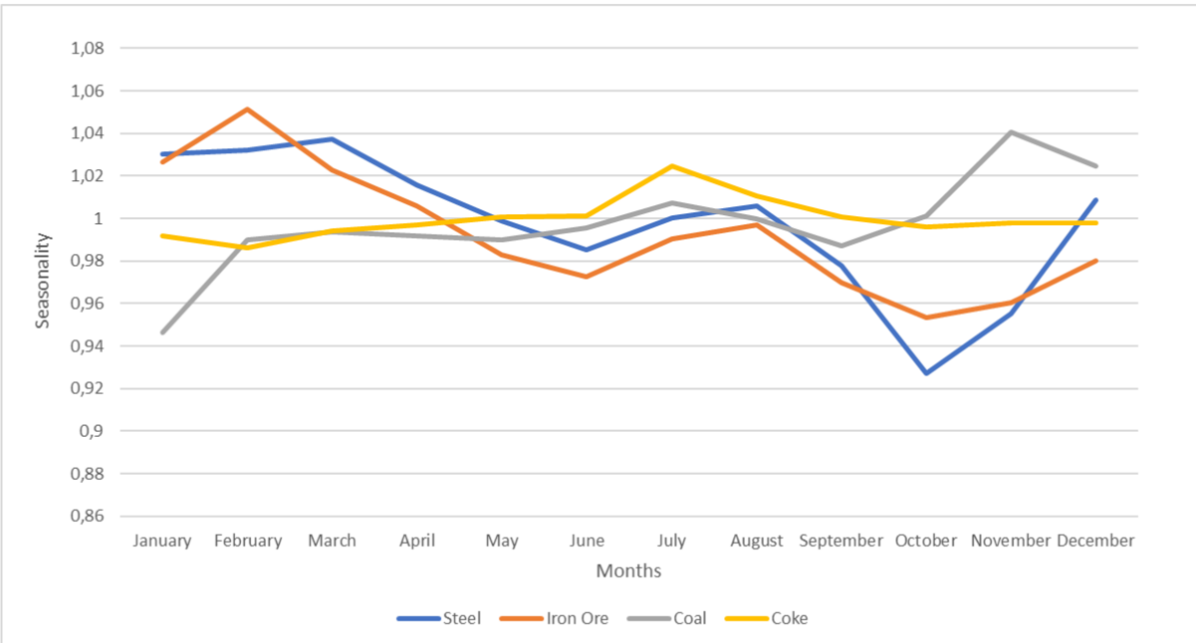


Figure 12 Seasonality curves for steel and its cost components.

The seasonality curves for steel and its cost components can be seen from Figure 12. Based on these results, it can be concluded that the seasonal part of the price of steel depends on the seasonality of iron ore, coal, and coke. After understanding the trends, in order to fulfil the second part of the research question, future cost forecasts of steel are analysed.

Future Forecasts

To estimate mathematical functions and simulate the functioning of complicated systems, Monte Carlo simulation combines random sampling and statistical modelling (Harrison, 2010). The conventional LCC analysis model takes into account all expenses from purchase to salvage. However, due to the rapidly changing environment, not all costs and expenses stay the same throughout the whole project. Hence, a stochastic LCC analysis is needed to quantify the uncertainties associated with the materials that contribute to valid decision-making (Huang et al., 2021). A stochastic LCC analysis model is more robust than the traditional deterministic ones.

Monte Carlo analysis allows the evaluation of the long-term trade-offs of economic performance for investment projects. It includes the stochastic nature of life cycle costing and analysis assessments (Baldoni et al., 2021). These methods create a layer of computational complexity and in this way, it is possible to include uncertainties or price volatilities in the life cycle cost evaluations.

The Monte Carlo analysis is used to understand the future variability of the price of materials with respect to their cost components. In this way, the intended result is to see what is the most probable value for the cost of the materials in 2030 and 2050. Those dates are selected due to the goals of the EU to reduce 50% of greenhouse gas emissions and become climate neutral respectively. For the Monte Carlo analysis for steel, its cost components are considered as indicators for future value. Table 6 shows the future costs of coal, coke, and iron ore for 2030 and 2050.

Table 6 The forecasted values for the cost components of steel.

Cost Component	2030 Value (€/kg)	2050 Value (€/kg)
Coal (Duic et al., 2020)	0.08	0.09
Coke (KPMG, 2023)	0.02	0.01
Iron Ore (Kempken et al., 2021)	0.08	0.06

Before moving on with the Monte Carlo analysis, it is important to understand the forecasted values for the cost components and how their trends change depending on the years. The cost of coal will be 0.08 and 0.09 €/kg in 2030 and 2050 respectively. Due to renewable energy resources being used more often in the future. The cost of coal will remain nearly stable, only increasing by 1 cent in 20 years which is due to the inflation and increased scarcity of coal (European Commission, 2014). The decrease in the cost of coke compared from 2030 to 2050 is due to finding alternatives for the usage of coke, hence decreasing the demand for it. (KPMG, 2023). The cost of iron ore will decrease due to the increased circular usage of iron and increased efficiency in the steel-making process resulting in less usage of iron ore (Kempken et al., 2021). It should be noted that there is quite high uncertainty in the forecasts of the costs depending on the literature, since different scenarios for future usage of different materials and methods varies depending on the scenarios.

The coal values used to generate Figure 13 and Figure 14, is based on the International Energy Agency (IEA)'s Current Policies Scenario. The other two scenarios mentioned in Duic et al. (2020)'s paper are also investigated for coal. Based on their work, there are three different scenarios which are Current Policies Scenario, New Policies Scenario, and 450 Scenario.

The demand for coal is expected to increase more quickly, by 1.2% annually, until 2040 under the Current Policies Scenario, which makes no additional assumptions beyond those now in place. Without the drive of many of the policy reforms suggested by the COP21 commitments, this is the society we live in today. In this scenario, the decarbonization of the electricity system proceeds more slowly, and coal continues to be the fuel of choice for producing electricity, accounting for 36% of global electricity production in 2040, well outpacing renewable energy sources (29%) and natural gas (24%) (International Energy Agency, 2016). This scenario assumes there are no additional incentives given to change to renewables than what it is now.

The New Policies Scenario, on the other hand, takes into consideration all currently implemented policies and initiatives as well as the proclaimed goals, objectives, and intentions, even if they have not yet been fully carried out. A wide range of recently announced policy initiatives, including those to promote energy efficiency, reduce air pollution, ease energy poverty, boost low-carbon fuels, and put a price on carbon dioxide (CO_2) emissions, have an impact on future coal markets. According to the policy, macroeconomic, and demographic assumptions in the New Policies Scenario, coal consumption will increase by 0.2% year between 2014 and 2040, a sharp decline from the 2.4% annual growth rate seen over the previous 25 years. The declining cost of renewable energy sources and the nation-level climate commitments laid out at COP21 are particularly reflected in this trend (International Energy Agency, 2016). In this scenario it is important to not the increase decline of the coal compared to the Current Policies Scenario.

The 450 Scenario outlines an energy course that is consistent with a 50% likelihood of keeping the global temperature increase to 2 °C, a goal that cannot be achieved with continued coal use. In this scenario, the demand for coal declines significantly at a pace of 2.6% annually. By 2040, the world's consumption of coal has decreased to 13% of total primary energy supply, which is only half what it was in the New Policies Scenario. Coal's share in power generation falls to 7% in 2040, considerably behind nuclear (18%), gas (16%), and renewables (58%). By that point, power plants with carbon capture and storage still produce 70% of the electricity from coal (International Energy Agency, 2016). Based on those three scenarios, there are three different coal price values predicted for 2030 and 2050. In Table 7, the predicted values can be seen. The graphs for the other two scenarios can be seen in Appendix E.

Table 7 Predicted coal price values for 2030 and 2050 based on different scenarios.

Scenario	2030 Value (€/kg)	2050 Value (€/kg)
Current Policies Scenario	0.08	0.09
New Policies Scenario	0.07	0.08
450 Scenario	0.06	0.05

After understanding future forecasts for the cost of coal, regression results are used to come up with the predictions of steel's price. For the coal, the regression values used can be found in the following Table 8.

Table 8 Coal values used for Monte Carlo analysis of steel based on the regression results.

	Coefficient	Standard Error
Intercept	0.361	0.027
Coal (€/kg)	2.250	0.398

The coefficient corresponds to the type of relationship steel has with coal. Since it is positive, it signifies that an increase in prices of coal would increase the price of steel. Based on the Monte Carlo analysis using values in Table 8, below are the graphs for the cost of steel for 2030 and 2050.

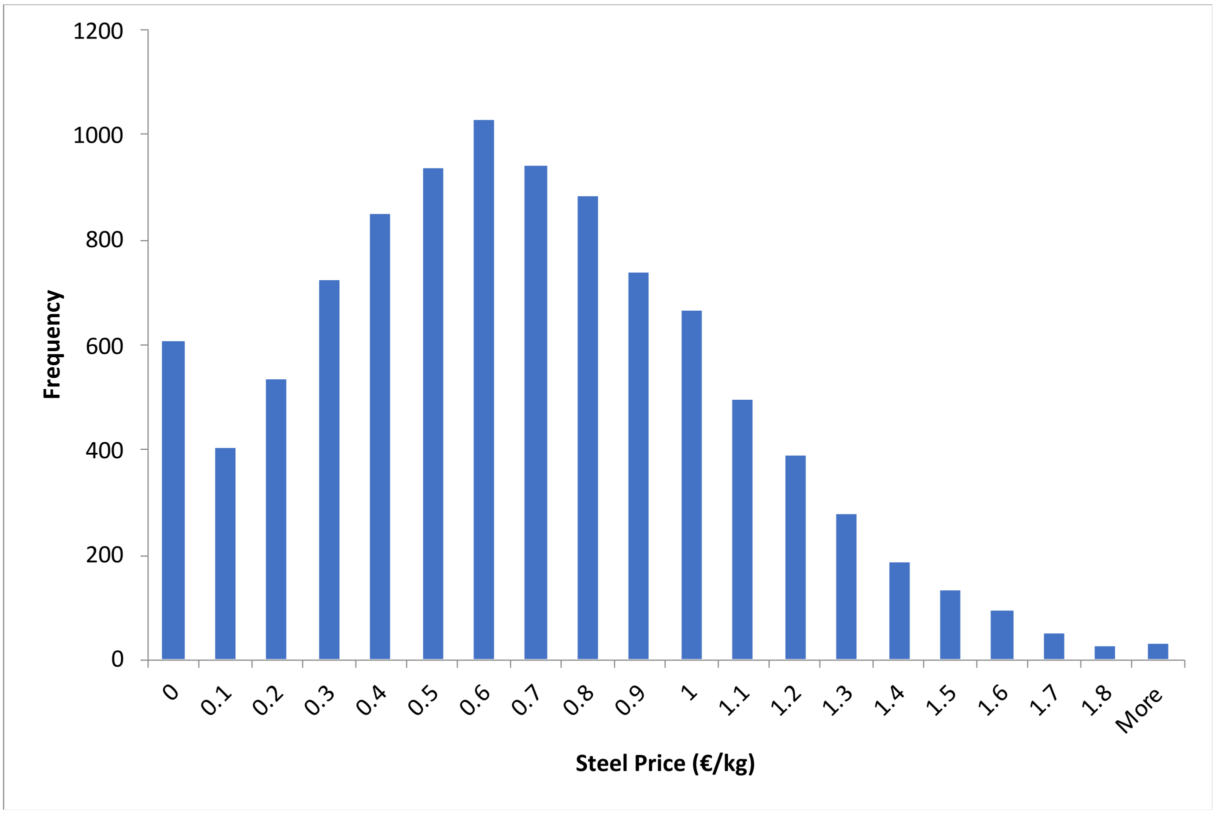


Figure 13 Monte Carlo results of steel price in 2030 using coal with the Current Policies Scenario.

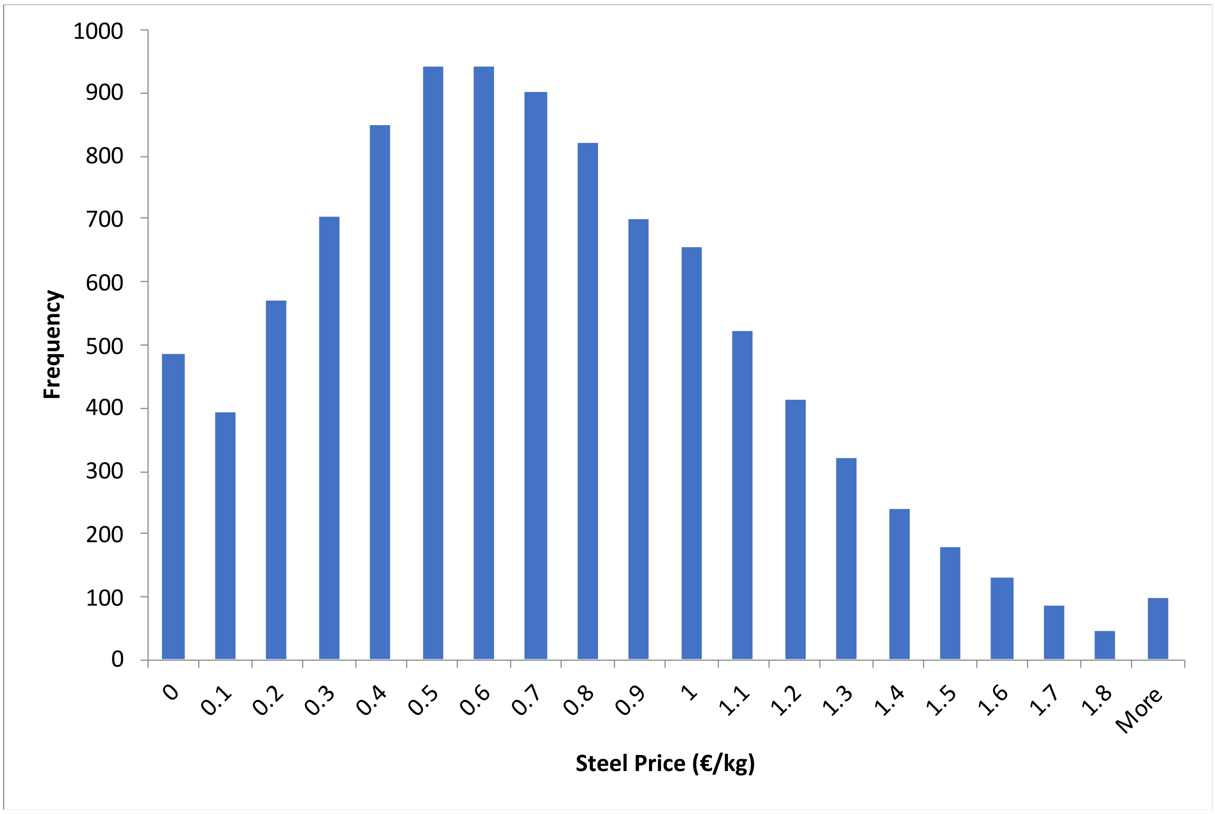


Figure 14 Monte Carlo results of steel price in 2050 using coal with the Current Policies Scenario.

By looking at the Figure 13, it is possible to see that the most probable cost for steel is 0.6 €/kg in 2030, since it is the most frequent value. Similarly, for the Figure 14, the cost value for steel is the same as 2030. The forecasted price does not change. The most frequent value for the steel's price remaining the same is due to variability being larger in 2050, thus it does not give exact results. The same process is done for coke and iron ore. Below, the values for the regression analysis can be seen in Table 9 and Table 10.

Table 9 Coke values used for Monte Carlo Analysis of steel based on the regression results.

	Coefficient	**Standard Error**
Intercept	0.588	0.067
Coke (€/kg)	-0.848	0.734

Table 10 Iron ore values used for Monte Carlo analysis of steel based on the regression results.

	Coefficient	**Standard Error**
Intercept	0.511	0.019
Iron Ore (€/kg)	-0.002	0.250

As can be seen from the Table 9, the coefficient for coke is negative which indicates that a price increase in coke will lead to a decrease in the price of steel. A negative coefficient was not an expected result, since by logic, the cost components of a material should have a positive correlation with the material itself. However, it can be concluded that the reason for a negative value is due to the low R-square value generated by the linear regression of coke and steel.

However, since the value for coefficient value for iron ore is very close to zero, it is evaluated as the price change in iron ore does not affect the price changes in steel which is also backed up with the results found in the previous section where the R-square results for linear regression was 0.006, indicating a low correlation between the cost of iron ore and steel.

The results for the Monte Carlo analysis can be seen in Table 11. The graphs can be found in Appendix E.

Table 11 Monte Carlo results for steel.

	Type	Minimum Value	Maximum Value	Most Frequent Value
2030	Steel-Coal (Current Policies Scenario)	0	>1.8	0.6
	Steel-Coal (New Policies Scenario)	0	>1.8	0.6
	Steel-Coal (450 Scenario)	0	>1.8	0.6
	Steel-Iron Ore	0	1.6	0.6
2050	Steel-Coal (Current Policies Scenario)	0	>1.8	0.6
	Steel-Coal (New Policies Scenario)	0	>1.8	0.6
	Steel-Coal (450 Scenario)	0	>1.8	0.6
	Steel-Iron Ore	0	1.8	0.6

Based on Table 11, the most frequent value for steel is forecasted to be 0.6 €/kg for 2030. Moreover, for 2050, all the analysis results in a future predicted steel price of 0.6 €/kg. For the analysis using coke, the results were not conclusive due to the negative coefficient it ended up with having price values with similar frequencies, not resembling a histogram. The forecast values did not change for 2030 and 2050 due to two reasons. The first reason is I have checked the values with a 0.1 €/kg range, which might not be enough to understand the variability. The second reason is that there is uncertainty regarding future prices and the values only converge to 0.6 €/kg. The range of the minimum and maximum values vary for iron ore. The reason for that is since the R-squared value of iron ore was higher than the other cost components, Monte Carlo analysis results in a narrower range compared to other cost components' predictions. Moreover, for the price prediction of steel using coke for 2050, the most probable value cannot be determined since the frequency of all the possible values are same.

Hence, it can be concluded that Monte Carlo analysis does not give exact results for the price forecasts of the future but rather it gives a range of possible values and the most probable cost value. This result, combined with the previous methods of moving averages and the trend and seasonality analysis for the power of cost components will give more accurate and detailed results for the forecasted price values for steel.

4.2.2. PP

To start the material analysis, outliers are detected using the same method as steel. The lowest possible value is found to be 0.8663 €/kg and the highest possible value is found to be 1.1799 €/kg. Based on the data set there were no outliers. Since there are no outliers found, the PP data set is decomposed similarly to steel. In Figure 15, the decomposition of PP's cost curve can be seen.

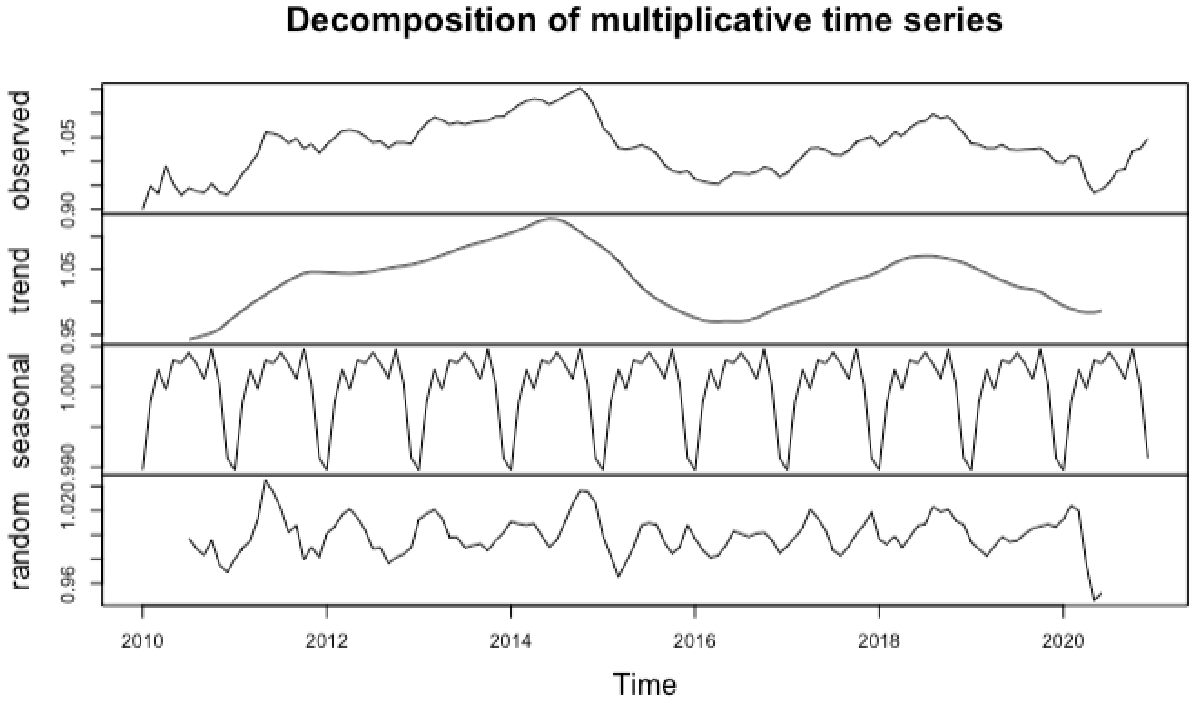


Figure 15 Decomposition of PP.

When the decomposition is analysed, for PP, there is an increasing trend with time, especially from 2010 to 2014 and from 2016 to 2018. Moreover, regarding seasonality, it is seen that the beginning and end of the year seasonality is more or less the same. Also, the variability of the seasonality is incremental, due to the market structure of PP where the contracts are done yearly. After the decomposition of the materials, its cost components are checked.

Cost Component Analysis

Utilizing literature review, the cost components of PP is found. For PP production costs, 36% of the price variability is explained by the cost of natural gas and crude oil (Marczak, 2022). Also, the other fuels consumed to produce PP can be seen in Figure 16.

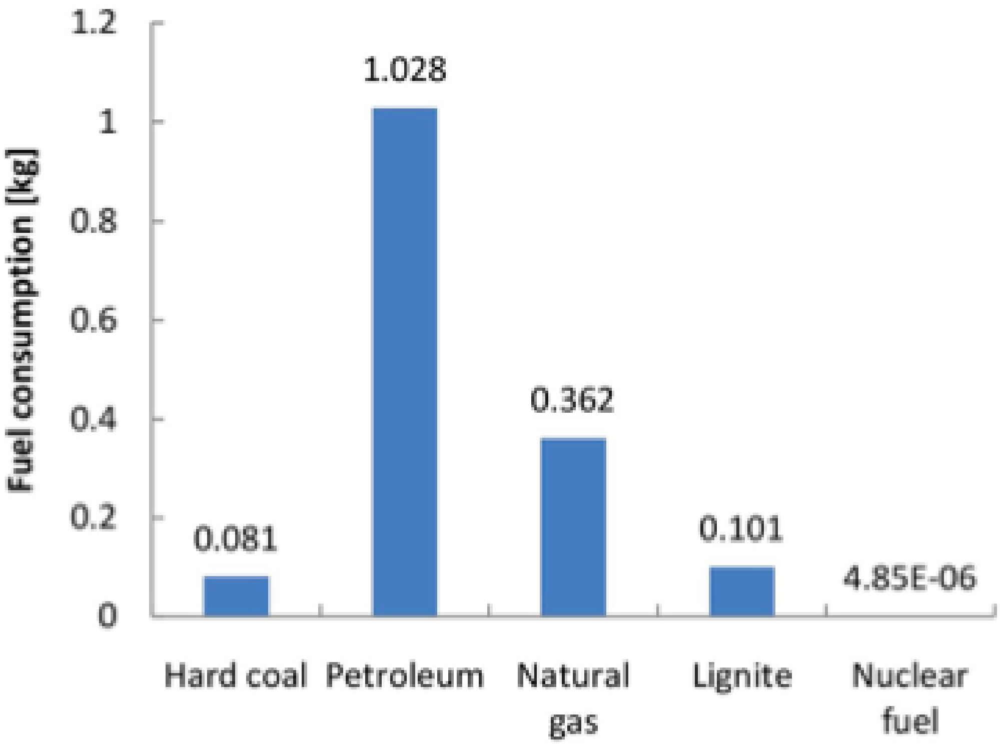


Figure 16 Consumption of primary energy carriers (expressed in kg/kg of product) at the PP production for 2017 (Marczak, 2022).

As can be seen in the figure, the top two cost components for the PP production is crude oil and natural gas. Hence, those are selected for the main two cost components of PP. The cost curves of natural gas and crude oil compared to PP can be seen in Figure 17.

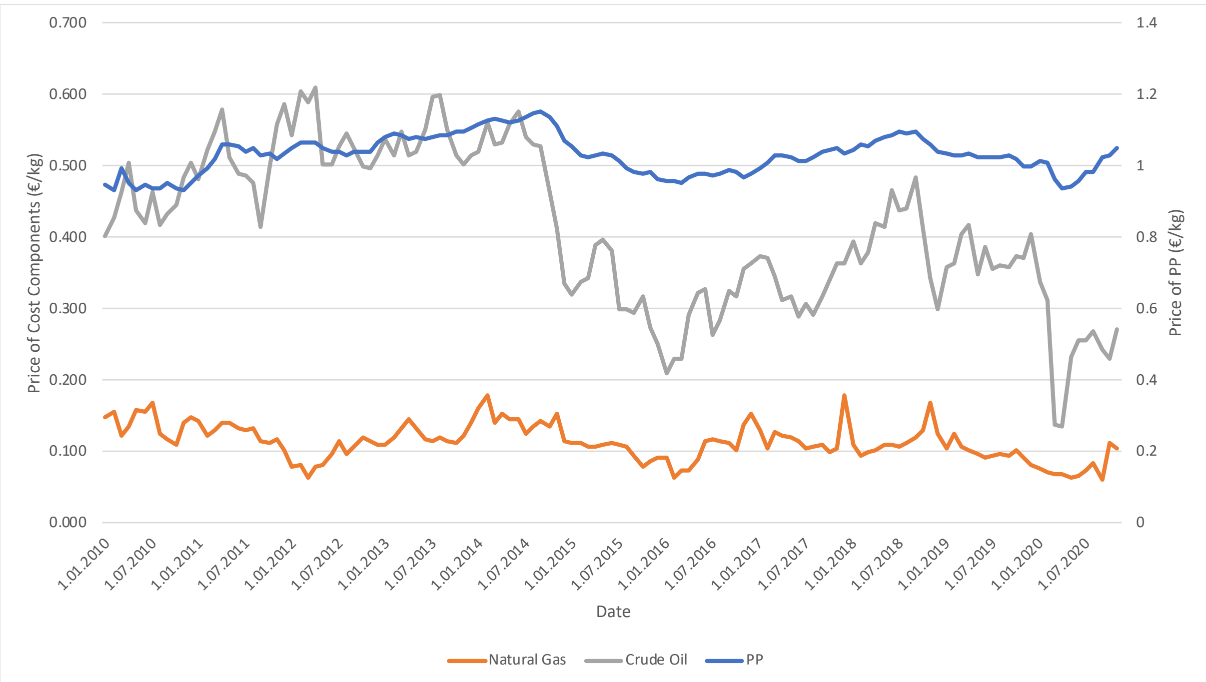


Figure 17 Cost curves of PP and it's cost components.

The outlier analysis is done for the cost components of PP as well. The only outliers are found for the natural gas. The lower and upper most acceptable values are found to be 0.0494 €/kg and 0.1767 €/kg. There are two values that are outside this range. The values and the reasons for that can be seen in Appendix A.

Moreover, the detection of the type of time series is done for the cost components of PP and it is found that both of them are multiplicative time series. Afterwards, their decomposition is done that can be found in Appendix B. The decomposition analysis of natural gas shows that there is a decline in the trend. Moreover the volatility of its seasonality is 5 %, increasing mostly in the winter months due to the increased demand. When crude oil's decomposition graph is checked, there is a steep declining trend from 2014 to 2016. However, the seasonality effects seem to be less with only 4% change throughout the year.

After doing the decomposition of cost components, regression analysis is done to understand the relationship between PP and its cost components. The procedure is the same as steel's where the same three different types of time frames are selected. Also, the same three types of regression is analysed using SPSS. The R-square results for the regression analysis can be seen in Table 12.

Table 12 Regression results for PP's cost components.

Natural Gas			
Regression Type	**Monthly**	**Bi-Annually**	**Annually**
Linear	0.066	0.100	0.129
Parabolic	0.082	0.102	0.129
Hyperbolic	0.104	0.102	0.130
Crude Oil			
Regression Type	**Monthly**	**Bi-Annually**	**Annually**
Linear	0.302	0.328	0.339
Parabolic	0.303	0.331	0.347
Hyperbolic	0.307	0.331	0.350

As can be seen from Table 12, the highest R-square found is for crude oil regressed through the annual data set of PP. The graph of it can be seen in Figure 18.

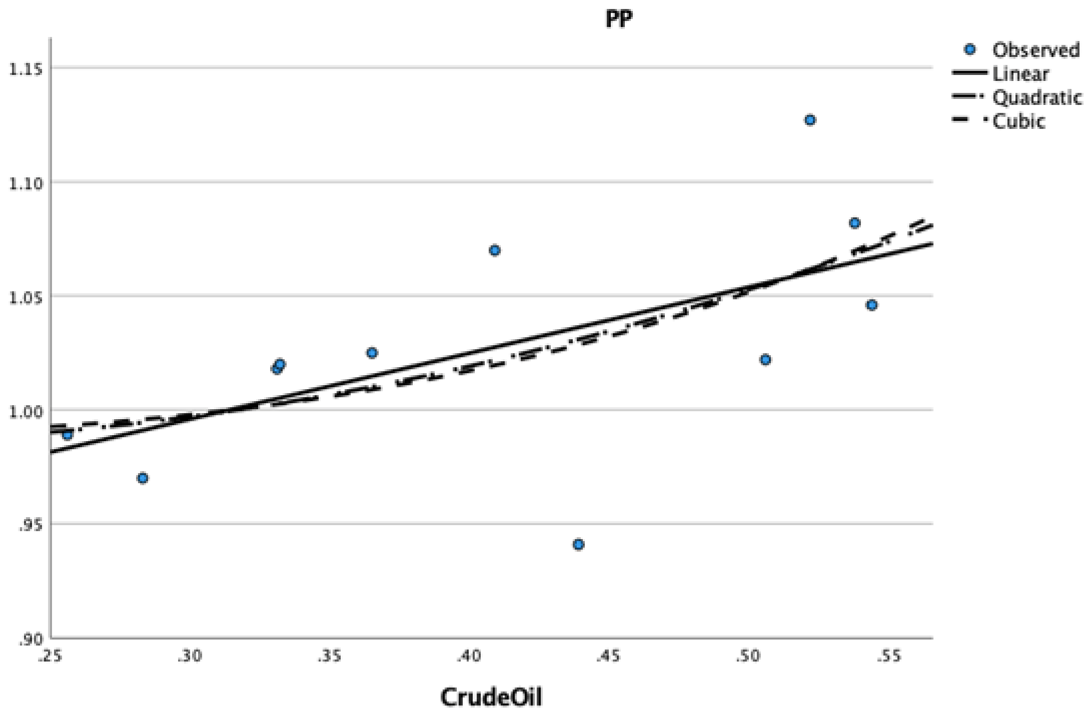


Figure 18 Regression curves for PP and crude oil annually data set.

The rest of the graphs of each regression can be seen in Appendix C. Another investigation is done to try to increase the R-square and check whether the decomposed data sets of cost components have a relationship between PP. Linear regression is done to assess the correlation of cost components' trend and seasonality to PP's. The highest R-square is found to be 0.5987 for monthly trend of PP including all of its cost components.

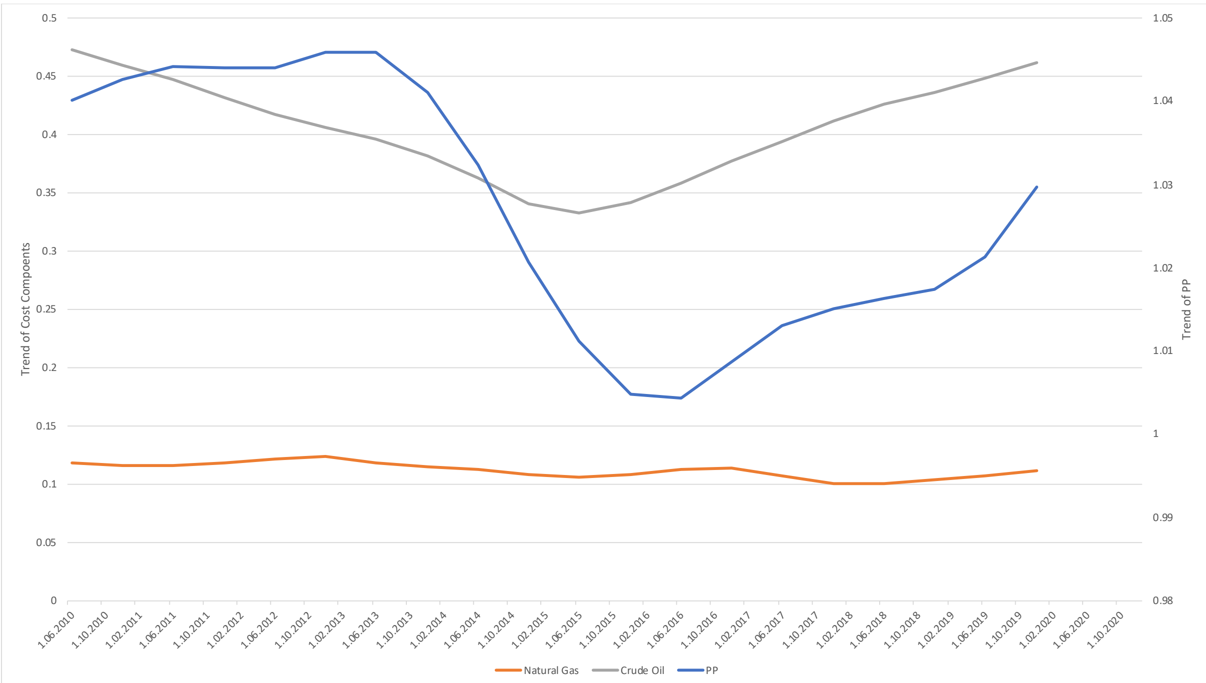


Figure 19 Monthly trend curve for PP and its cost components.

By looking at Figure 19 it can be understood that nearly 60% of the trend of PP can be explained by the trends of natural gas and crude oil. As can be seen from the figure, the trend of crude oil seems to have lower dips compared to the plastic. This is due to the fact that crude oil is a raw material used in the manufacturing of PP and the price trend does not change a lot since the contracts are done yearly. However, PP has higher dips, the reason for that is there are other components that affect the price of PP. Moreover, as can be seen from the Figure 19, both of them have similar curvature. On the other hand, the trend of the natural gas remains stable over time.

However, compared to the steel, the R-square is lower. Hence, another investigation is conducted to try to improve it. Since the R-squared results are not high enough for PP to determine the price trend, lagged method is applied. This method is done separately for the two cost components. The ACF results can be seen in Figure 20 for the natural gas and PP. Moreover, the R output is shown also in Figure 21.

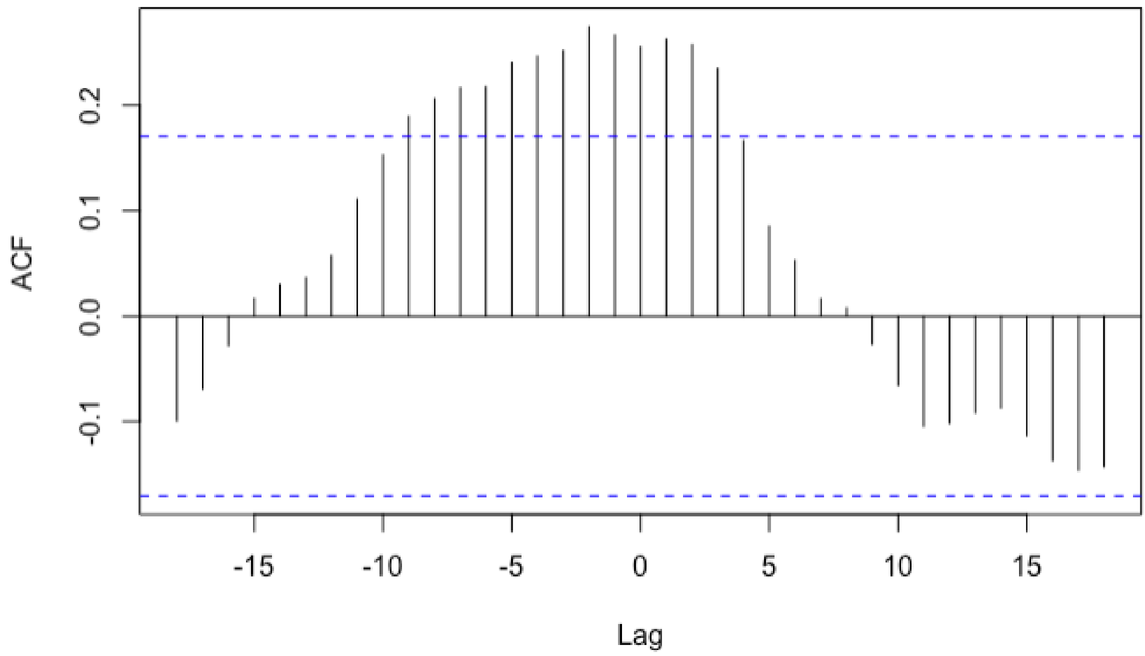


Figure 20 ACF results for the lag method between PP and natural gas.

```
Autocorrelations of series ‘X’, by lag

   -18    -17    -16    -15    -14    -13    -12    -11    -10     -9     -8     -7     -6
-0.099 -0.069 -0.028  0.017  0.030  0.036  0.057  0.111  0.153  0.189  0.206  0.217  0.218
    -5     -4     -3     -2     -1      0      1      2      3      4      5      6      7
 0.241  0.246  0.252  0.275  0.267  0.255  0.263  0.258  0.235  0.166  0.085  0.053  0.016
     8      9     10     11     12     13     14     15     16     17     18
 0.008 -0.027 -0.066 -0.105 -0.102 -0.092 -0.087 -0.114 -0.137 -0.146 -0.143
```

Figure 21 R output for the ACF results.

The highest ACF value is found when the lag was -2 with the value 0.275. This result means that the natural gas prices leads the prices of PP. When the R-square result is checked there was a 20% increase in results with 0.081 compared to the no lag scenario.

The same investigation is done for crude oil as well. The ACF graphs and R output can be seen in Appendix D. The highest value is found for the lag -1, with a value of 0.575, this result corresponds to crude oil prices leading the PP prices for one month ahead. Hence, if the prices of crude oil are known one month ahead, then it is possible to forecast the prices of PP or vice versa if we know today's crude oil price, we can forecast the price of PP for the next month. The R-square is resulted with 0.362. Although, this method is done in an attempt to increase the correlation between the cost curves of PP and its cost components, unfortunately, the lagged method did not produce enough increase in the R-square. Hence, the volatility of PP is still better explained by the decomposed time series of it and its cost components. After understanding the uncertainty, similarly to the steel, Monte Carlo analysis is used to determine the future price forecasts of PP.

Future Forecasts

After understanding the trends, Monte Carlo analysis is done for PP in a similar manner to steel. For the Monte Carlo analysis for PP, its cost components are considered indicators for future value Table 13 shows the future costs of natural gas and crude oil for 2030 and 2050.

Table 13 The forecasted values for the cost components of PP.

Cost Component	2030 Value (€/kg)	2050 Value (€/kg)
Natural Gas (Duic et al., 2017)	0.47	0.62
Crude Oil (Duic et al., 2017)	0.87	1.12

Before moving on with the Monte Carlo analysis, it is important to understand the forecasted values for the cost components and how their trends change depending on the years. The cost of natural gas will be 0.47 and 0.62 €/kg in 2030 and 2050 respectively and for crude oil, it will be 0.87 and 1.12 €/kg in 2030 and 2050 respectively. For both of the cost components, the values will increase since their availability of them will decrease and as the shift towards green energy continues (European Comission, 2014). Hence, they will be used more often.

Similarly to coal, there are also three different values for the predicted prices of natural gas and crude oil depending on the scenario implemented. In Table 13, the values from the Current Policies Scenario is used for both of the cost components.

For crude oil the demand increases until 2040 under the Current Policies Scenario at a rate of little under 1 mb/d per year on average. In this scenario, unrealized policy goals are ignored, leading to minimal slowing in demand growth over the subsequent 25 years, necessitating ever-rising prices to bring the market into balance. By 2040, just under three-quarters of all oil consumption—up from two-thirds today—will be accounted for by two industries: transportation and petrochemical feedstocks (International Energy Agency, 2016). This scenario is used as the worst case scenario where there are no policies implemented for the push to the renewables.

Between the Current Policies Scenario and the New Policies Scenario, when tighter fuel requirements start to bite and fuel switching to biofuels, electricity, and natural gas happens more swiftly, there are major shifts in demand. Even over the following five years, these changes start to stand out. After 2020, economic development among major consumers will take a different shape, technical advancements will continue, and government regulations to lessen the impact of energy supplies on the environment will go into force. In these conditions, the rate of increase in the world's oil demand decreases to less than 400 kb/d per year on average through 2040. By 2040, demand is around 13.5 mb/d lower than in the scenario based on current policies (International Energy Agency, 2016). In contrast to the scenario based on current policies, stricter fuel restrictions are taken into account in this scenario.

The differences between the New Policies Scenario and the 450 Scenario shows that, the Paris Agreement's commitments fall far short of the long-term goal of keeping global temperature increases to below 2 degrees Celsius (°C). The global oil demand peaks in the 450 Scenario in 2020 at just over 93 mb/d. The subsequent reduction in demand quickens yearly, and by the late 2020s, the worldwide demand is declining by more than 1 mb/d annually. Reduced demand in the transportation sector is mostly to blame for the 30 mb/d difference in 2040 global oil demand between the New Policies Scenario and the 450 Scenario. In the 450 Scenario, oil use in passenger vehicles decreases from almost 24 mb/d now to 15 mb/d in 2040, which is almost 10 mb/d less than the 2040 level in the New Policies Scenario. Greater adoption of electric vehicles and biofuels replaces oil use (International Energy Agency, 2016). The enhanced decarbonisation policies pursued in the 450 Scenario encourage the use of more efficient sources

For the natural gas the Current Policies Scenario shows how it would develop in an energy future where only laws and regulations already in place as of mid-2016 would have any impact. As coal faces significantly less legislative obstacles in this scenario, natural gas consumption grows more quickly, on average by 1.9% per year. Gas's contribution to the primary energy supply rises from 21% in 2014 to 24% in 2040, well behind coal's and oil's respective shares of 28% and 27% by the conclusion of the projection period (International Energy Agency, 2016). Similarly for the other two cost components, this scenario is the most undesirable one.

In the New Policies Scenario to 2040, the average annual growth rate of the world gas consumption is 1.5%, which is comparable to the growth rate anticipated over the medium term. This decline, which contrasts with the 2.3% annual growth noted over the previous 25 years, represents two significant trends. First, there is the broader background of primary energy demand's slower growth, which is anticipated to increase at only half the rate seen between 1990 and 2014. Second, there is the effect of some mature markets becoming saturated, coupled with a more competitive gas market. But gas does manage to steadily increase its contribution to the world's energy, supported by demand for both power and industrial gas consumption (International Energy Agency, 2016). Hence, the increase is still less than the Current Policies Scenario.

According to the 450 Scenario, there is a 50% possibility of keeping the increase in global temperature to 2 °C. This scenario depicts a remarkably different picture of the future gas markets: gas demand increases through the middle of the 2020s before beginning to level off, leading to an average annual growth rate of 0.5% for the projected period. This scenario demonstrates forcefully that even gas is too carbon intensive for long-term growth in a decarbonizing energy system, despite the fact that gas performs noticeably better than other fossil fuels where oil and coal drop by 1% and 2.6% per year, respectively (International Energy Agency, 2016). Based on those three scenarios, the varied predicted prices for natural gas and crude oil for 2030 and 2050 can be seen in Table 14. The graphs for the other two scenarios can be seen in Appendix E.

Table 14 Predicted crude oil and natural gas price values for 2030 and 2050 based on different scenarios.

Crude Oil		
Scenario	**2030 Value (€/kg)**	**2050 Value (€/kg)**
Current Policies Scenario	0.87	1.12
New Policies Scenario	0.76	0.93
450 Scenario	0.59	0.49
Natural Gas		
Scenario	**2030 Value (€/kg)**	**2050 Value (€/kg)**
Current Policies Scenario	0.47	0.62
New Policies Scenario	0.44	0.53
450 Scenario	0.40	0.44

Since the reasons for the predicted prices of natural gas and crude oil is explained, the next step for calculating the forecasted costs of PP is gathering the regression results for its cost components. For the natural gas and crude oil, the regression values used can be found in the following Table 15and Table 16.

Table 15 Natural gas values used for Monte Carlo analysis of PP based on the regression results.

	Coefficient	Standard Error
Intercept	0.966	0.021
Natural Gas (€/kg)	0.551	0.183

Table 16 Crude oil values used for Monte Carlo analysis of PP based on the regression results.

	Coefficient	Standard Error
Intercept	0.915	0.016
Crude Oil (€/kg)	0.275	0.037

The coefficient corresponds to the type of relationship PP has with its cost components. Similarly to the values found with steel and coal, all the coefficients for natural gas and crude oil are positive indicating a positive proportion with the cost of PP and the costs of natural gas and crude oil. Below are the results for the Monte Carlo analysis for PP using crude oil with the Current Policies Scenario. In Figure 22, the range of possible values for PP in 2030 can be seen. Similarly, for the results of 2050, Figure 23 can be seen. The rest of the graphs for both of the Monte Carlo analysis can be seen in Appendix E. Based on the analysis, the results are summarized in the following Table 17.

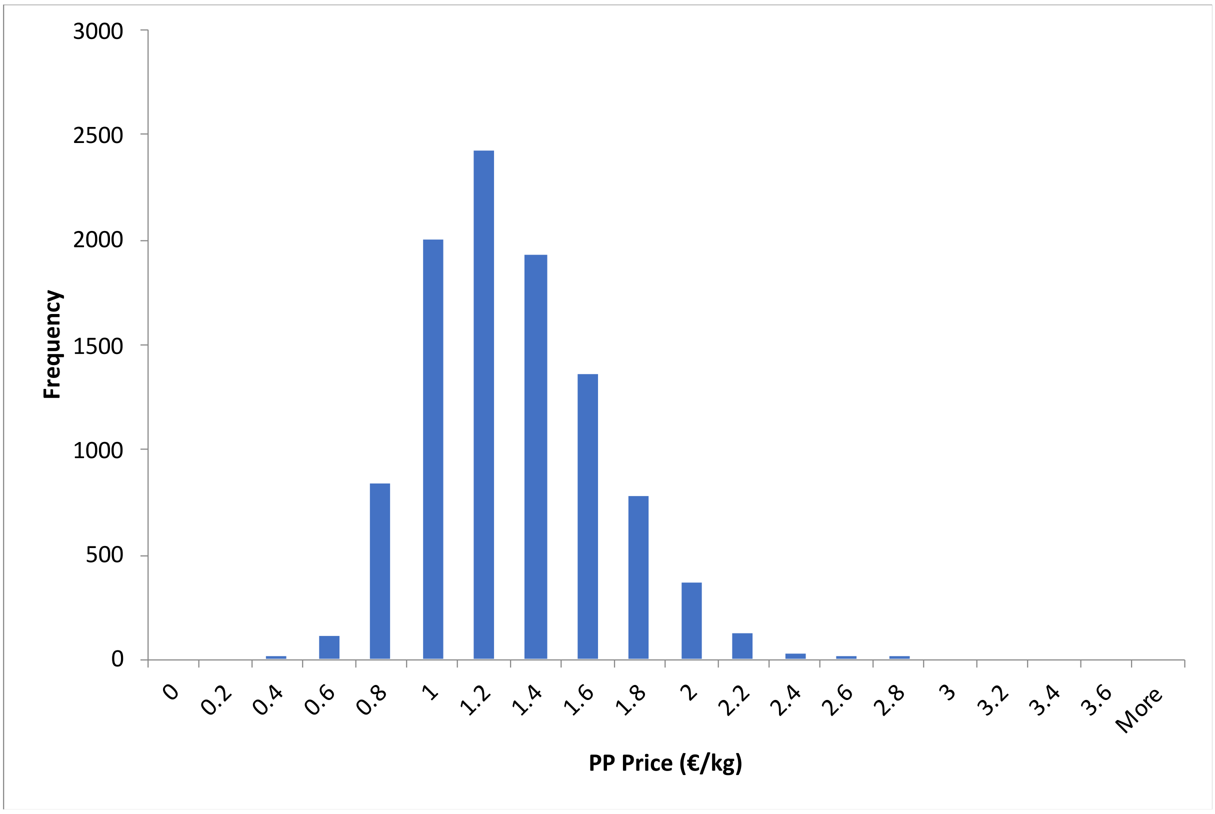


Figure 22 Monte Carlo results of PP price in 2030 using crude oil with the Current Policies Scenario.

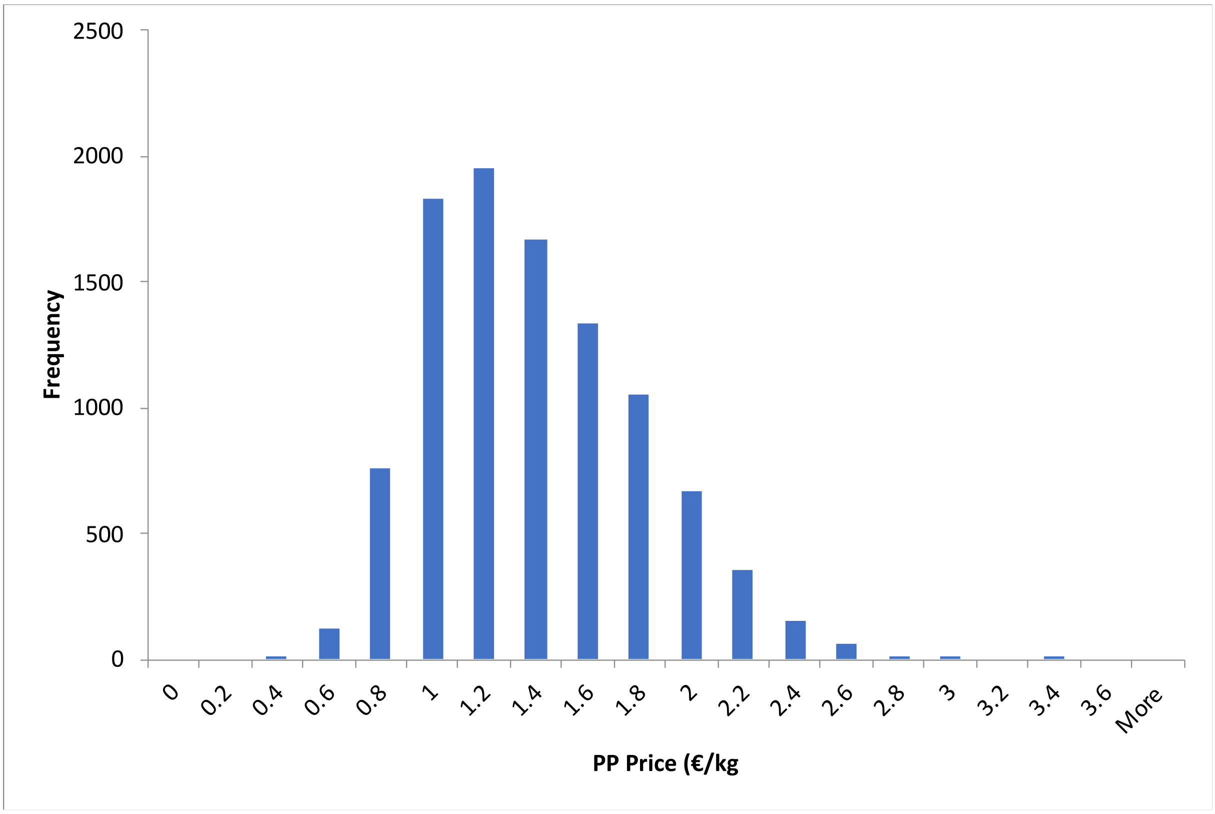


Figure 23 Monte Carlo results of PP price in 2050 using crude oil with the Current Policies Scenario.

Table 17 Monte Carlo results for PP.

	Type	Minimum Value	Maximum Value	Most Frequent Value
2030	PP-Natural Gas (Current Policies Scenario)	0.2	>3.6	1.2
	PP-Natural Gas (New Policies Scenario)	0.4	>3.6	1.2
	PP-Natural Gas (450 Scenario)	0.4	>3.6	1.2
	PP-Crude Oil (Current Policies Scenario)	0.4	2.8	1.2
	PP-Crude Oil (New Policies Scenario)	0.4	3.2	1.2
	PP-Crude Oil (450 Scenario)	0.4	2.2	1.2
2050	PP-Natural Gas (Current Policies Scenario)	0.2	>3.6	1.2
	PP-Natural Gas (New Policies Scenario)	0.2	>3.6	1.2
	PP-Natural Gas (450 Scenario)	0.2	>3.6	1.2
	PP-Crude Oil (Current Policies Scenario)	0.4	3.4	1.2
	PP-Crude Oil (New Policies Scenario)	0.4	3.0	1.2
	PP-Crude Oil (450 Scenario)	0.4	2.2	1.2

As can be seen from the results, the most frequent value for PP is forecasted to be 1.2 €/kg for both 2030 and 2050. The range of possible values for natural gas is more than the crude oil analysis. It is due to the standard error being high with the natural gas. The standard error determines the possibility of deviation from the line that is generated by linear regression using the coefficients and the intercepts provided in Table 15. The forecast values remained stable although the costs for natural gas and crude oil. The reason for a constant cost prediction of PP for 2030 and 2050 is similar to the steel's where the analysis is considered 0.2 €/kg incremental changes within the cost and it is possible that it is not sensitive enough to capture the slight differences that are less than that range in the future costs.

Overall, the Monte Carlo analysis is used to understand the future variability of the price of materials with respect to their cost components. Based on the analysis, it can be concluded that Monte Carlo analysis does not give exact estimations for the future cost values of the materials. On the other hand, it provides a range of possible values and what could be the future possibilities. The aim of this analysis was to quantify the probable cost values for the materials and to be used as a guiding tool for the possibilities. If it is combined with other methods such as the decomposition analysis and lagged method, it could provide a more holistic picture of the situation.

4.2.3. Battery

After the explanation of steel and PP, this section will provide information about the cost structure about EV batteries and forecasts regarding it. Rechargeable batteries are an essential tool for achieving the long-term objective of creating a society that is climate neutral. Battery costs are viewed in this revolution as a major barrier to the commercial success of battery-powered technologies. Lithium-ion batteries (LIBs), the most advanced technology for EVs and possibly the most cost-effective technology for stationary energy storage, have seen a sharp decline in price. These battery technologies promise further cost savings due to lower raw materials costs or new concepts for cell components such as anode-free cells (Mauler et al., 2021). This has been made possible by advancements in cell chemistry, process technology, and increased production scale.

In the past ten years, a number of research aiming to estimate these costs have been published, encouraged by the need for further lower battery costs. These studies seek to provide answers to issues that arise in a wide range of key areas, such as effective subsidy designs, ideal R&D expenditure plans, forecasts for EV penetration, cost-effective technology selection, and raw material market estimates. However, LIB pack cost projections for 2030 range from below 100 to above 400 $/kWh, signalling significant cost uncertainties that could lead to ineffective policies, improper timing of mobility transformations, missed investment opportunities, and firm insolvency filings (Mauler et al., 2021). Signalling high inconsistencies within the literature itself.

A lithium-ion battery pack's cost has decreased by over 90% over the past ten years, from over 1000 $/kWh in 2010 to 156 $/kWh towards the end of 2019, suggesting a learning curve. During the same time period, a lithium-ion battery cell's specific energy increased from 140 Wh/kg to 240 Wh/kg, nearly doubling. Engineering advancements, the use of materials with higher capacities and voltages, and the development of techniques to boost stability for longer life and improved safety are the main causes of the improvement in performance and cost (Muratori et al., 2021). Performance and cost improvements are also aided by advancements in cell, module, and pack design.

By using a framework to an initial set of more than 2000 research linked to battery cost, the study done by Mauler et al. (2021), seeks to fill this gap and identify 53 pertinent publications with original battery cost or price estimates from peer-reviewed literature. Figure 24 summarizes the findings of publications that were analysed and used technical learning to produce time-specific battery cost projections. Pack-level pricing observations that are representative of the industry average are also included and are shown as a histogram for comparison.

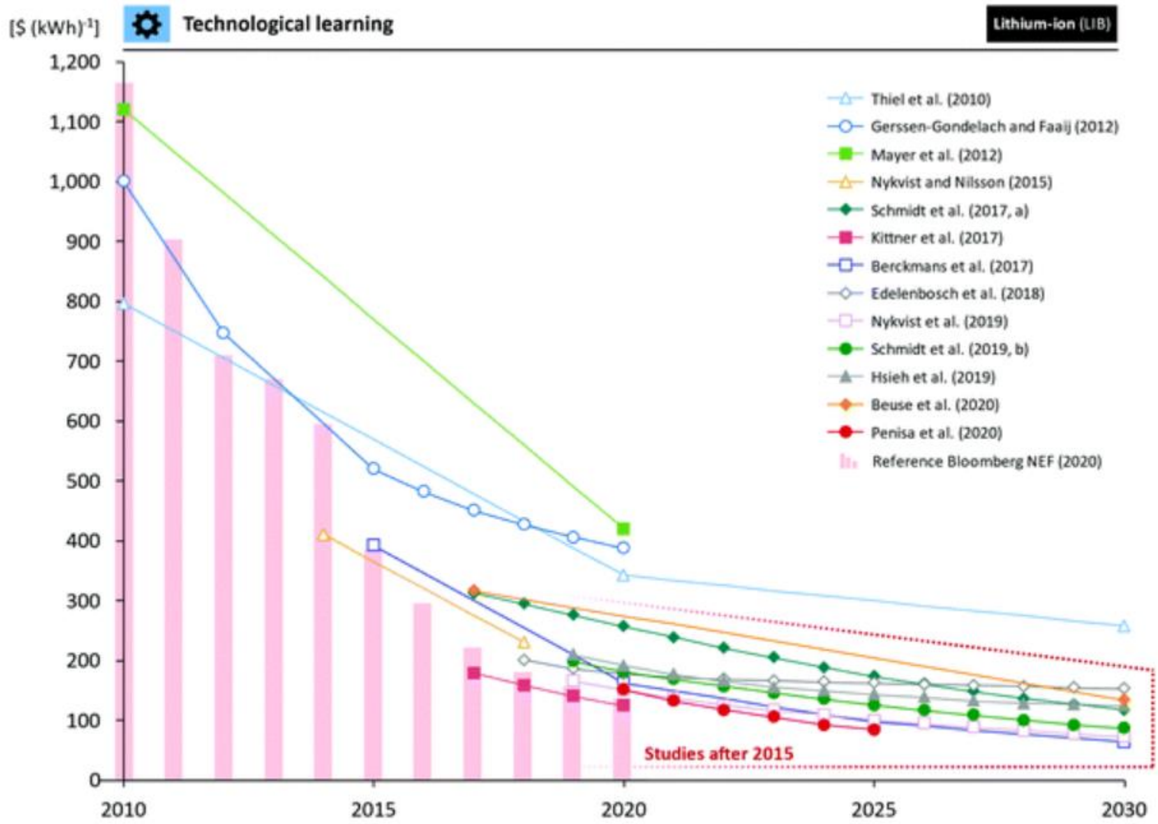


Figure 24 Forecasted values of studies applying technological learning methods to derive time-specific estimates (Mauler et al., 2021).

A large absolute drop can be seen, notably in the first half of the decade, from 1160 $/kWh in 2010 to 384 $/kWh in 2015, when examining the empirical price history from 2010 to 2020. This decrease can be attributed to high costs during the early stages of the expansion of EV sales, which were marked by low production quantities, significant pack volatility, and inexperienced pack production procedures that facilitated quick learning. More gradual absolute decreases are shown in the second half of the decade, and they peak in 2020 at 137 $/kWh. All studies anticipate a decrease in LIB cost, just with the growth of industry data. Average estimates for individual studies range from 1120 $/kWh for 2010 to 63 $/kWh for 2030. Most estimates through 2020 are higher than actual price observations compared to the industry average, and there are significant differences between research and publication dates in anticipated levels and developments (Mauler et al., 2021). These differences can be explained by variations in methodological approaches and particular assumptions.

Moreover, on Figure 24, it is possible to see that based on the literature there are various forecasts about what the price of batteries will be. Also, not only within the literature itself, but also with the actual reference values represented as pink columns, shows great variability to the actual price. This situation shows a need for a way that stabilises the cost predictions of the battery.

Across all studies, at least one type of battery output, capacity, or sales volume is designated as a learning element. The authors base their time-specific projections on "experience," such as cumulative battery production, cumulative battery sales, or cumulative installed battery capacity, and "economies of scale," such as annual battery production (Mauler et al., 2021). For the sake of simplicity, these collectively will be referred to as "the battery market."

The choice of three factors has a considerable impact on each anticipated value, regardless of the particular learning component. First, the time series' starting point, which has an impact on the precision of later estimates. Second, the learning rate, which is also known as the experience rate when it comes to prices and denotes the anticipated item's rate of decline for each doubling of the learning component. Third, the anticipated rate of learning factor growth reflects the rate of development over the forecasting period and enables conversion to a chronological scale (Mauler et al., 2021). These show how they have an impact on the predicted cost value.

After analysing the literature about how forecasts regarding the cost of batteries are done. I have checked empirical data to come up with my own learning curve model. In this model, based on the historical prices I have got from Bloomberg's (Frith, 2021) data about EV battery price, I have plotted against time for the price for two different units for €/kg and €/kWh. The reason for investigating in two different units is that unlike the previous two components, the cost of battery is expressed as €/kWh since the energy density varies depending on the model. Hence, I have checked the data for this unit. Moreover, since for the rest of the two materials I have checked in €/kg and everything is on the weight basis, I have also included that unit as well in the study. In order to do the conversion, the energy density of the battery is considered. It is found that an average battery has 265 Wh/kg energy density, which suggests from the values obtained from Bloomberg's report (Frith, 2021) were first converted to €/kWh values and then based on the energy density rate, the obtained data is multiplied with 0.265. The cost decline curve of the battery can be seen in Figure 25.

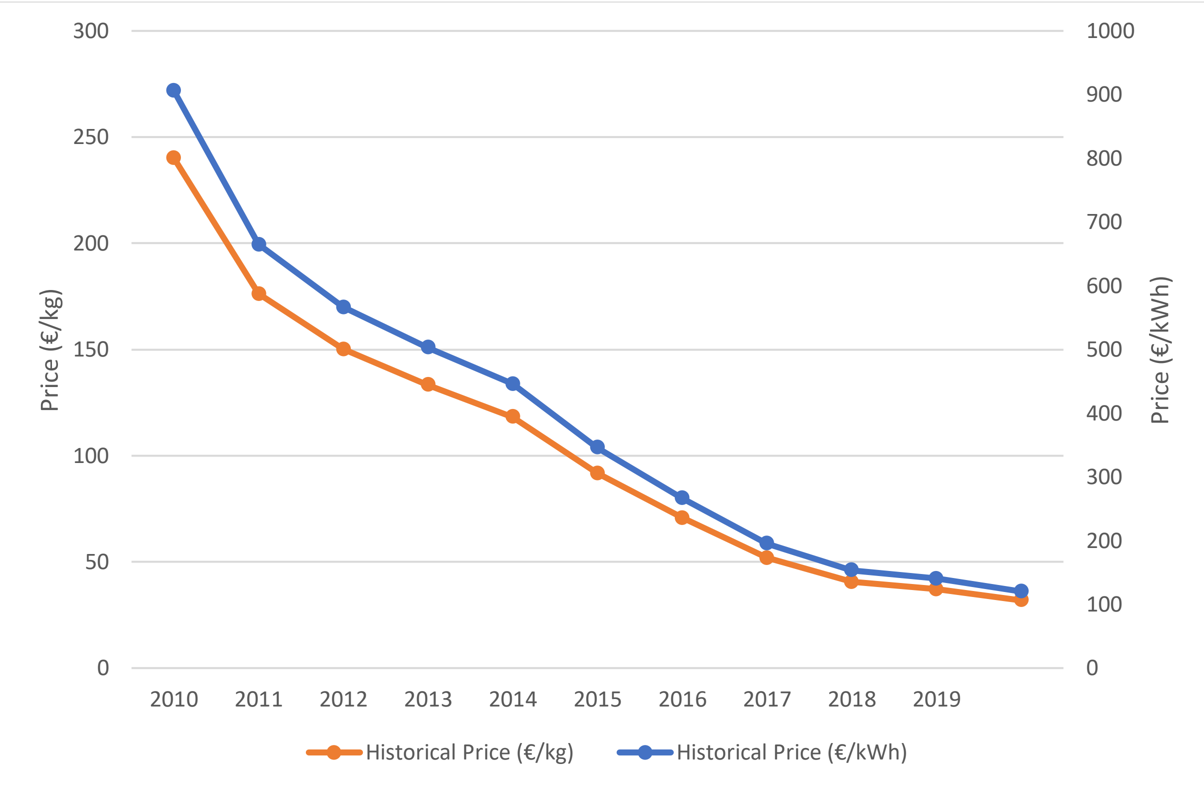


Figure 25 Historical price of battery. Adapted from Frith (2021).

It is clear to see a decline in the price, corresponding to an experience curve. By using the prices in Figure 25 and Penisa et al. (2020)'s study on the price decline of lithium-ion batteries for electric vehicles, a learning curve model was implemented for battery prices. A learning curve of 24.5 % is found for the price of the battery, with the learning components of cumulative battery production. This result suggests that the battery price per kilogram weight, considering the energy density of the battery will remain the same in the future, will be 20.3 €/kg in 2030 and 12.5 €/kg in 2050. The results agree with Penisa et al.'s article (2020) that states the price of battery packs will be below 110 €/kWh in 2024, with the demand for Li-ion NMC batteries to increase by 33% each year. The predicted prices using the learning curve model with the historical prices can be seen in Figure 26.

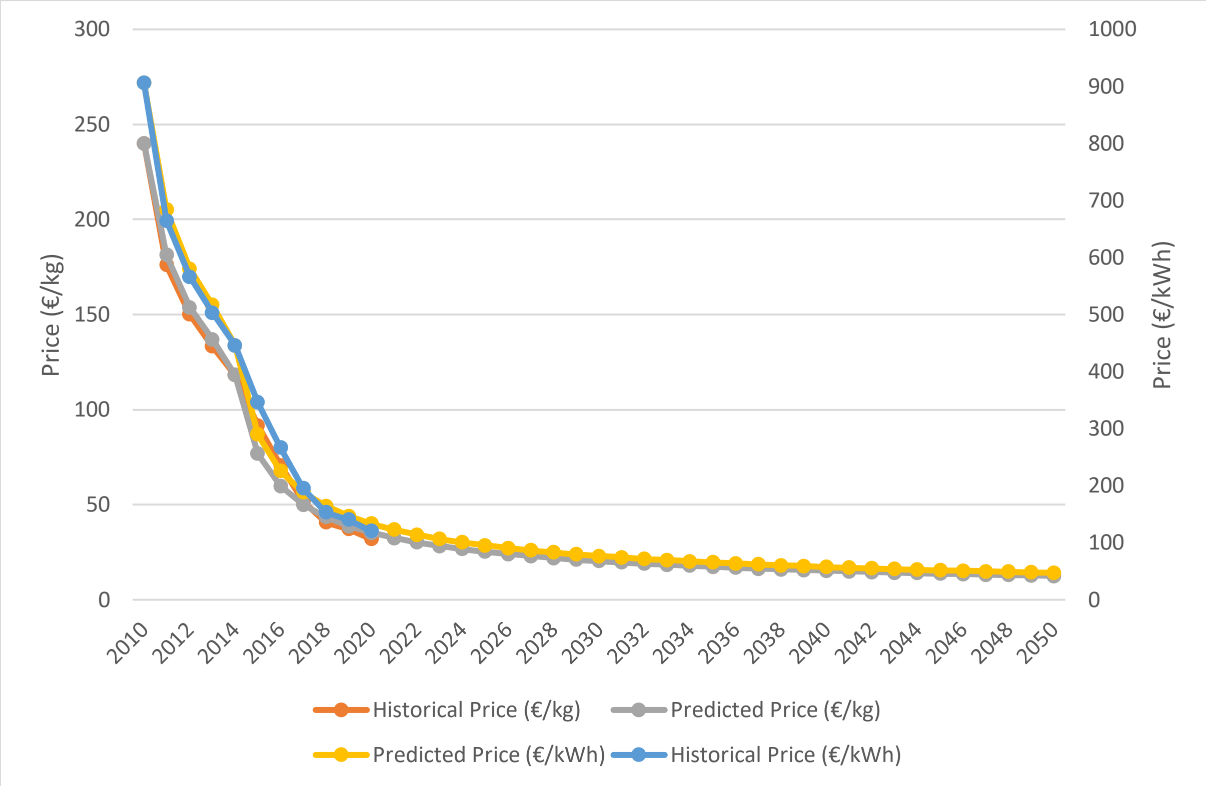


Figure 26 Predicted prices for the battery.

In the Figure 26, both historical and predicted prices are represented in weight and power terms. In both, there is a mismatch in the predicted price and historical price of the battery between 2014 and 2016. The reason for that is the costs have halved between 2014 and 2018, however based on the previous years' decrease the predicted learning curve model shows a steeper decrease in the cost creating a disparity.

By looking at the empirical data obtained and previous studies, a large drop on the prices of the battery can be seen when the data from 2010 to 2020 is considered, especially in the first half of the decade from 1160 $/kWh in 2010 to 384 $/kWh in 2015. This decrease can be attributed to high costs during the early stages of the expansion of EV sales, which were marked by low production quantities, significant pack volatility, and inexperienced pack production procedures that facilitated quick learning (Mauler et al., 2021). A more gradual absolute decrease is shown in the second half of the decade.

Moreover, based on the study done by Mauler et al. (2021) with 237 data points representing the anticipated time-specific price of battery estimations, the majority of predicted values are higher than market observations when compared to empirical data that is available for the period from 2010 to 2020. While the anticipated values for the period between 2010 and 2014 are similar to or lower than the empirical findings, the estimated values for the period between 2015 and 2020 are 90% more gloomy than the observed prices.

Cost reductions are greatly aided by increases in manufacturing volume brought on by the sales of EVs (Muratori et al., 2021). However, for EVs to achieve purchase-price parity with ICEVs, further battery cost reductions are required. According to the U.S. Department of Energy (DOE), this parity may be reached for less than $100 per kWh of battery, ideally under $80. At that moment, EVs should outperform ICEVs in terms of both initial cost and lifetime running costs. Such financial advantages will probably result in sharp rises in EV sales.

The capacity of materials like Si anodes has improved, the percentage of active material components has increased, lower-cost elements are used, packaging has improved, and automation has continued to increase yield while extending the electric range, all of which are expected to result in lower battery prices in the future. However, price rises for several metals, including Ni and Li, may make it impossible to meet the lower-battery cost forecasts (Muratori et al., 2021). Hence, it ends up with the availability of the critical raw materials.

The future demand for important battery materials is estimated by taking into account prospective changes in the electric car fleet, battery chemistry, and battery reuse and recycling. It is discovered that in a lithium nickel cobalt manganese oxide battery scenario, demand is predicted to rise by factors of 18–20 for lithium, 17–19 for cobalt, 28–31 for nickel, and 15-20 for most other materials from 2020 to 2050 concerns (Xu et al., 2020). This will likely lead to further resource discovery as well as a significant expansion of the supply chains for lithium, cobalt, and nickel. A variety of raw materials, including some essential ones with uncertain supply, are used in the fabrication of LIBs. Concerns have been raised about the criticality of lithium, cobalt, and natural graphite. The substantial supply risk associated with these elements could result in shortages and price volatility (Rajaeifar et al., 2022). According to Hsieh et al. (2019), due to the materials accounting for an ever-increasing portion of the overall cost of the battery, it seems unlikely that EVs employing lithium-ion NMC batteries would rule the global automobile market by 2030 and beyond unless new battery chemistries are introduced (Rajaeifar et al., 2022). Additionally, rising urbanization where the rise in demand for the more affordable BEVs will increase the share of them in the automotive sector and lead to potential improvements in battery capacity (Edelenbosch et al., 2018). Moroever, in the end the main determinant for the battery costs will be about the money invested in the technological advancement and large-scale industrial production (Statharas et al., 2019). Moreover, understanding the potential hazards in their supply chains may also be aided by studying the supply and demand forecasts for EV LIB materials.

Overall, there is an undeniable decrease in the costs of the battery over the years. It is expected that the decline will continue in the following years while the rate will be diminished due to several factors. The main reason for the trend of decrease being lowered is the manufacturing technology of the battery will become more mature as the demand will increase, making the learning rate smaller. Moreover, the availability of critical raw materials will decrease and there will be a need to find other ways to produce the battery. Whatever the trend will be in the price of the battery, it is certain that it will be one of the main driving factors of the cost of an electric vehicle.

4.3. Future Vehicle Prices

In the previous sections, the costs of the main materials compromising the electrical vehicle are investigated. The investigation is done to understand the price volatility and trends of materials and their cost components. Via this analysis, it is shown that for the price of steel and PP, the cost drivers are their cost components. On the other hand, for the battery price, its cost components are not as crucial as the learning rate of manufacturing the battery itself. In the end, the main aim of this study was to find the future prices of the EV considering its materials with decreased uncertainty.

Based on the goal, firstly the volatility of steel and PP are analysed. This analysis is done by using SPSS software to understand the compatibility of the cost curves of the materials and their cost components. Since there were no apparent rapport, another method is utilised. With this method, the cost curves were decomposed into trend and seasonality components. Via using linear regression to check the coherence within the trend and seasonality components of steel and PP with their cost components, it is found that steel's trend is determined by its cost components with an R-square of 0.9834. Similarly, for PP the trend component is explained by its cost components. After understanding the volatility components, future prices for those materials are predicted using Monte Carlo simulation. Moreover, for battery, based on the cost curve, it is realised that it has a learning curve. Hence, that method is used for the prediction of prices. In Table 18, these results can be seen.

Based on this table, it is possible to see that the price of steel and PP will remain stable for 2030 and 2050. Moreover, due to the learning curve, battery's price will have a 40 % decline to 12.5 €/kg compared to 2050.

Table 18 Predicted prices (€/kg) of the materials.

Material	2030	2050
Steel	0.6	0.6
PP	1.2	1.2
Battery	20.3	12.5

After gathering the predicted prices, in order to find the total material cost of the EV, I have used the Bill of Materials provided by TNO in Section 4.1 to multiply the prices of the selected three materials with their weight to come up with the expected total EV cost in 2030 and 2050. In Table 19, the current price of EV and the expected future prices can be seen.

Table 19 EV costs for 2023, 2030, and 2050.

	2023	2030	2050
Total EV Cost	**23,800 €**	**14,700 €**	**9,670 €**
Battery	22,300	13,200	8,100
Brake rotor material	69.60	69.60	69.60
Cable	15.00	15.00	15.00
Cast iron	0.01	0.01	0.01
Copper	32.70	32.70	32.70
Glass	40.10	40.10	40.10
Inverter material	100.00	100.00	100.00
PP	82.80	121.00	121.00
Steel	407.00	407.00	407.00
Tire material	18.40	18.40	18.40
Traction motor material	608.00	608.00	608.00
Others	168.00	168.00	168.00

Table 19 is constructed based on the assumption that the price of the materials except for steel, PP, and the battery will remain same or change so little that it could be disregarded. This assumption is based on the cost percentage graph shown in Section 4.1, where the majority of the cost of an EV is due to the battery cost. Based on the results, it is clear that similar to the current situation the price of the EV will mostly be determined by the price changes in the battery in the future as well.

The decrease in the manufacturing cost of EVs will result in a lower purchase price. Similar to the findings from the empirical research, literature backs this claim by stating that with the battery cost reductions, $89/kWh in 2025 and $56/kWh in 2030, it will advance the cost compatibility of the EVs compared to the conventional fuel cell cars (Lutsey and Nicholas, 2019). Moreover, based on the results, it is found that batteries have the greatest financial impact at the component level for the cost of the EV. It could be stated that regardless of the price change in steel and PP, batteries will continue to be the leading cost components of EVs (Grube et al., 2021).

The deployment of EVs turns out to be very sensitive to the anticipated costs of batteries, where the production cost will determine the market viability of electric vehicles. It is found that the floor cost of the battery is more significant than the rate of cost drop since the expected ultimate cost will determine how cheap EVs can get (Edelenbosch et al., 2018). Hence, it is clear that although there are other parts contributing to the cost of EVs, the main cost component is the batteries and they will continue to play an important role for the material cost of EVs in the future as well.

Overall, it is clear that EV's will have a great part in the automotive industry in the future and it is important to understand how future developments will affect the material cost of EVs. Via analysing the findings, it is probable that the main cost driver of EV will be the cost of the batteries and especially how fast or slow learning rate occurs in them.

This chapter aimed to understand the current situation in the pricing of electric vehicles. This is done by firstly checking the bill of materials to figure out the materials of EV. Then, with the selected materials that contributed to more than 80% of cost and battery, their price volatility is investigated using various techniques. Based on the analysis, it is understood that the main drives of cost variability in materials are due to their cost components. Afterwards, future price values of the materials are determined to compose the future electric vehicle material cost. In this chapter, sub-questions are answered by empirical data research via utilising the methods mentioned in the previous chapter. Next chapter will include conclusions, recommendations, and future work to merge all the work done throughout this study.

5. Conclusion, Discussion, and Further Work

In the previous chapter, the materials of the EV is investigated to understand their price volatility components and how those affect the cost uncertainty of the electric vehicle. Moreover, the future cost estimations are also done and a forecasted EV price is found. The aim of this chapter is to provide an overview of the answer to the main research question and summarise the key findings from the previous chapters, along with a discussion and further work.

5.1. Conclusion

The aim of this study was to gain a thorough understanding of the price volatility of electric vehicles and its impact on the LCC assessment of them. The research focuses on understanding the causes of price volatility in electric vehicles and how does that uncertainty be translated into the prospective costs of it.

The research aims to answer the following main research question:

"How do the price volatility and uncertainty in the cost forecasts affect the life cycle cost analysis of electrical vehicles?"

In which two sub-questions are formulated:

1. Can the cause of price volatility and uncertainty in the cost forecasts of EVs be found?
2. Can those causes be included in the LCC of it?

The purpose of framing the first sub-question in this way is that this study attempts to provide a comprehensive picture of the concept of EV price volatility and to identify the causes of this uncertainty in the first place, which can be used as a basis for the second sub-question. The first sub-question can be further divided into two parts. The first part examines price volatility at the material level, which is examined for the materials that affect the EV, and then examines price volatility for the cost components of the materials. To answer the first sub-question, a material analysis is carried out. In this analysis, three main materials that represent 80% of the cost and weight of EVs are selected as the main causes of EV price volatility. The selected materials are steel, PP and battery. It is found that the cost curves of steel and PP are mostly dependent on their cost components, which are found to be iron ore, coal, coke for steel and natural gas, and crude oil for PP. The assessment is made through decomposition analysis and regression.

As discussed in the previous section, the first sub-question provides the basis for the second. The main objective of the second sub-question is to gather information on how the price volatility found in the first sub-question can be used in estimating the future costs of electric vehicles. To formulate an answer to this question, the projected cost values of the selected materials are determined using Monte Carlo analysis and learning curves. After determining the expected cost of the materials, the expected cost of EVs for 2030 and 2050 is determined.

Based on the results found, it can be concluded that the price of PP and steel will remain same for 2030 and 2050. The PP cost will be 1.2 €/kg and the steel cost will be 0.6 €/kg. The reasons for the stable trend for both of them are similar. Firstly, based on the different scenarios for the cost components only the range of the minimum and maximum price values change, not the most probable value because none of the cost components can be the singular identifier of the cost of the main material. However, this situation does not hinder the explanation of volatility of their prices. For PP, the price uncertainty is mostly explained by the trend of its cost components. Specifically, the essential cost component that determines the price trend of PP is crude oil. This anticipated result is due to the nature of PP and crude oil where PP is manufactured from crude oil. Hence, it is the main determinant.

Similarly to PP, steel's price curve is also dictated by the price trends of its cost components, especially the iron ore. On top of that, coal also has a high influence on the uncertainty of the price of steel. Another aspect that in PP did not found is that the seasonality also has a high influence on the price of steel. Especially the seasonal component of iron ore follows a similar pattern to the steel. In this analysis, the least effective cost component is found to be coke for steel and for PP, since PP is made from crude oil, it had a bit more influence on the price volatility of PP than natural gas.

On the other hand, for the cost of battery, a completely different approach is implemented. Due to the novel nature of the manufacturing technology of battery, learning curve model is used. With this approach, a learning curve of rate 24.5 % is found for the price of the battery with the learning component of cumulative battery production. This model suggests that in 2030 the price of the battery will be 76.70 €/kWh and in 2050 it will be 47.30 €/kWh. The results show a significant decrease in the price of the battery.

Based on these results, the prospective cost of the EV for the years 2030 and 2050 is calculated. The total material cost of an electrical vehicle in 2030 is expected to be 14,700 € and in 2050 it will decrease to 9,670 €. To conclude, it is found that the main cause of price change in the EV is due to the steep price decline of the battery.

5.2. Discussion and Recommendations

This section aims to discuss about the reliability of the study and potential bias that occurred during the research. Moreover, it will end with recommendations regarding how to interpret the results based on varied stakeholders and the policy implications.

To start with, the potential for bias should also be identified. Firstly, in selecting the cost data for the materials, there may be a sample selection bias, as most of the available resources are from organisations in the US. It should be noted that since US data were selected, the cost trends may differ from the European costs of the materials. However, in both cases, most materials are either sourced from China or manufactured domestically. The cost of domestic production is more or less the same for the US and the EU, as both use similar technologies. Import costs vary from country to country. To overcome this distortion, material costs are mostly given in index terms, which are then converted into their euro equivalent. In addition, to eliminate measurement bias in currency translation, daily USD to EUR values are checked and converted, rather than taking the average of the month and applying it to all values.

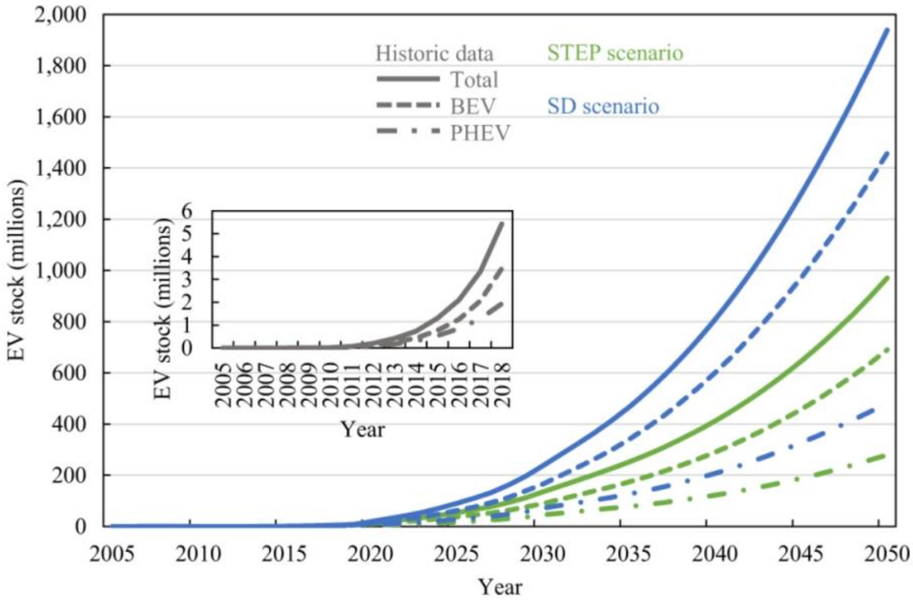
To eliminate confirmation bias and publication bias, I have conducted an extensive literature review, particularly on methods for forecasting prices. I looked at various methods for determining future prices and decided to use Monte Carlo analysis. Similarly, for the future cost of batteries, there were different opinions on what the learning rate should be and whether it was sustainable for the future. To avoid being influenced by other scholar's views, I came up with my learning rate and checked it against the literature.

Another aspect that needs to be discussed is the reliability of this research. Reliability refers to the consistency, stability and dependability of research findings or measurements. It indicates the degree to which the data collection techniques or tools produce consistent results when used frequently under similar circumstances. The results of a reliable study are therefore consistent and unaffected by random error or variation. To ensure the reliability of this study, all costs are calculated in €/kg throughout the study. In addition, established measurement techniques such as decomposition and regression are used to assess price volatility.

The practical value of my research varies depending on the stakeholders. For manufactures, this study will work as a guide to understand what aspects that cause volatility in the materials in the manufacturing process. Also, via assessing possible causes for price volatility, they will better price their vehicles, resulting in less profit losses and more accurate planning.

On the other hand, in a policy perspective, the price volatility in the EV will provide feedback regarding the issues that governments need to consider. For instance, high price volatility in PP or steel will result in a high price volatility in EV, knowing the price forecasts in advance, governments can create policies according to when the prices will be high to keep up with the cost parity of electric vehicles compared to internal combustion engine cars. A high-intensity policy indicates 3 to 5 percentage points greater proportions of EVs. As a hedging measure in case the policy aims to electrify car mobility, it is therefore worthwhile to intensify policies for infrastructure and standards given the uncertainties surrounding future battery costs (Statharas et al., 2019). Norway, for instance, offers incentives to lower the price of electric vehicles relative to conventional automobiles. As a result, sales of new all-electric vehicles grew from almost zero in 2012 to 30% in 2018 (Lutsey and Nicholas, 2019). The relative advancement in Norway emphasizes the value of incentives. Policies can promote or compel the development of additional electric vehicles. A combination of direct and indirect policy decisions affects the rate of the market penetration of electric cars as well as the price of batteries (Statharas et al., 2019).

By 2050, the European Commission (EC) has established challenging goals for the reduction of CO_2 emissions in the transportation sector. In this context, the majority of decarbonization scenarios for transportation predict that between 2030 and 2050, electric vehicles will have a significant market share (Statharas et al., 2019). The scenarios that are based on two IEA projections for the global automotive sector can be seen in Figure 27.



BEV battery electric vehicle, PHEV plug-in hybrid electric vehicle, STEP scenario the Stated Policies scenario, SD scenario Sustainable Development scenario.

Figure 27 EV stock compared to STEP and SD scenario (Xu et al., 2020).

The first scenario is Stated Policies (STEP) scenario that includes current government policies and the second scenario is called the Sustainable Development (SD) scenario which is in line with the Paris Agreement's climate goals and includes the goal of reaching a 30% global market share for EVs. These scenarios predict that by 2030, EVs, of which 89-166 million battery electric cars (BEVs) and 46-71 million plug-in hybrid electric vehicles (PHEVs), will account for 8-14% of the entire light-duty vehicle fleet. By adopting logistic growth curves, these scenarios are prolonged until 2050, when the worldwide fleet penetration of EVs will reach 25% in the STEP scenario and 50% in the SD scenario (Xu et al., 2020). As can be seen from the Figure 27, EV stock is expected to grow and by 2005 it is predicted that at least 1 out of 4 cars will be EV.

Electric car volume, battery costs, and policy all move together. The cost forecasts for electric vehicles in this analysis are based on an ongoing policy that encourages an increase in the volume of electric car batteries. Almost all of the electric vehicles on the planet are found in regions where laws mandate low-emission vehicles, provide incentives totalling thousands of dollars per vehicle, provide infrastructure for charging, and support awareness efforts (Lutsey and Nicholas, 2019). This is largely supported by automaker announcements of plans to significantly increase electric car manufacturing by 2025. Progress would be slowed by obstacles posed by laws and incentives, whereas the timeframe for cost parity would be accelerated by a stronger regulatory policy in more global marketplaces.

At the end, it is recommended that the empirical cost values should also be supported by governmental policies that give subsidies and incentives to both manufacturers of EVs and the users. Next section will provide information to better explain the limitations and further work that needs to be done.

5.3. Limitations and Further Work

As discussed earlier, only three materials are taken into consideration for this research. However, in reality, there are a lot of materials that constitutes the electrical vehicle. Hence, the research design can be improved by including more materials in the research to expand the causes of price volatility in the LCC of EVs.

In addition, this research only considers the material aspect. To extend the study, other cost items should be investigated. Costs such as labour, overheads and inventory are not considered in this study. Moreover, when calculating future costs, it is assumed that manufacturing technology and government policy will remain the same. However, there is a high probability that manufacturing techniques will change drastically and that there will be more subsidies to support the cost parity of EVs. Therefore, the impact of future changes should be considered to improve the research design.

Additionally, cost systems should not be regarded as only numerical data but rather it is a web of interconnected relations. This woven connection can be explained more by adding supplementary parts such as policy, technological changes, and recycling.

This chapter aimed to conclude the whole research by giving the main conclusions and their implications within different stakeholders. Moreover, it aimed to put a path forward in what else could be done to extend this research.

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APPENDIX

APPENDIX A: Outlier Analysis for Cost Components

Table 20 Outlier analysis for coke.

Date for the Outlier	Value (€/kg)	Reason
1-5-2020	0.0635	Due to the pandemic, the mining operations are halted and the coke from China could not be imported. Hence, there was availability of a lot of coke decreasing it's price. (Procurement Resource, 2023)
1-6-2020	0.0688	
1-7-2020	0.0678	
1-8-2020	0.0661	
1-9-2020	0.0682	

Table 21 Outlier analysis for natural gas.

Date for the Outlier	Value (€/kg)	Reason
1-3-2014	0.2229	Due to the hard winter conditions, there was a spike in the cost (State Utility Forecasting Group, 2018),
1-1-2018	0.2223	New natural gas export capabilities found and there was a growing domestic natural gas consumption (State Utility Forecasting Group, 2018),

APPENDIX B: Decomposition of Cost Components

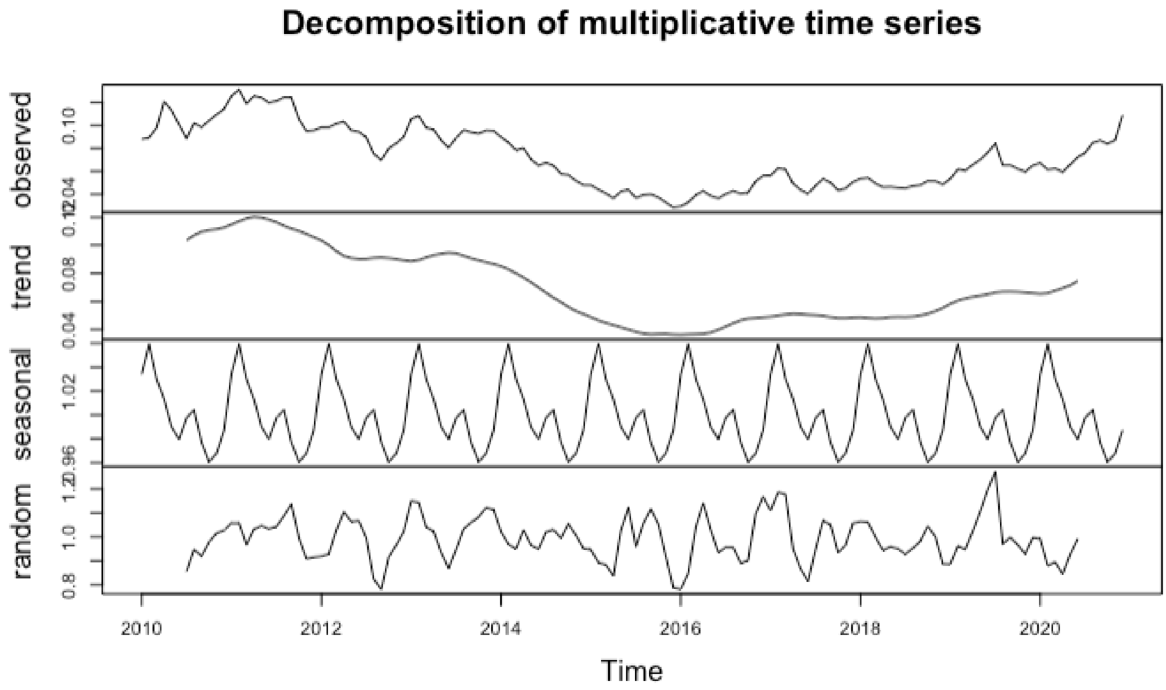

Figure 28 Decomposition of iron ore. Adapted from YCharts (2023a).

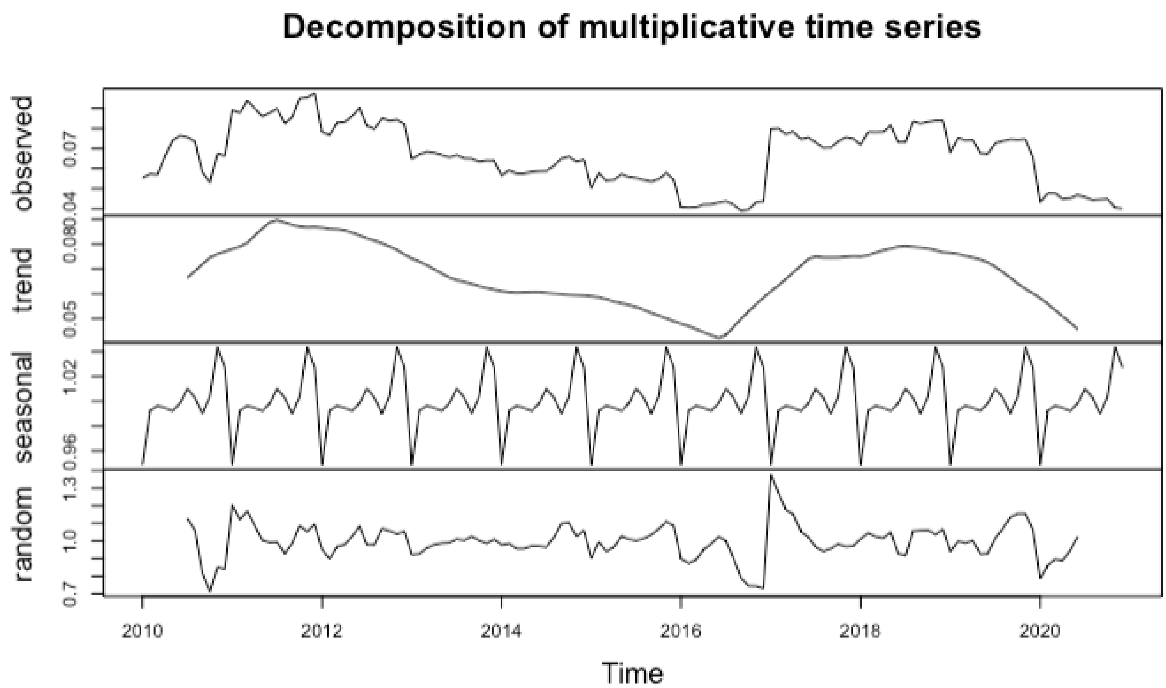

Figure 29 Decomposition of coal. Adapted from Market Insider (2023).

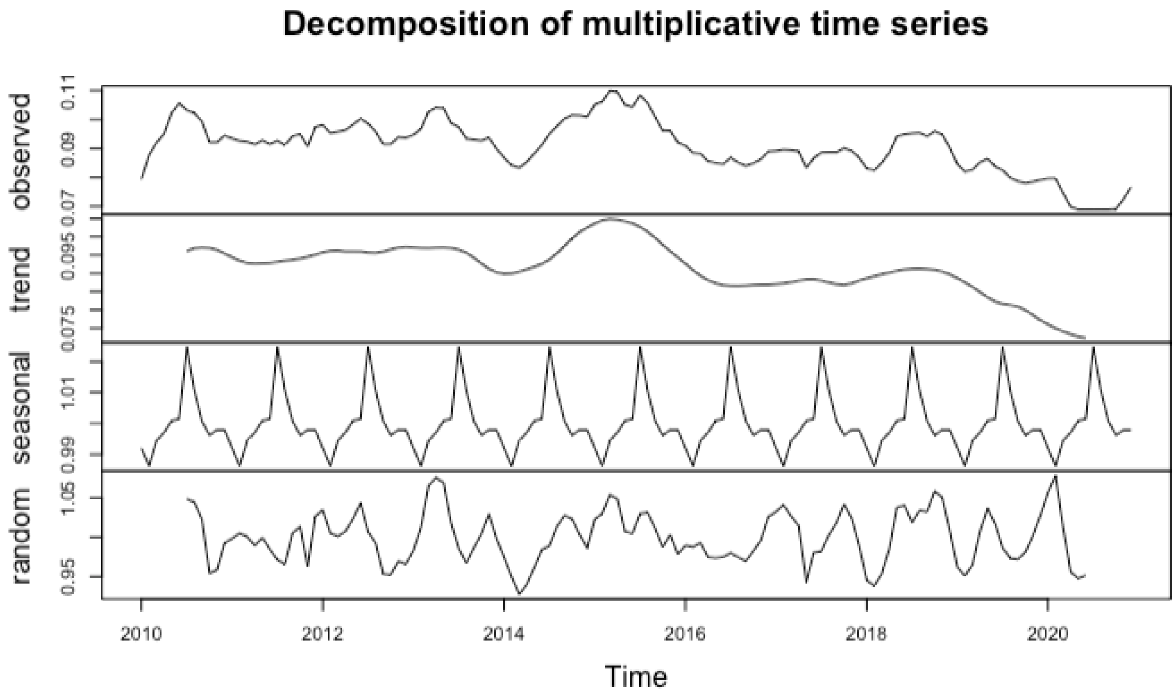

Figure 30 Decomposition of coke.. Adapted from YCharts (2023b)

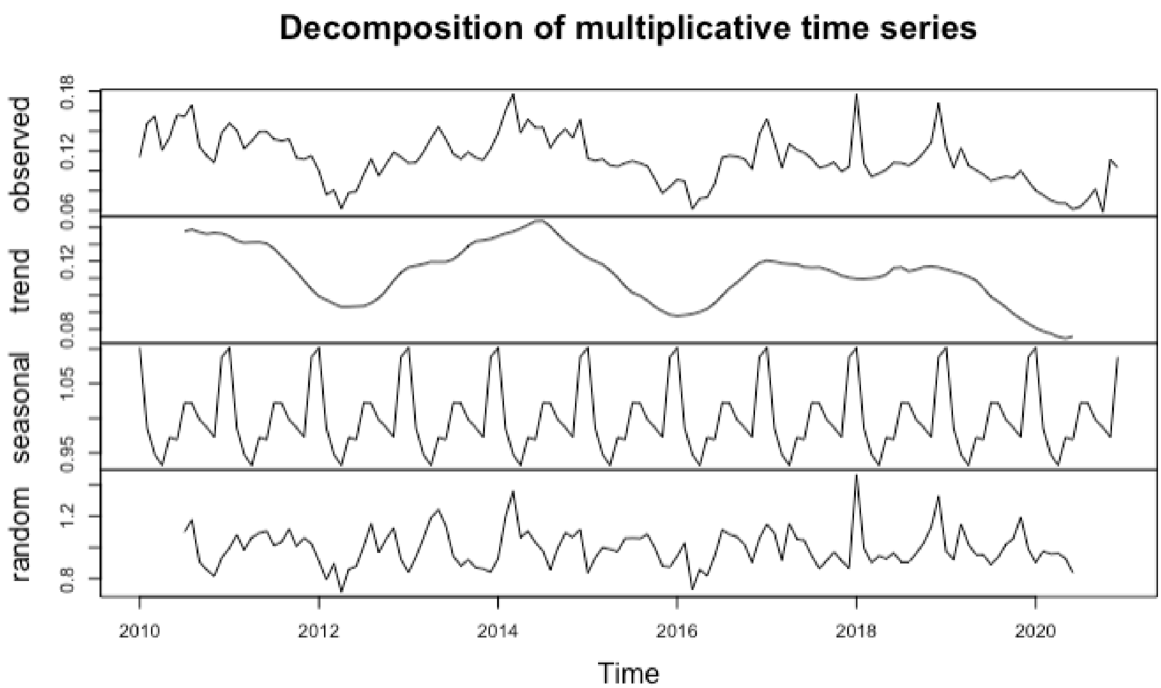

Figure 31 Decomposition of natural gas. Adapted from Macro Trends (2023b).

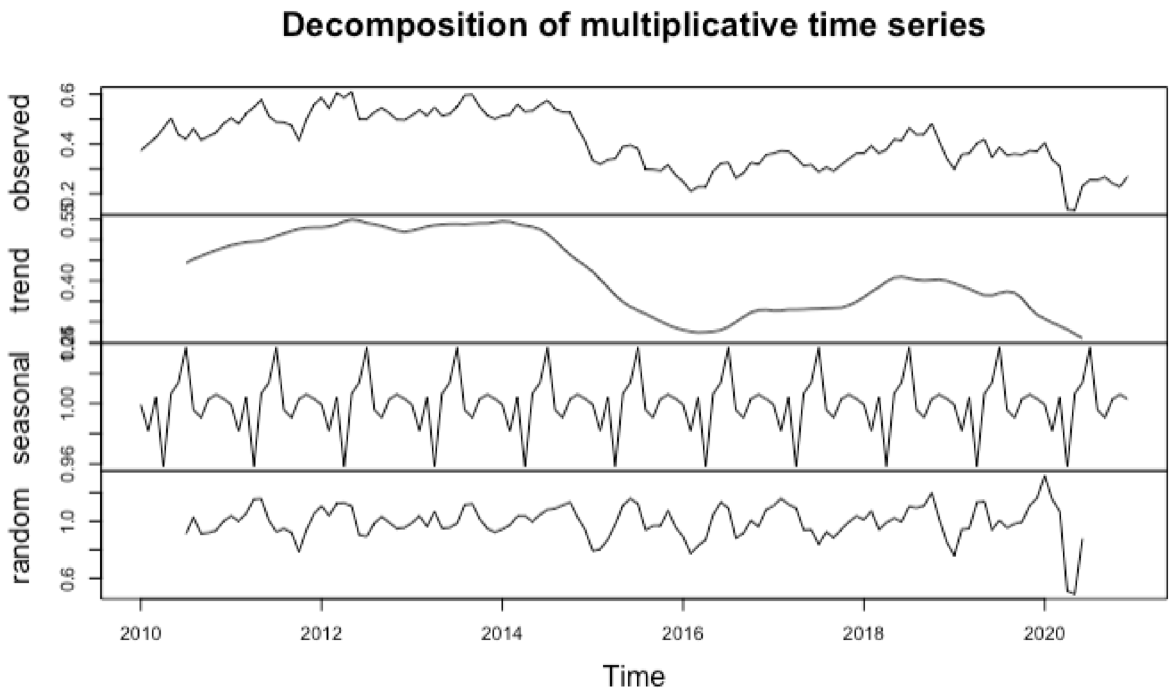

Figure 32 Decomposition of crude oil. Adapted from Macro Trends (2023c).

APPENDIX C: Regression Curves for Materials and Their Cost Components

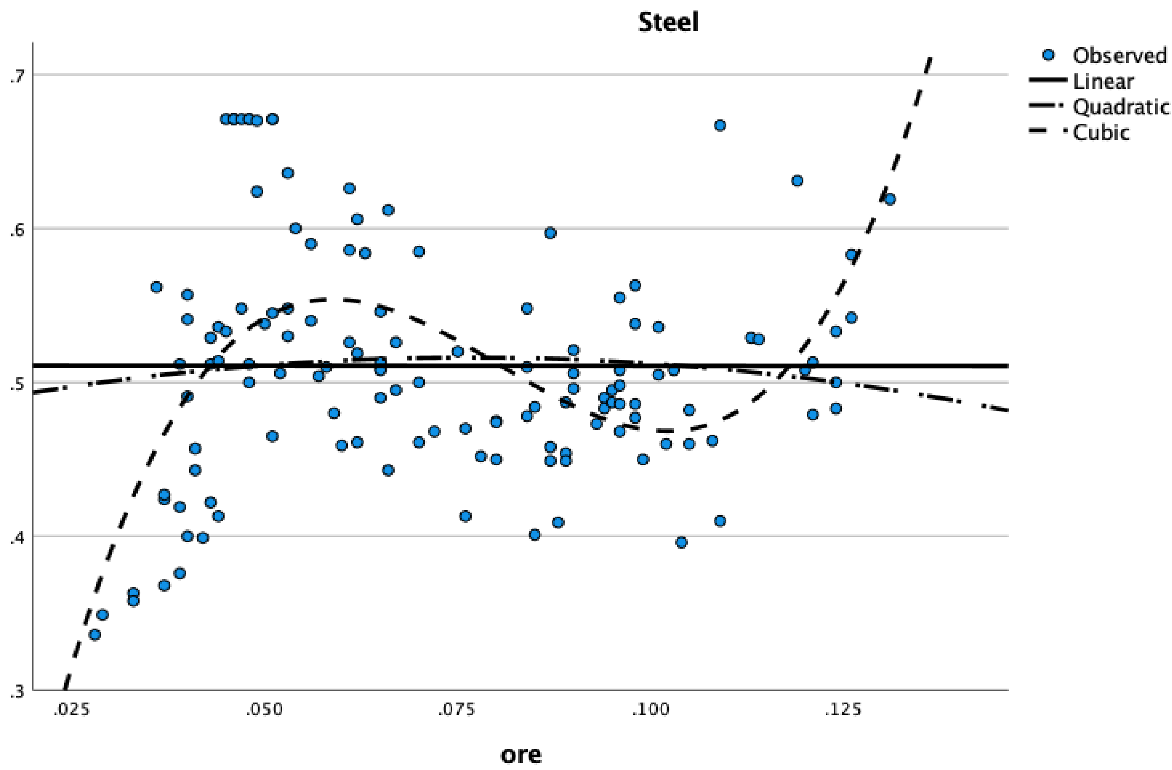

Figure 33 Regression curves for steel and iron ore monthly data set.

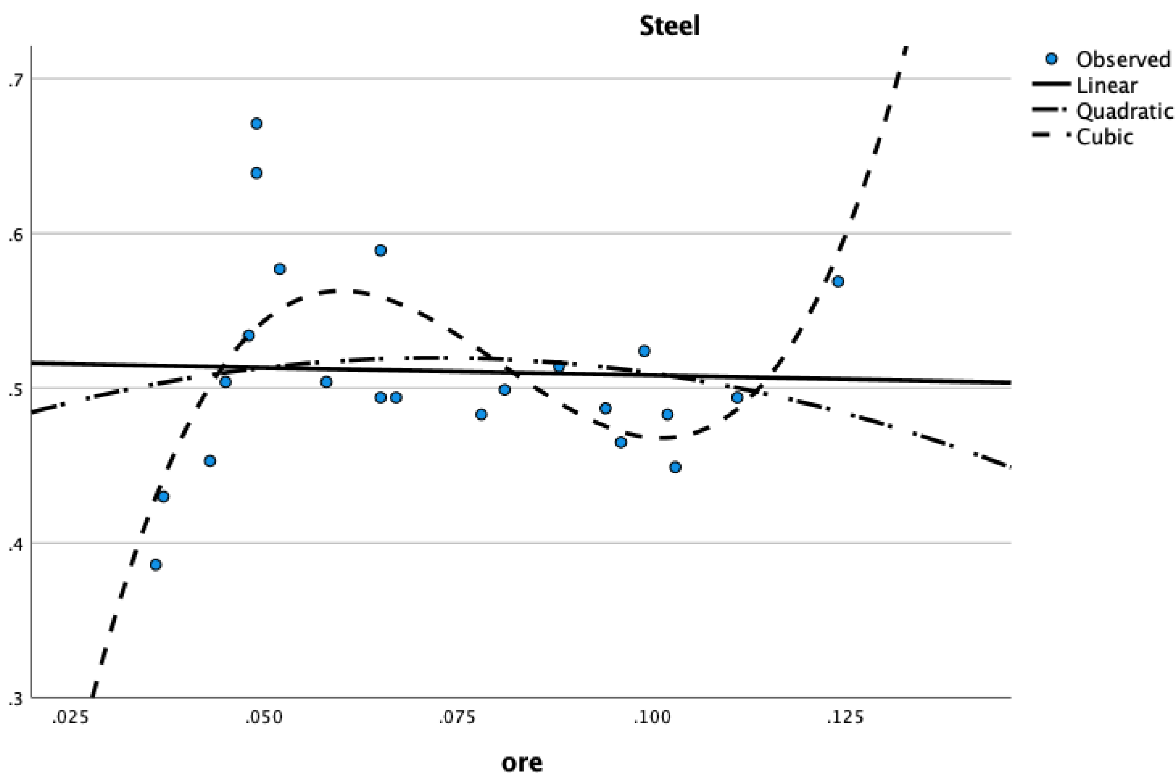

Figure 34 Regression curves for steel and iron ore bi-annually data set.

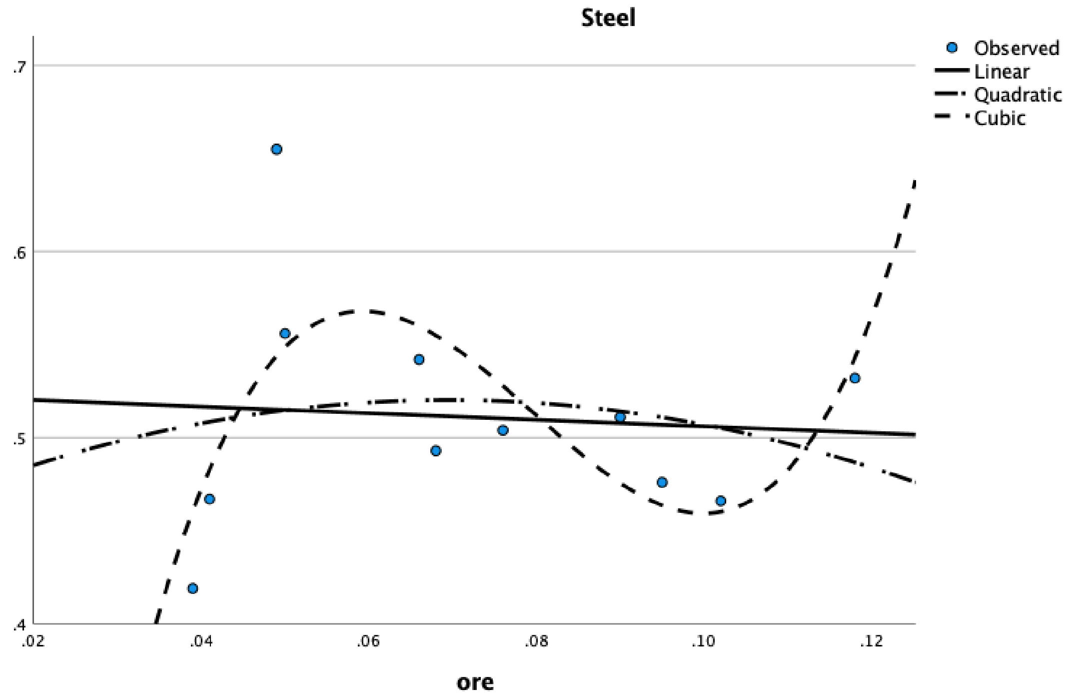

Figure 35 Regression curves for steel and iron ore annually data set.

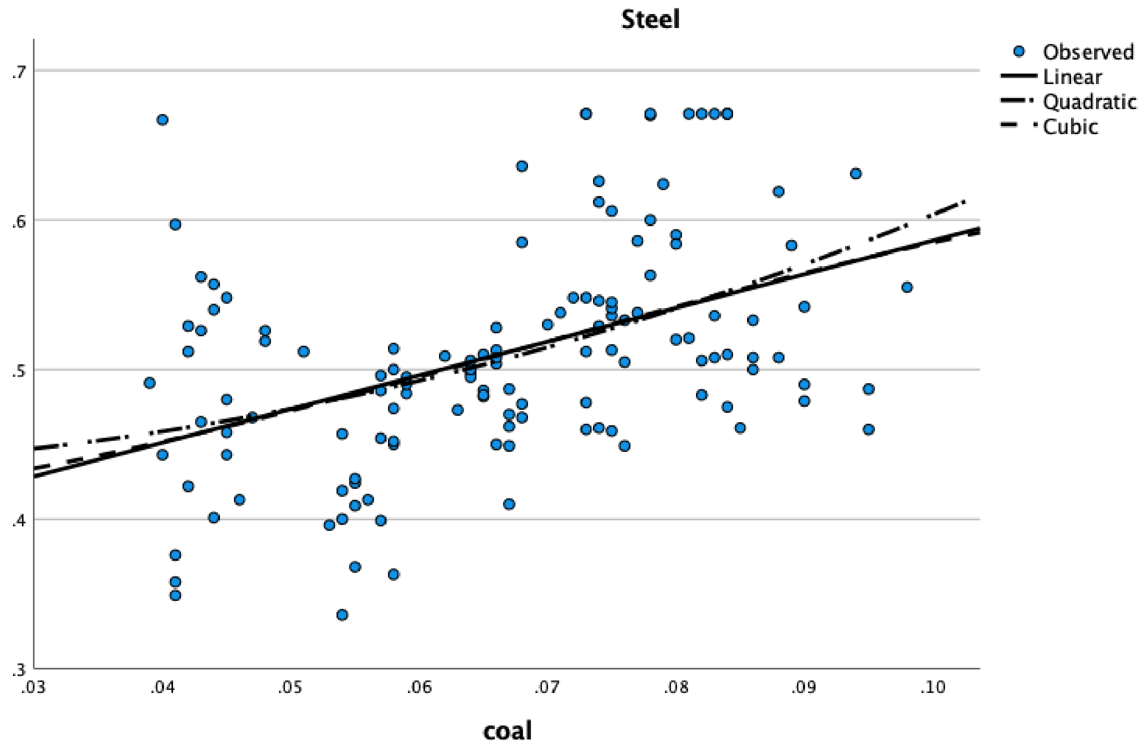

Figure 36 Regression curves for steel and coal monthly data set.

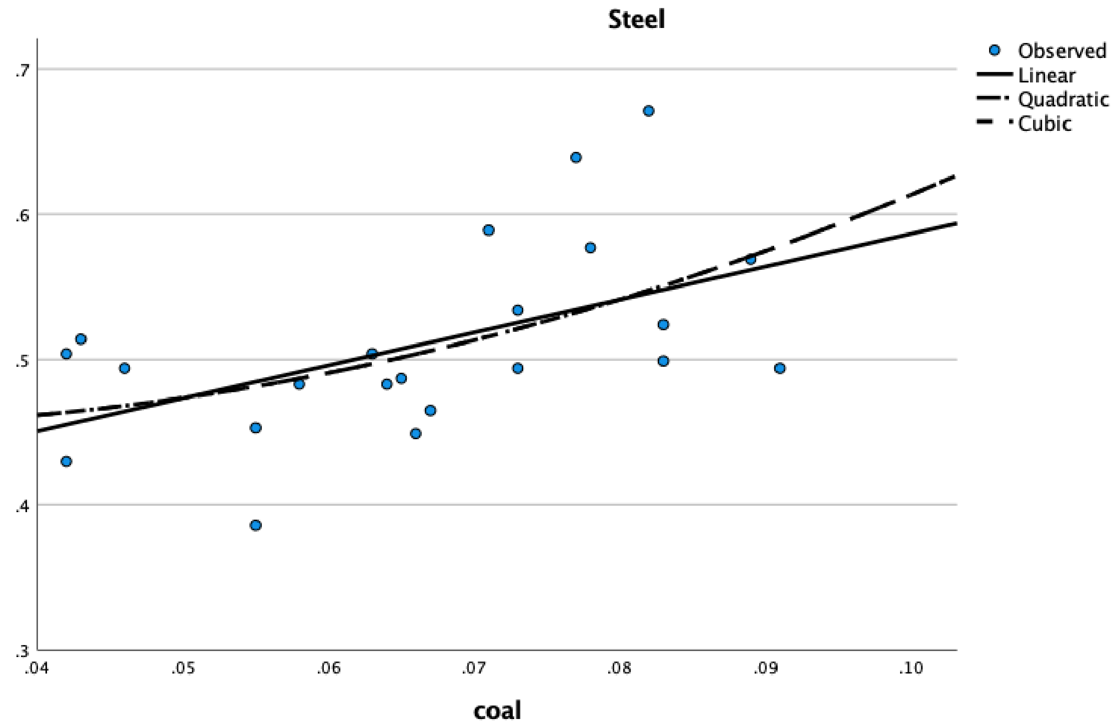

Figure 37 Regression curves for steel and coal bi-annually data set.

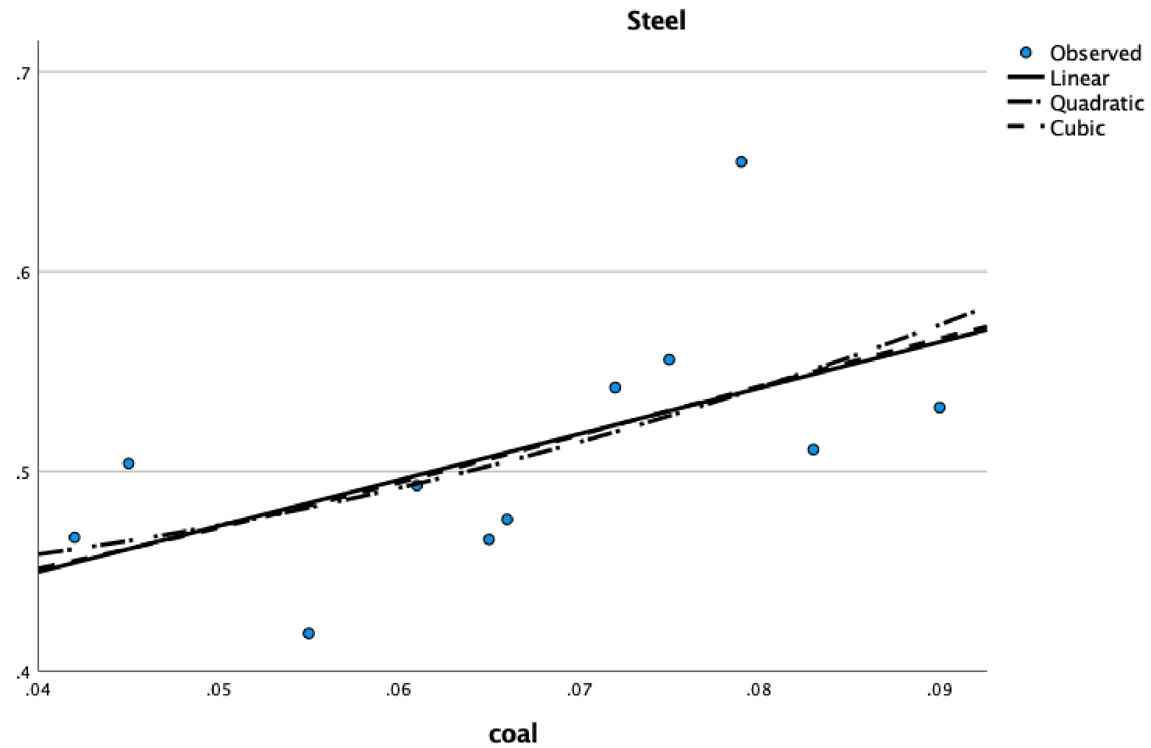

Figure 38 Regression curves for steel and coal annually data set.

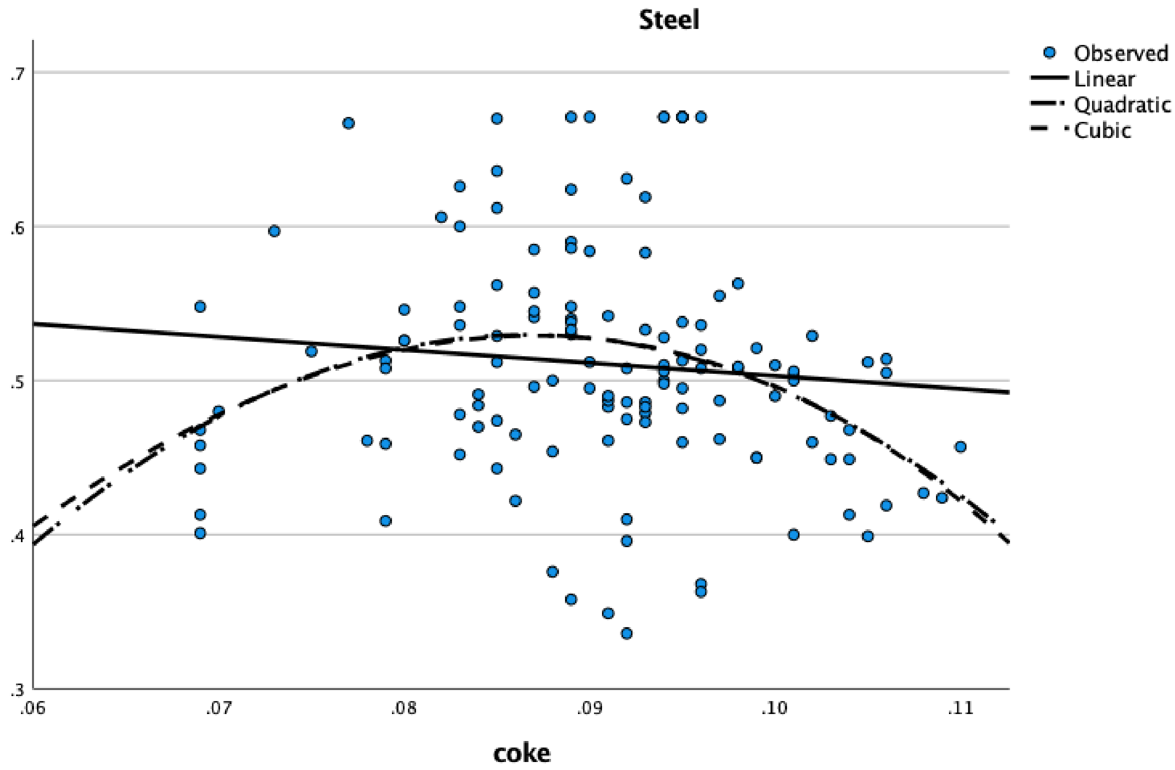

Figure 39 Regression curves for steel and coke monthly data set.

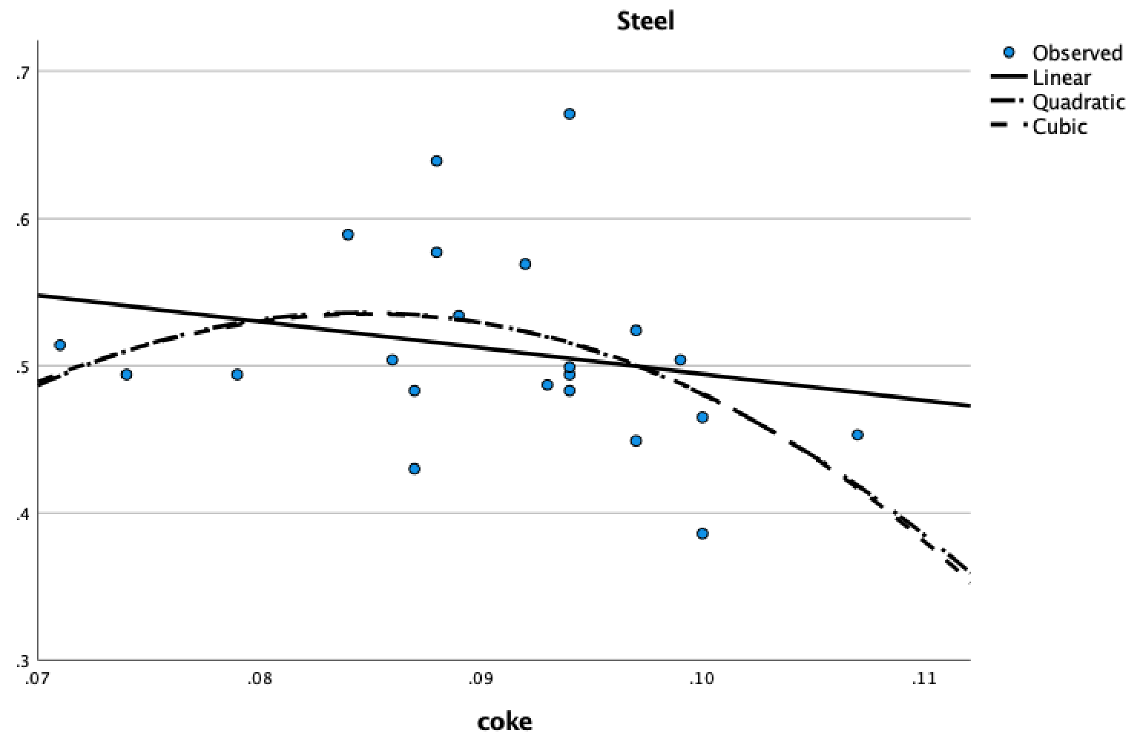

Figure 40 Regression curves for steel and coke bi-annually data set.

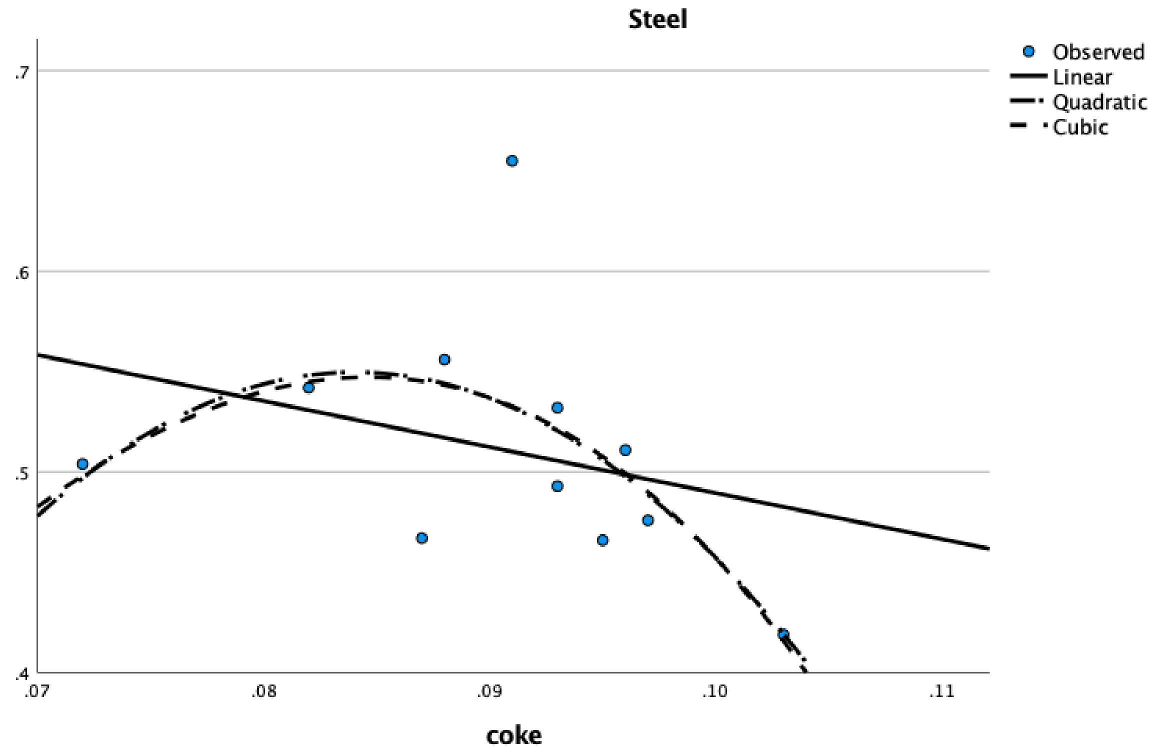

Figure 41 Regression curves for steel and coke annually data set.

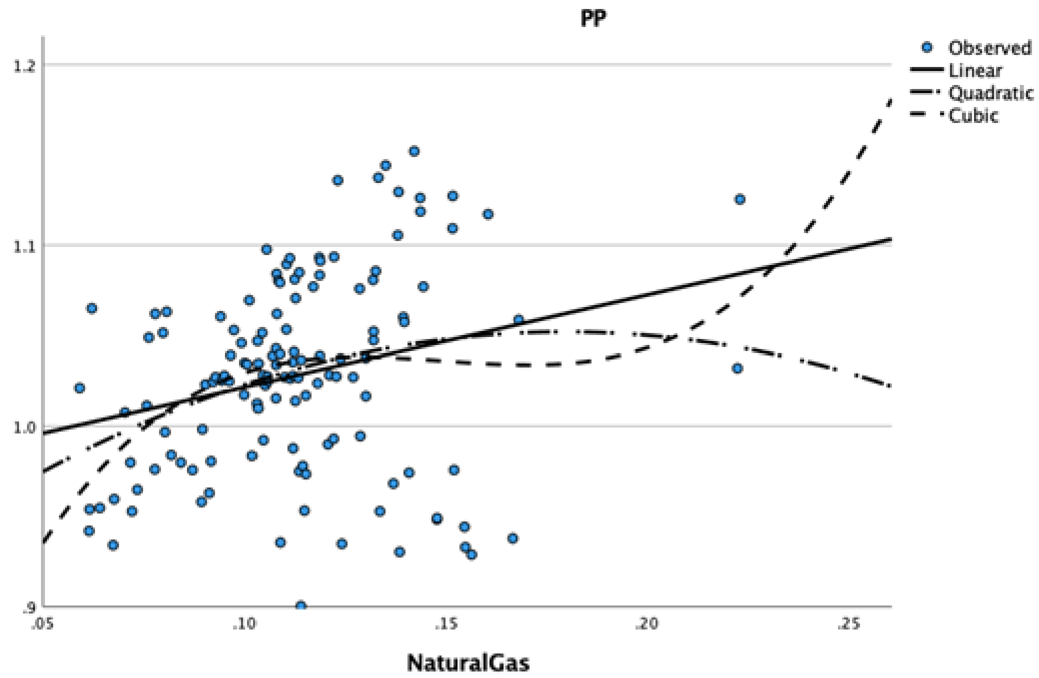

Figure 42 Regression curves for PP and natural gas monthly data set.

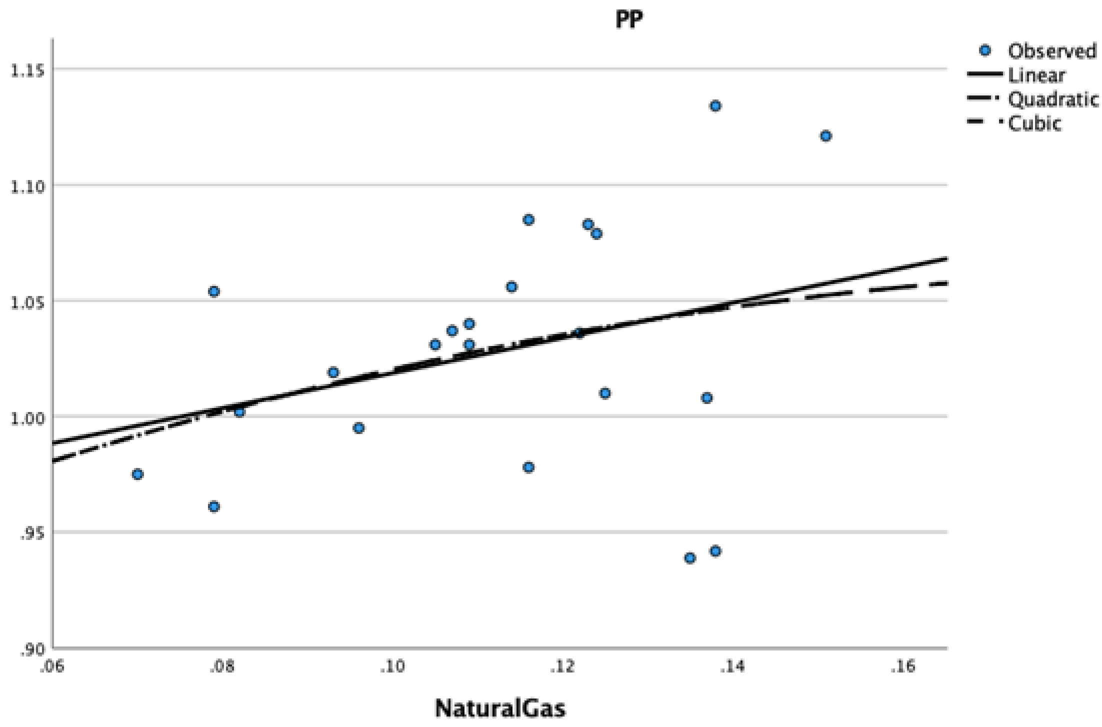

Figure 43 Regression curves for PP and natural gas bi-annually data set.

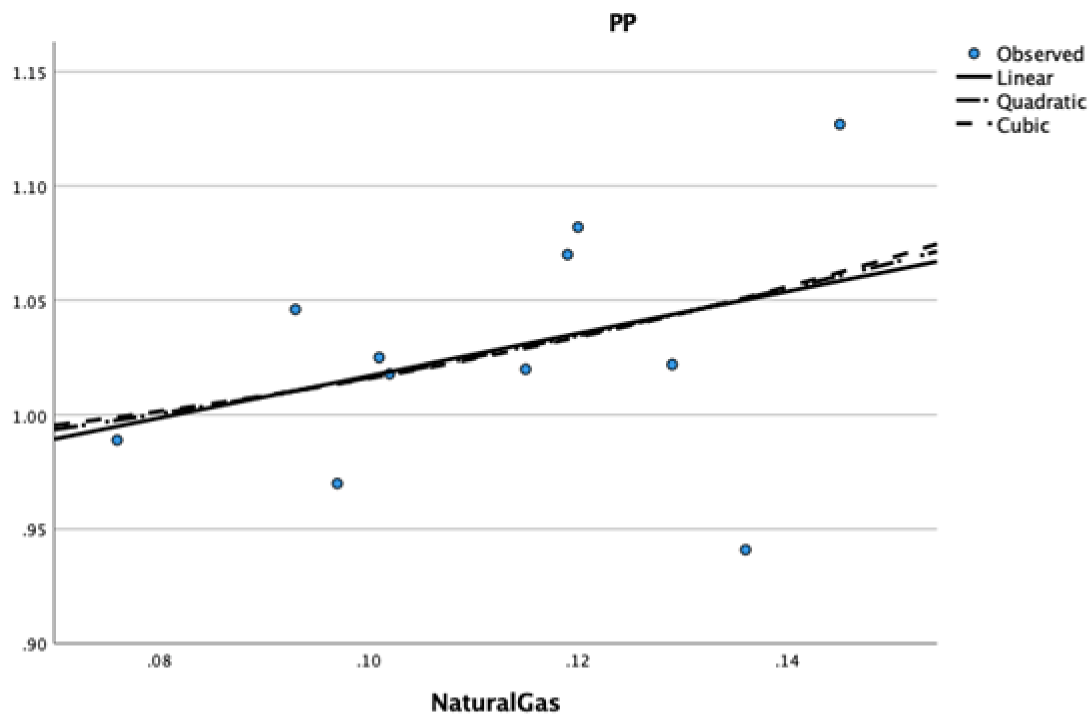

Figure 44 Regression curves for PP and natural gas annually data set.

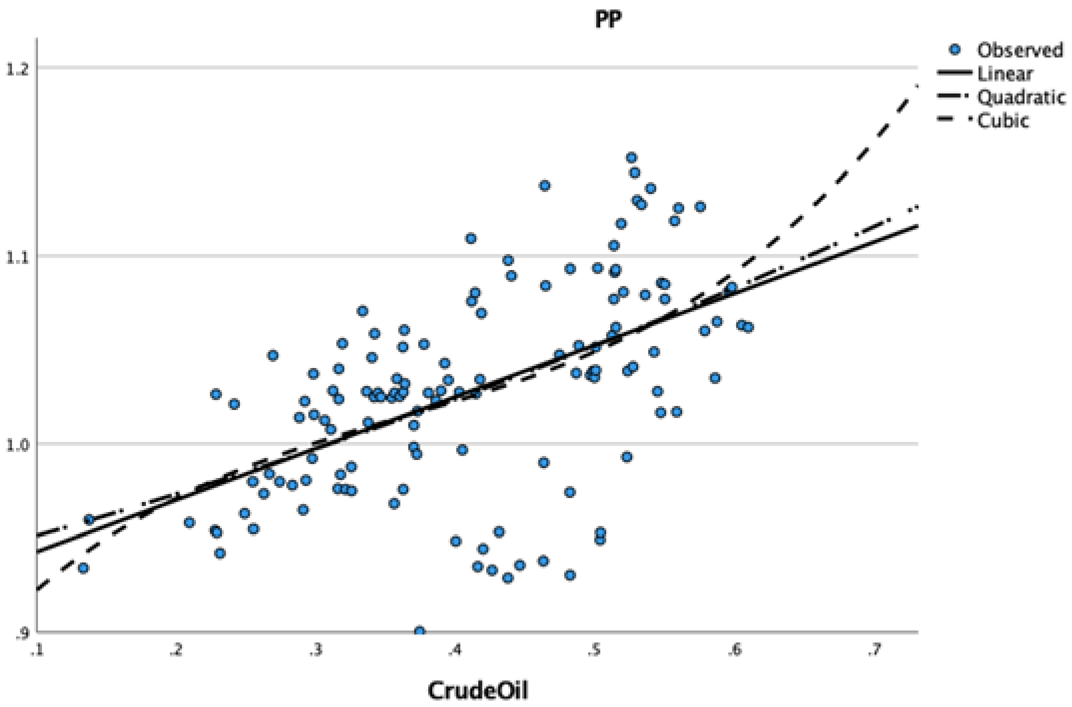

Figure 45 Regression curves for PP and crude oil monthly data set.

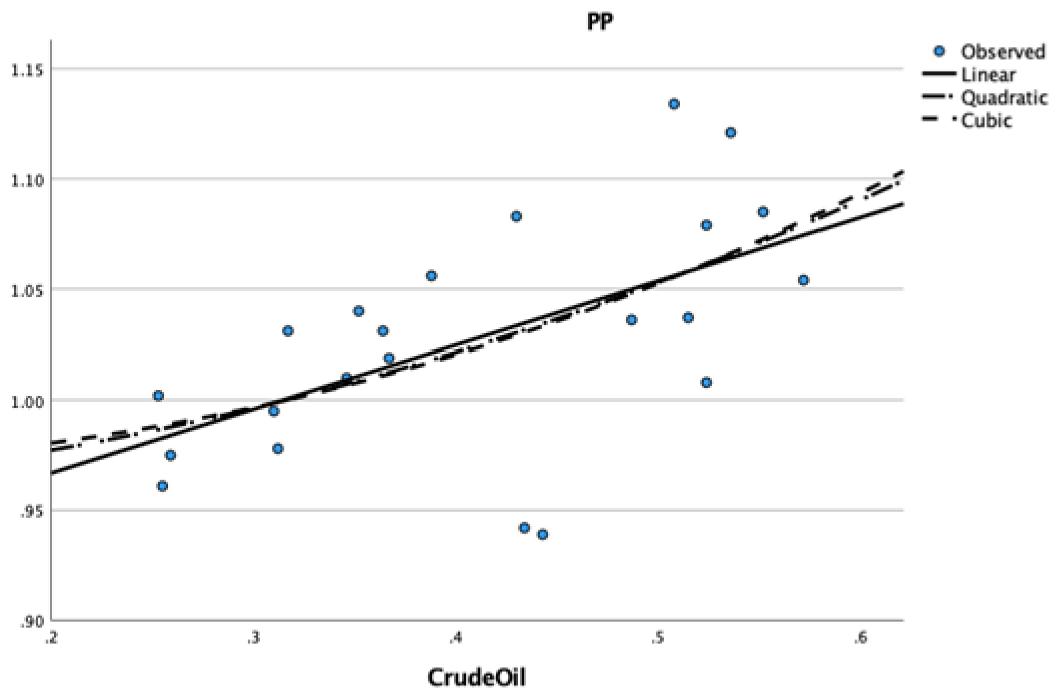

Figure 46 Regression curves for PP and crude oil bi-annually data set.

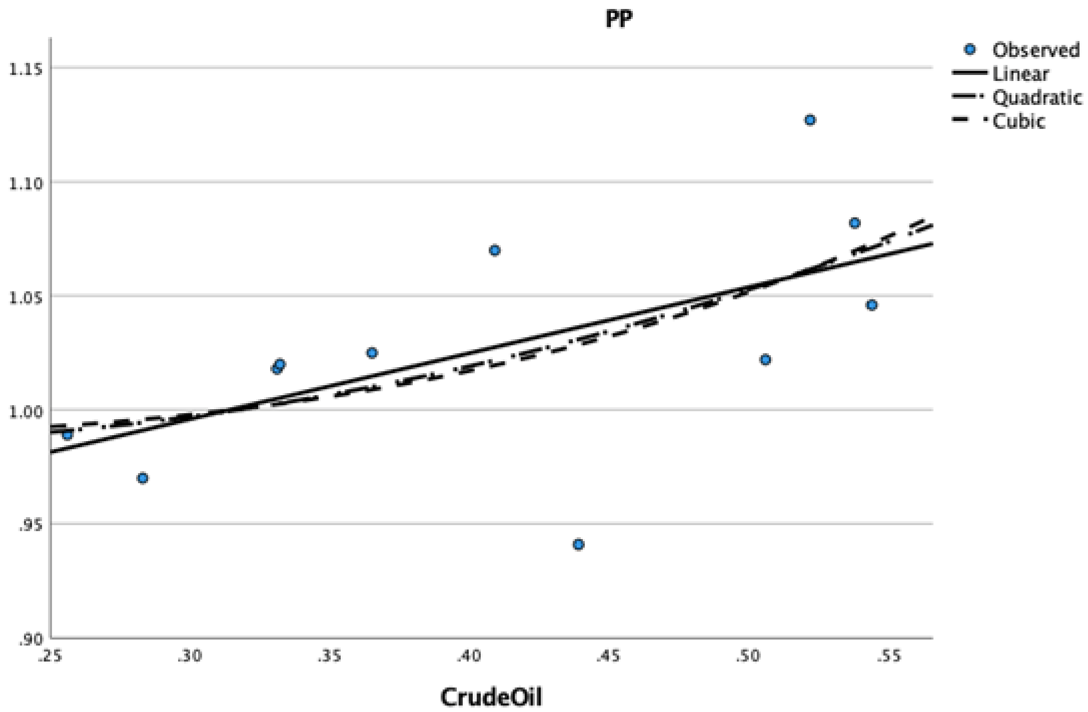

Figure 47 Regression curves for PP and crude oil annually data set.

APPENDIX D: Lagged Method Results

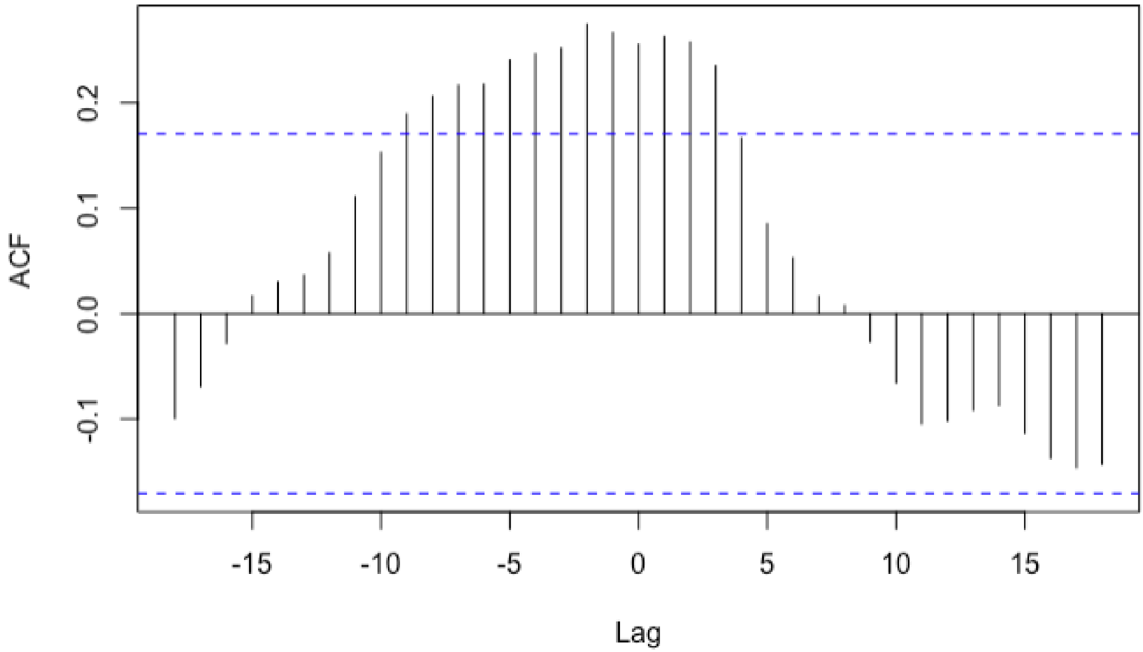

Figure 48 ACF results for the lag method between PP and natural gas.

```
Autocorrelations of series ‘X’, by lag

   -18    -17    -16    -15    -14    -13    -12    -11    -10     -9     -8     -7     -6
-0.099 -0.069 -0.028  0.017  0.030  0.036  0.057  0.111  0.153  0.189  0.206  0.217  0.218
    -5     -4     -3     -2     -1      0      1      2      3      4      5      6      7
 0.241  0.246  0.252  0.275  0.267  0.255  0.263  0.258  0.235  0.166  0.085  0.053  0.016
     8      9     10     11     12     13     14     15     16     17     18
 0.008 -0.027 -0.066 -0.105 -0.102 -0.092 -0.087 -0.114 -0.137 -0.146 -0.143
```

Figure 49 R Output for the ACF results for PP and natural gas.

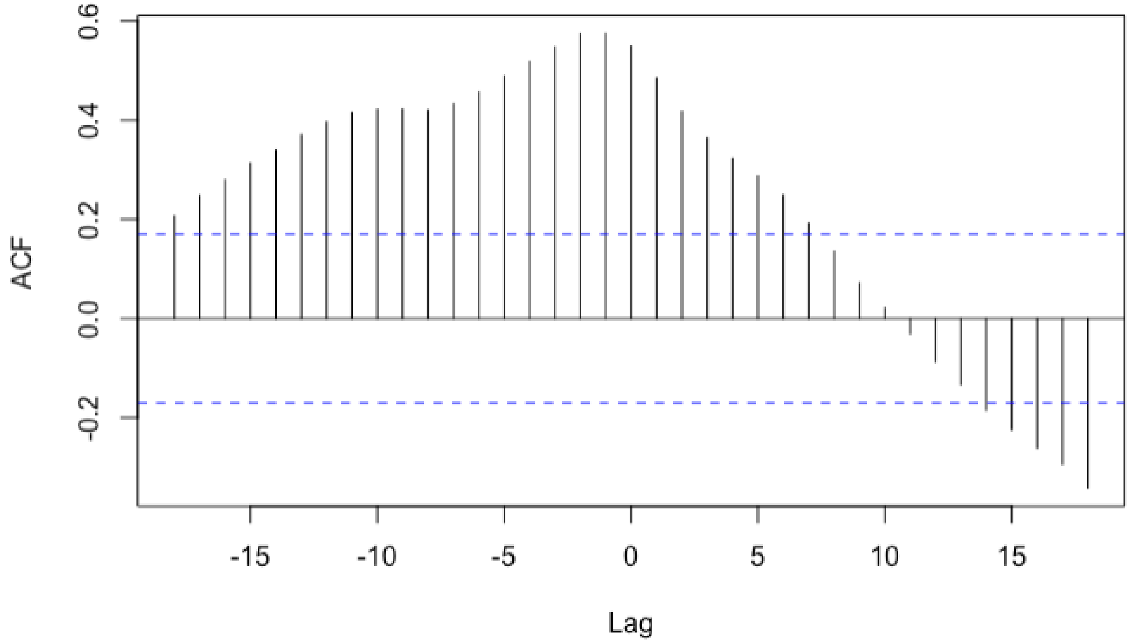

Figure 50 ACF results for the lag method between PP and crude oil.

```
Autocorrelations of series ‘X’, by lag

   -18    -17    -16    -15    -14    -13    -12    -11    -10     -9     -8     -7     -6 
 0.207  0.248  0.280  0.313  0.339  0.371  0.396  0.415  0.422  0.422  0.420  0.433  0.457 
    -5     -4     -3     -2     -1      0      1      2      3      4      5      6      7 
 0.489  0.518  0.547  0.574  0.575  0.549  0.485  0.418  0.364  0.323  0.287  0.248  0.192 
     8      9     10     11     12     13     14     15     16     17     18 
 0.136  0.072  0.021 -0.031 -0.087 -0.133 -0.185 -0.224 -0.262 -0.294 -0.342 
```

Figure 51 R output for the ACF results for PP and natural gas.

APPENDIX E: Monte Carlo Results

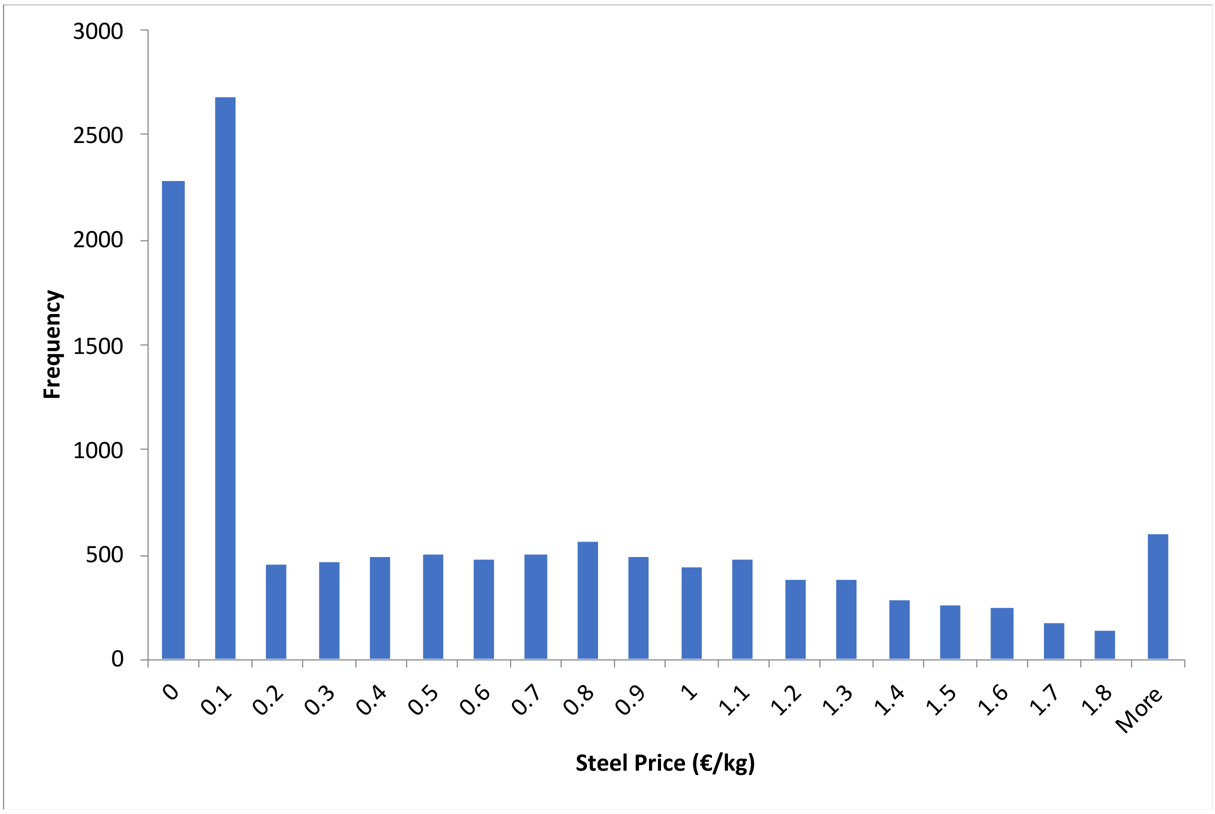

Figure 52 Monte Carlo results of steel price in 2030 using coke

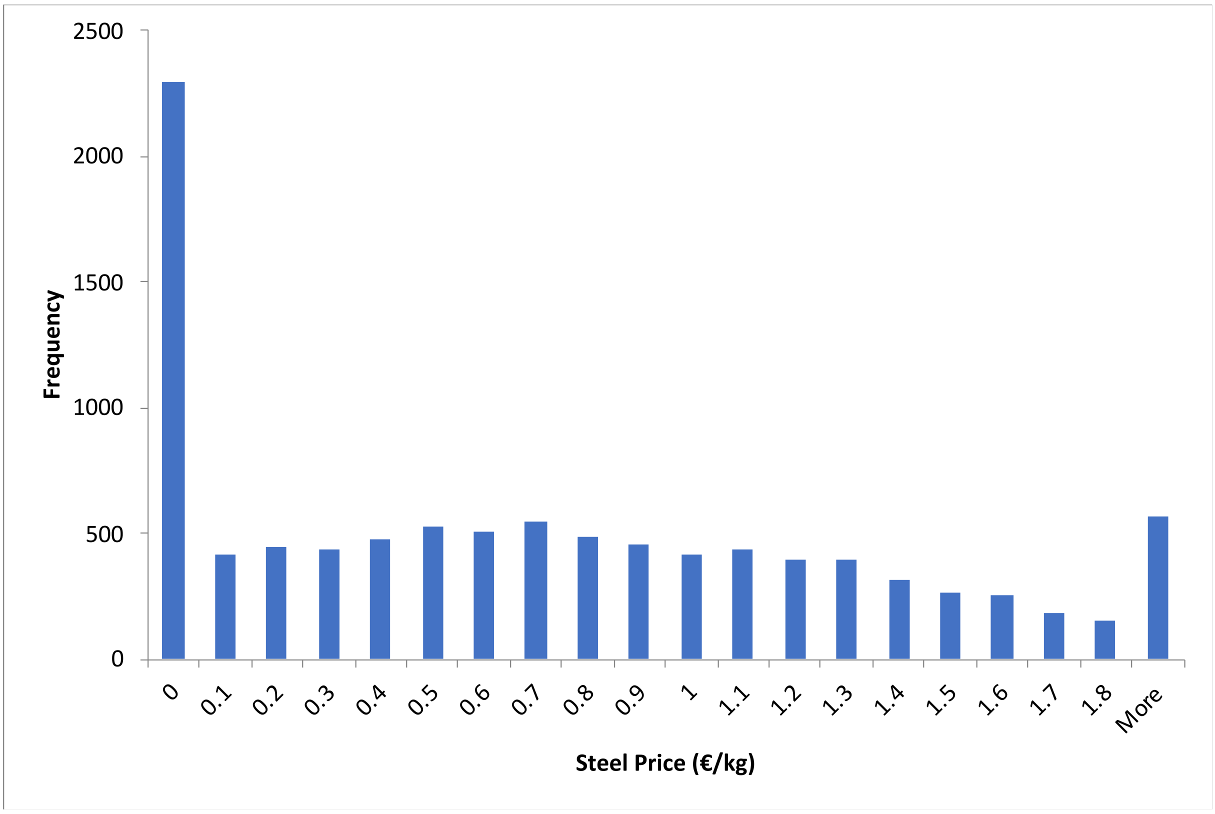

Figure 53 Monte Carlo results of steel price in 2050 using coke.

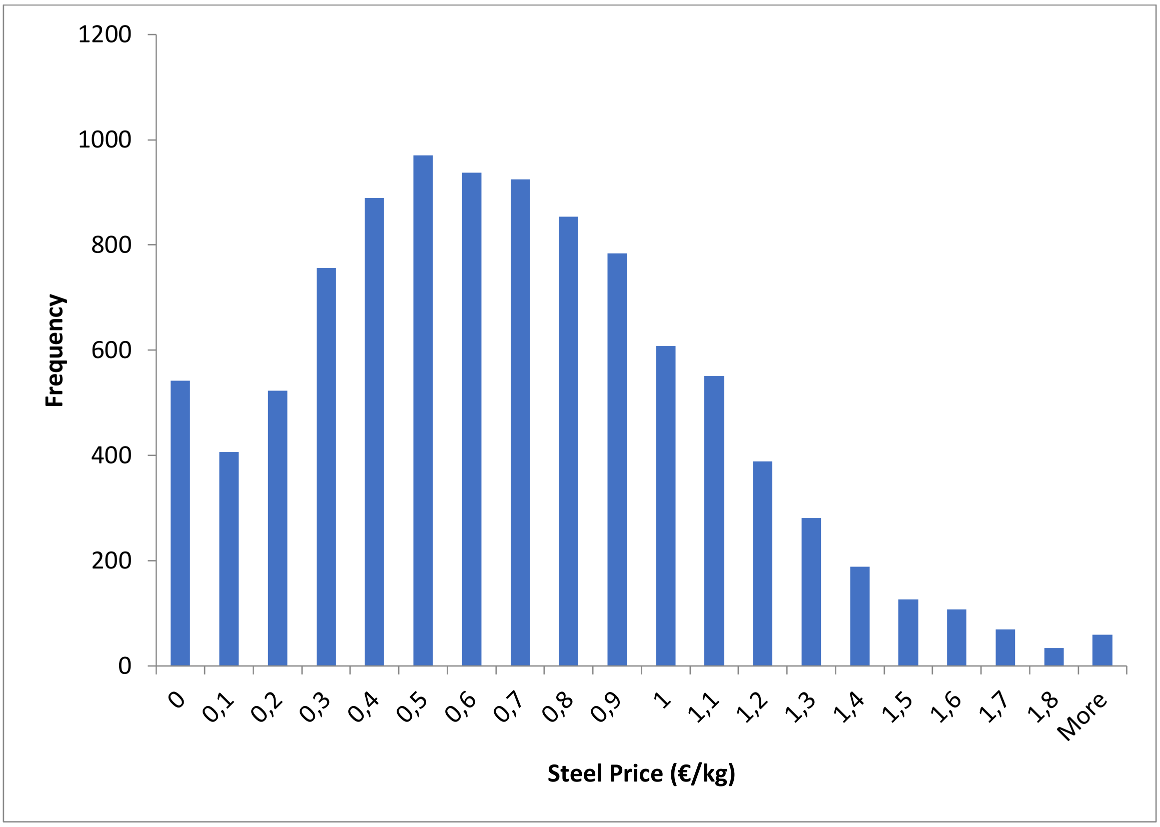

Figure 54 Monte Carlo results of steel price in 2030 using coal with the Current Policies Scenario.

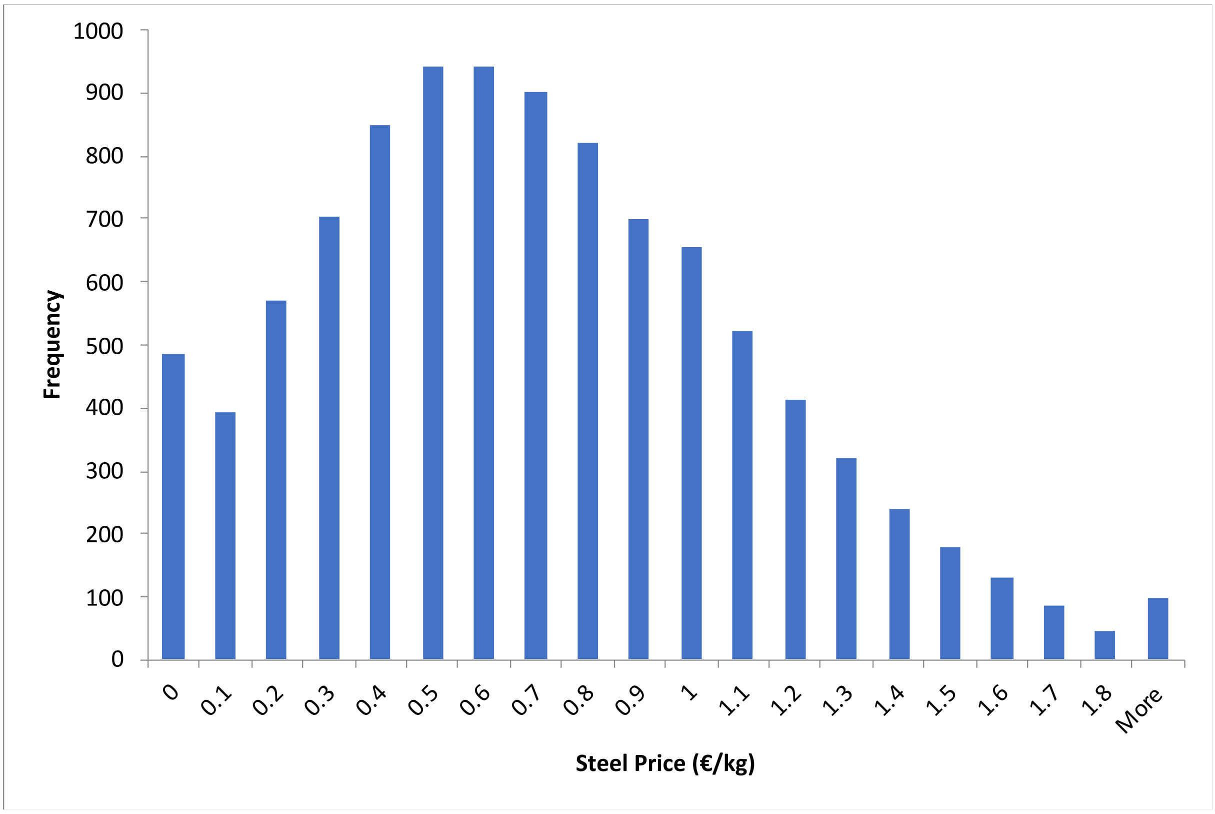

Figure 55 Monte Carlo results of steel price in 2050 using coal with the Current Policies Scenario.

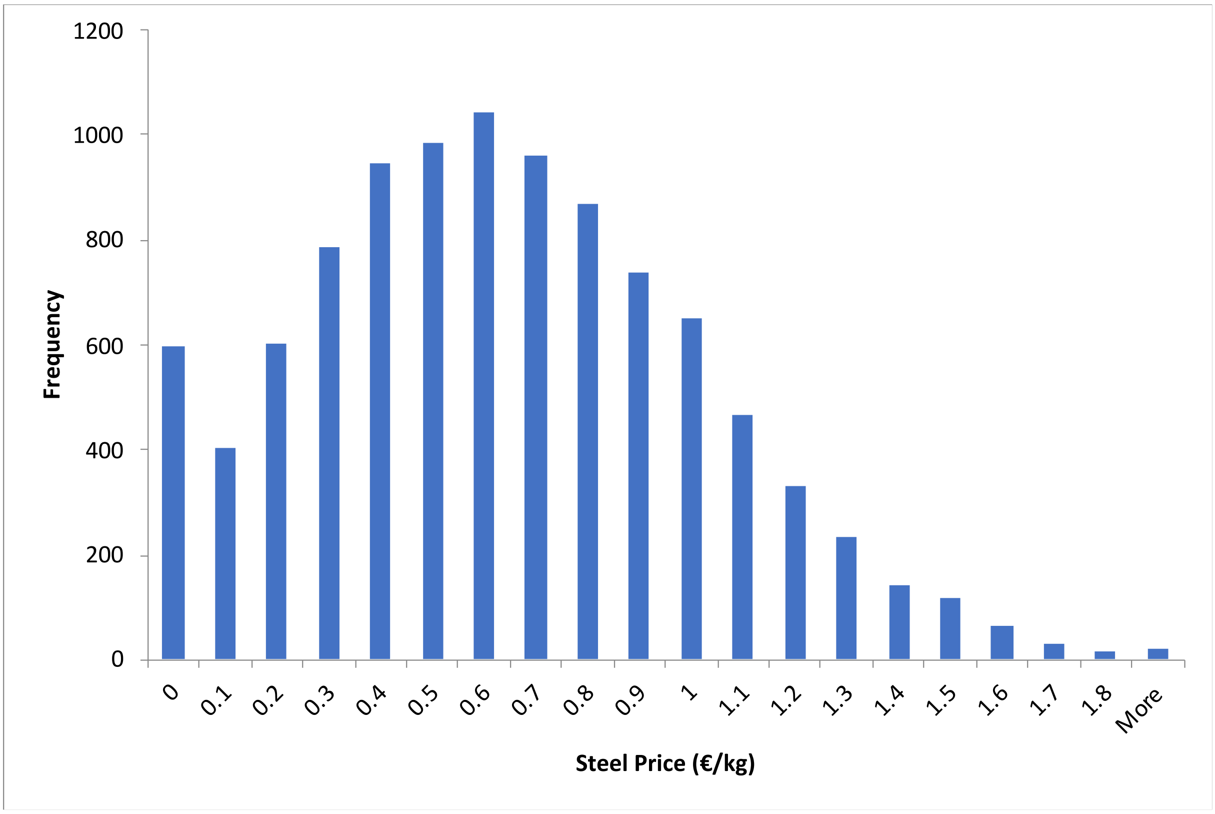

Figure 56 Monte Carlo results of steel price in 2030 using coal with the New Policies Scenario.

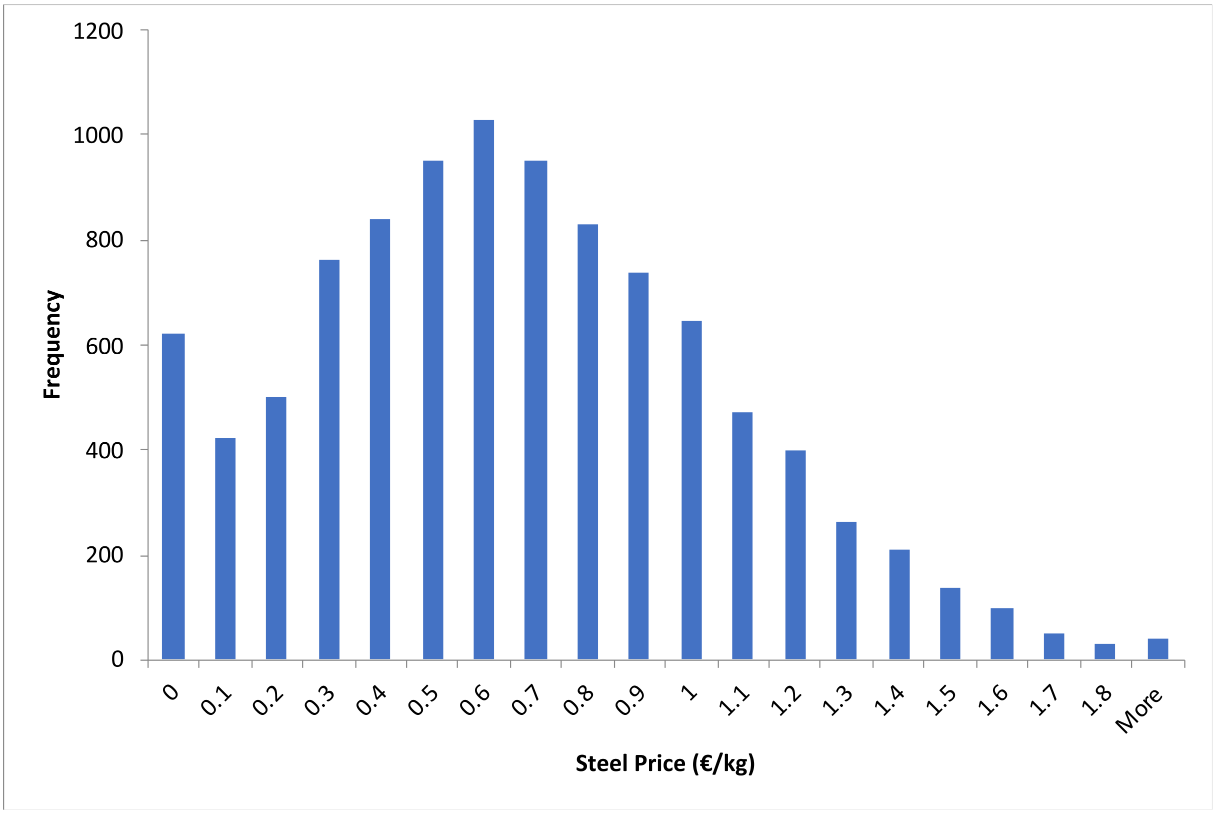

Figure 57 Monte Carlo results of steel price in 2050 using coal with the New policies Scenario.

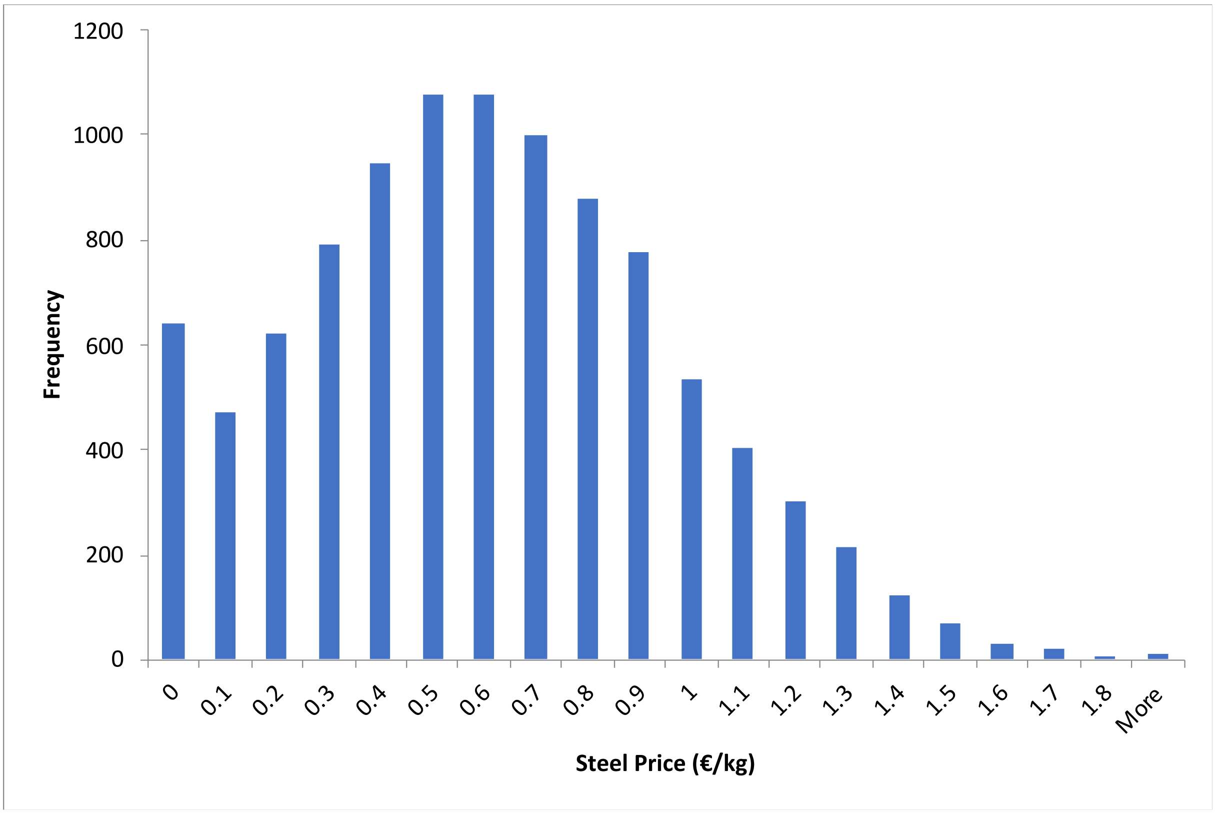

Figure 58 Monte Carlo results of steel price in 2030 using coal with the 450 Scenario.

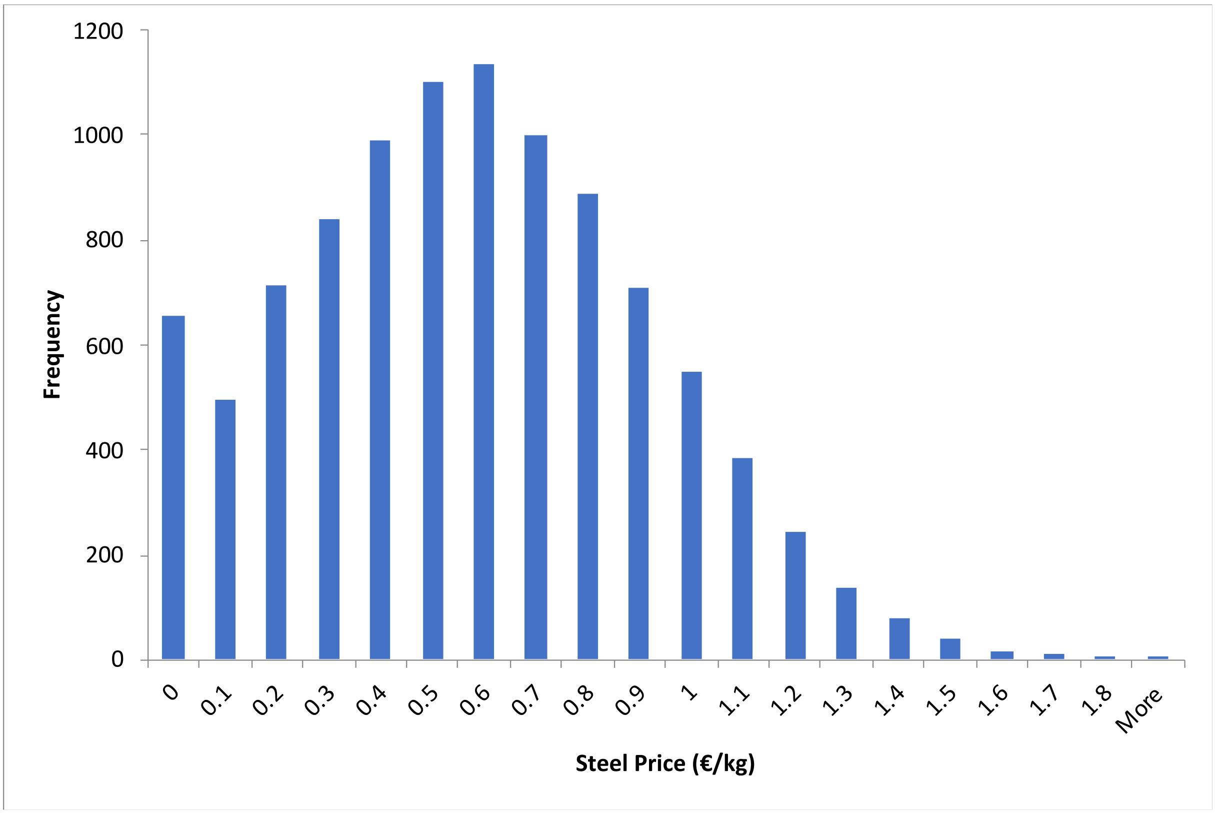

Figure 59 Monte Carlo results of steel price in 2050 using coal with the 450 Scenario.

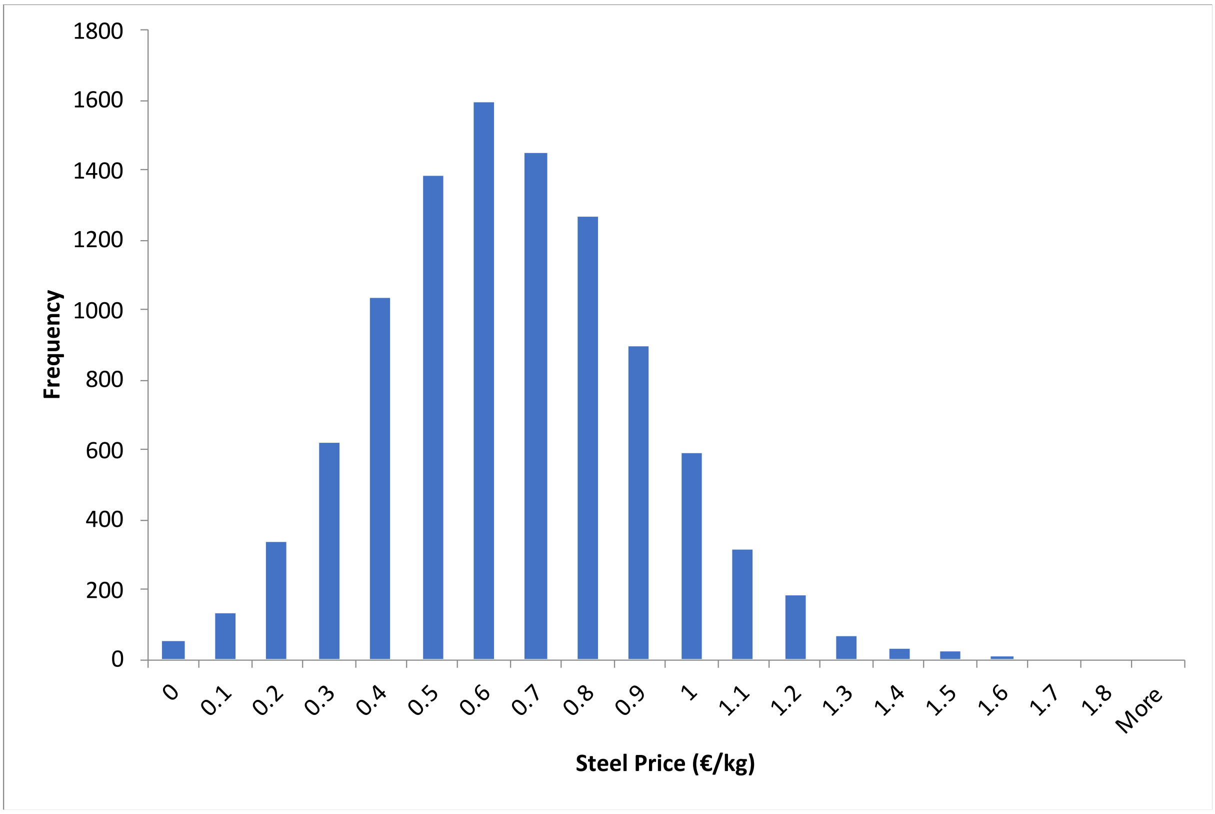

Figure 60 Monte Carlo results of steel price in 2030 using iron ore.

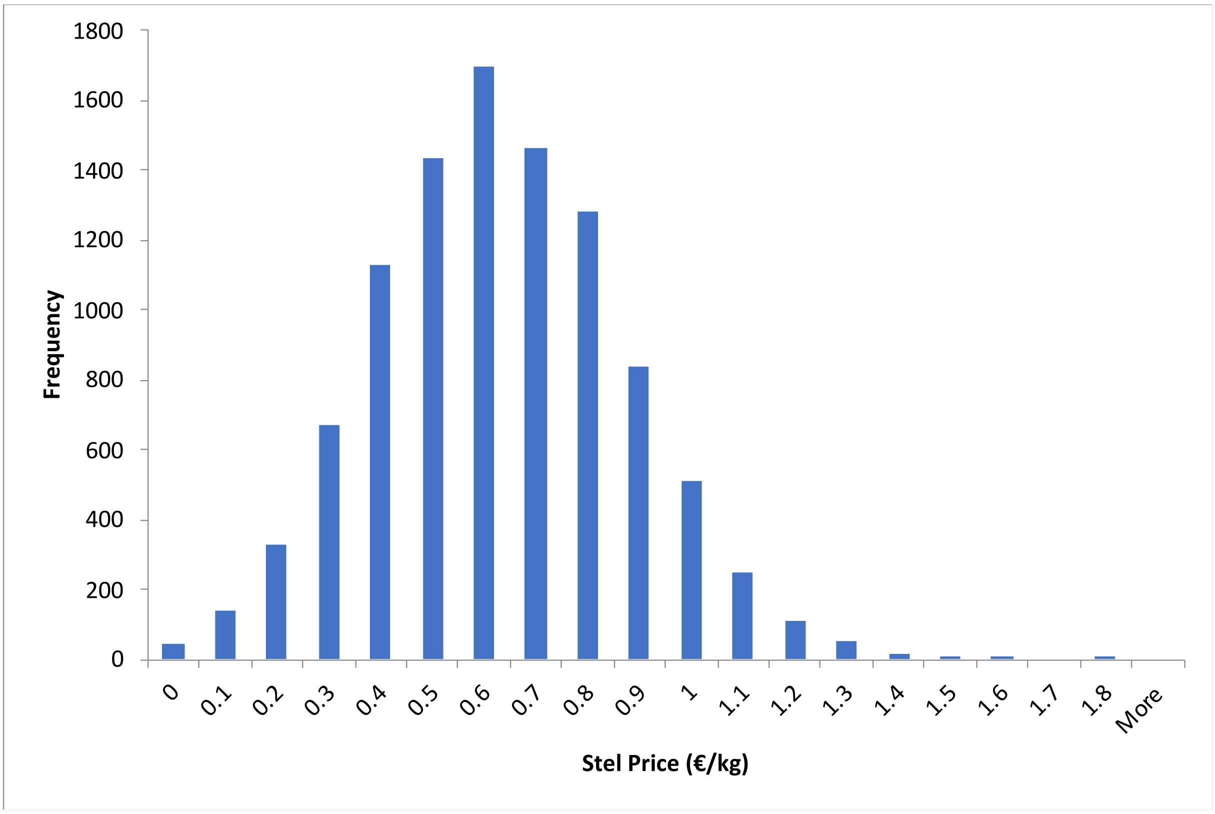

Figure 61 Monte Carlo results of Steel price in 2050 using iron ore.

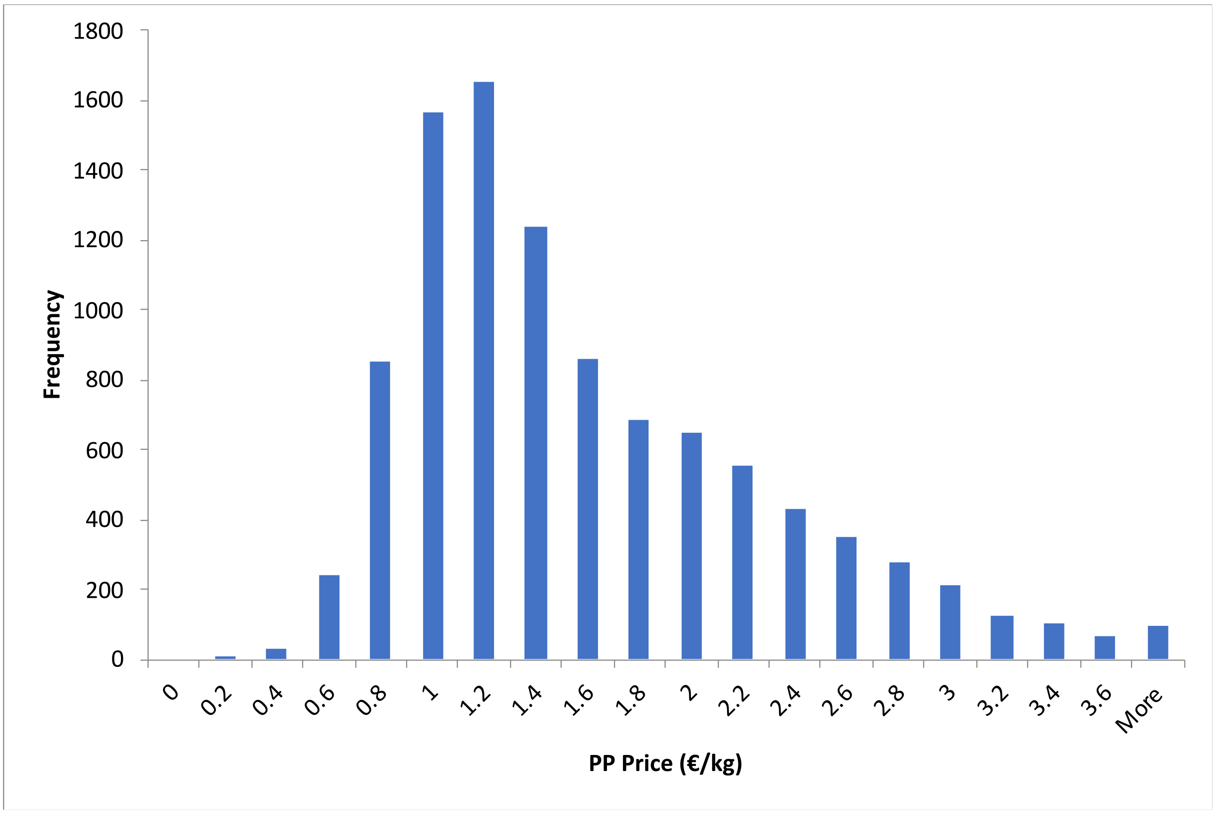

Figure 62 Monte Carlo results of PP price in 2030 using natural gas with the Current Policies Scenario.

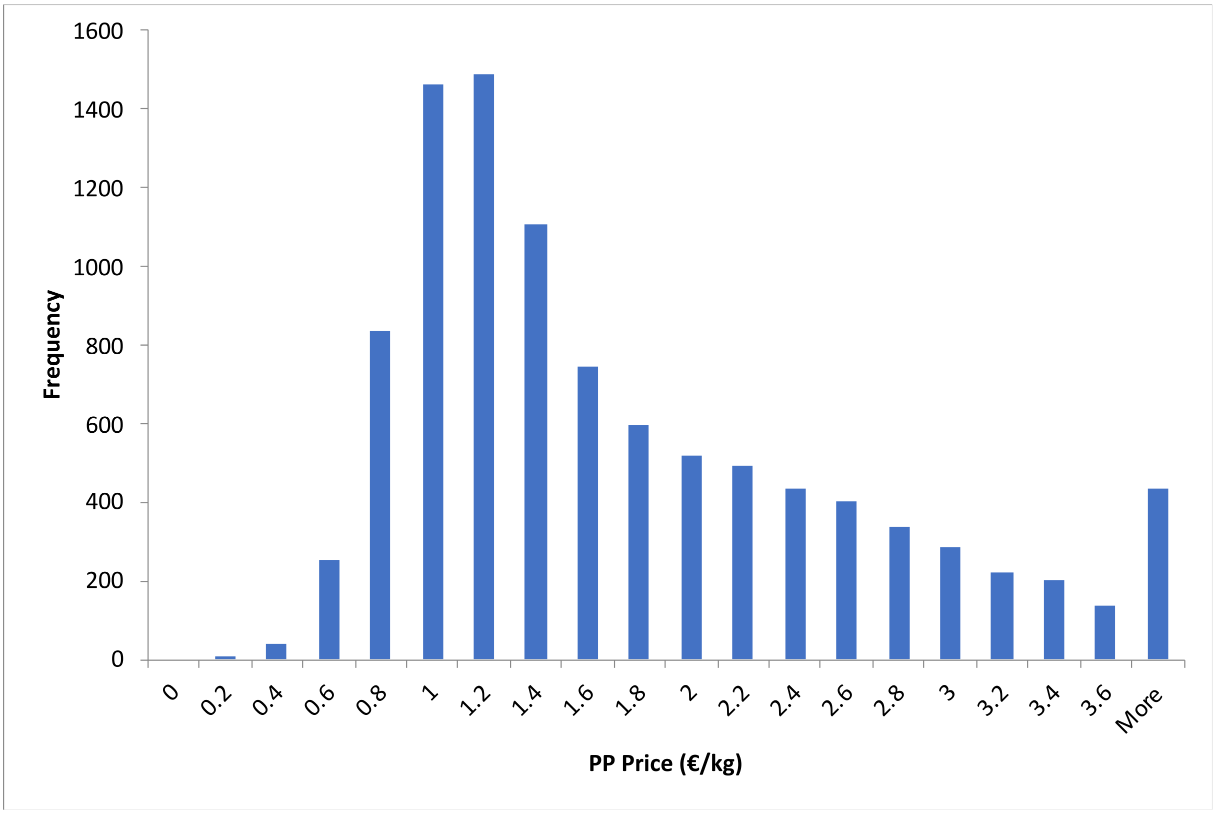

Figure 63 Monte Carlo results of PP price in 2050 using natural gas with the Current Policies Scenario.

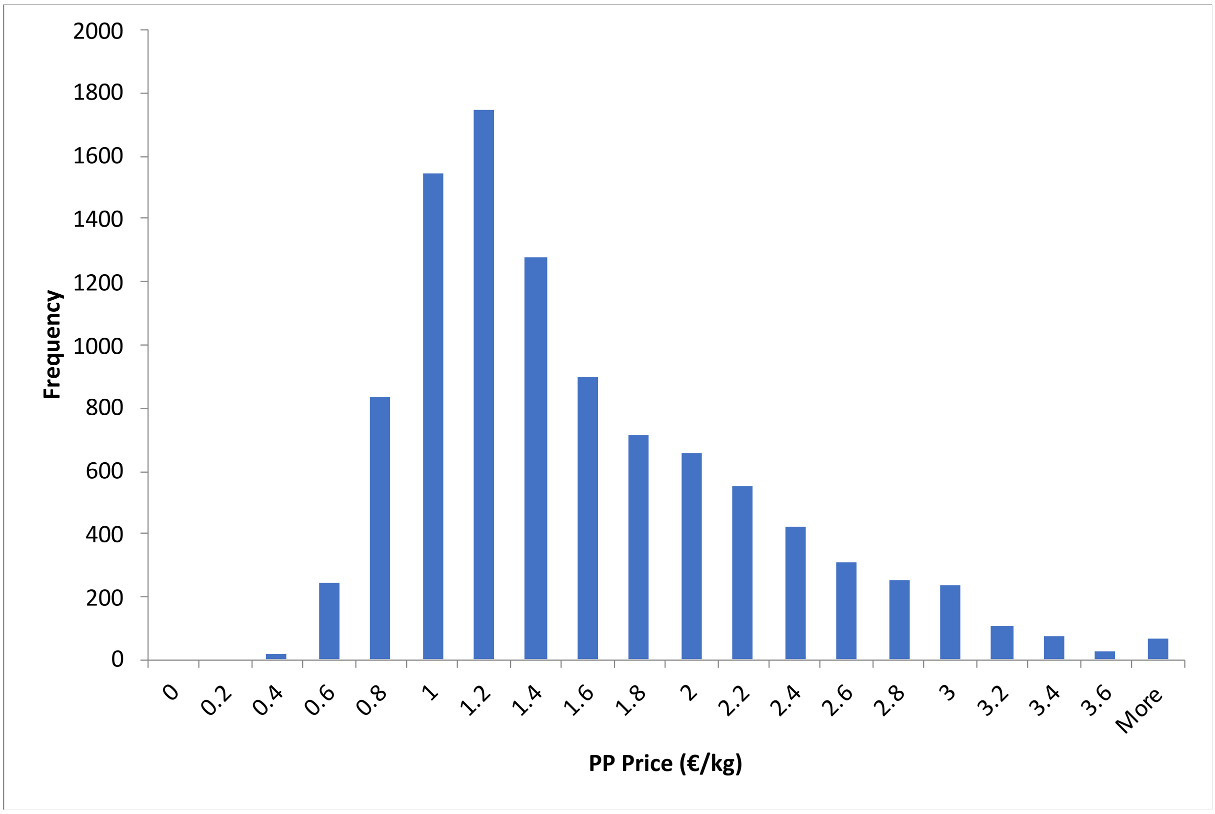

Figure 64 Monte Carlo results of PP price in 2030 using natural gas with the New Policies Scenario.

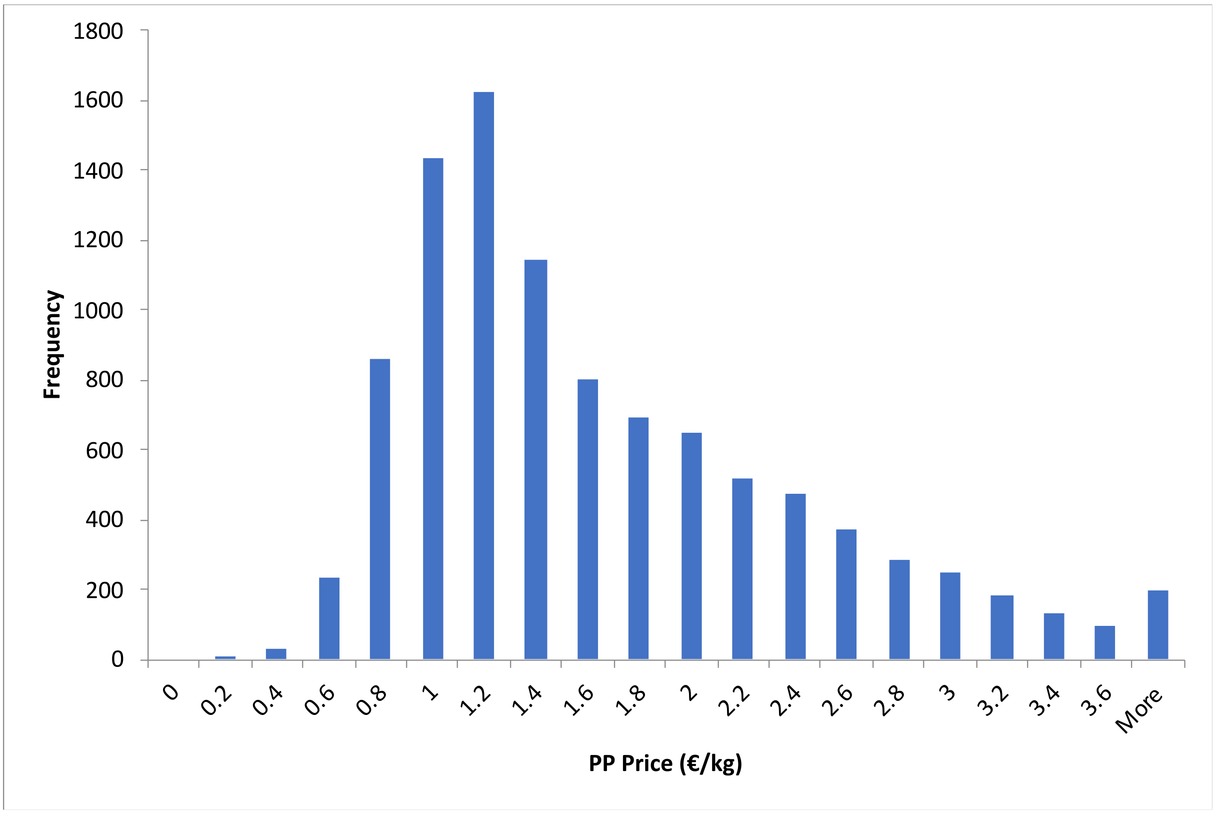

Figure 65 Monte Carlo results of PP price in 2050 using natural gas with the New Policies Scenario.

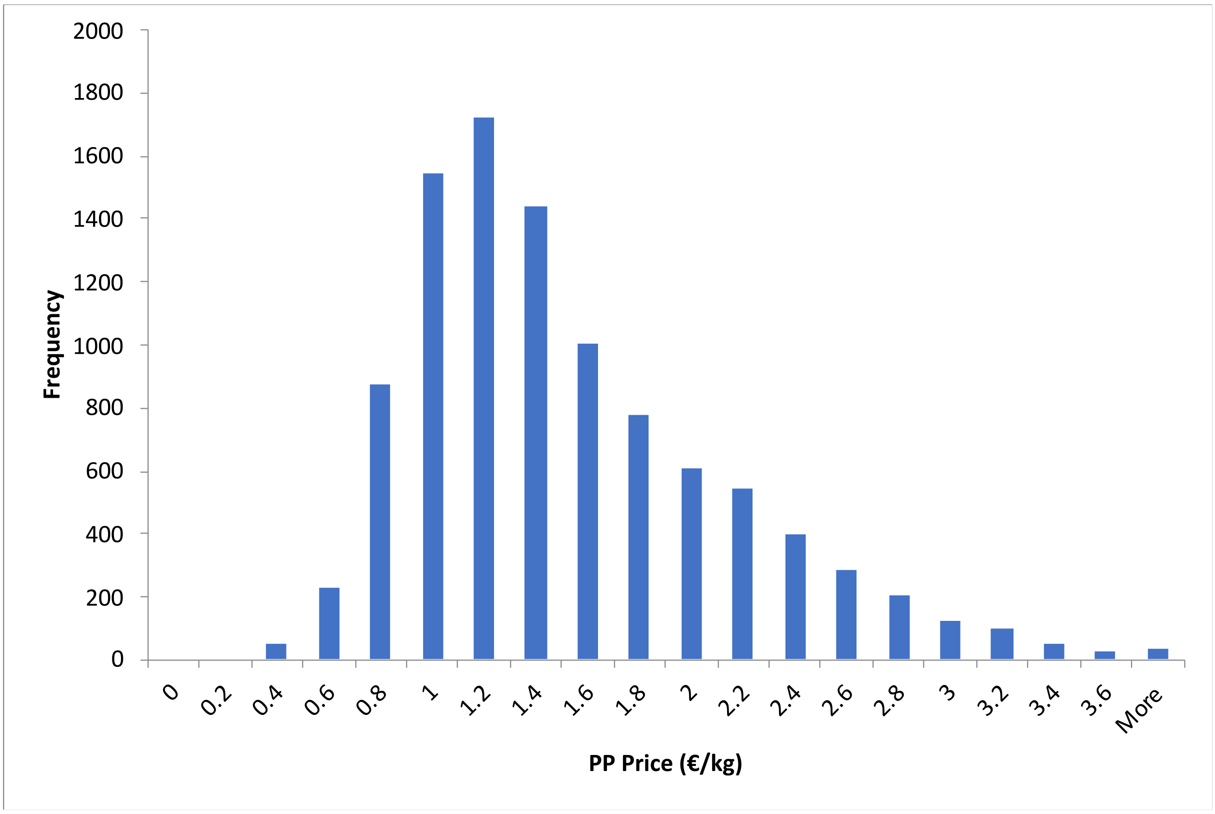

Figure 66 Monte Carlo results of PP price in 2030 using natural gas with the 450 Scenario.

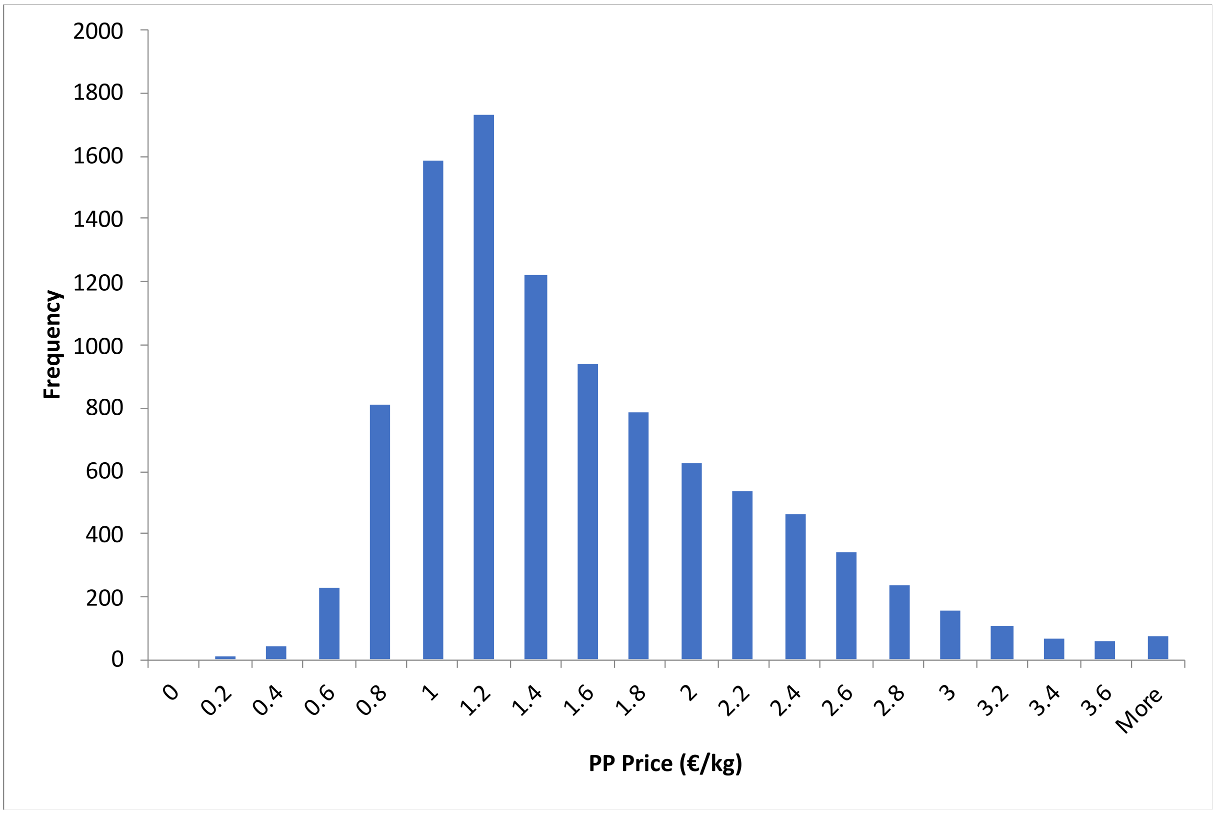

Figure 67 Monte Carlo results of PP price in 2050 using natural gas with the 450 Scenario.

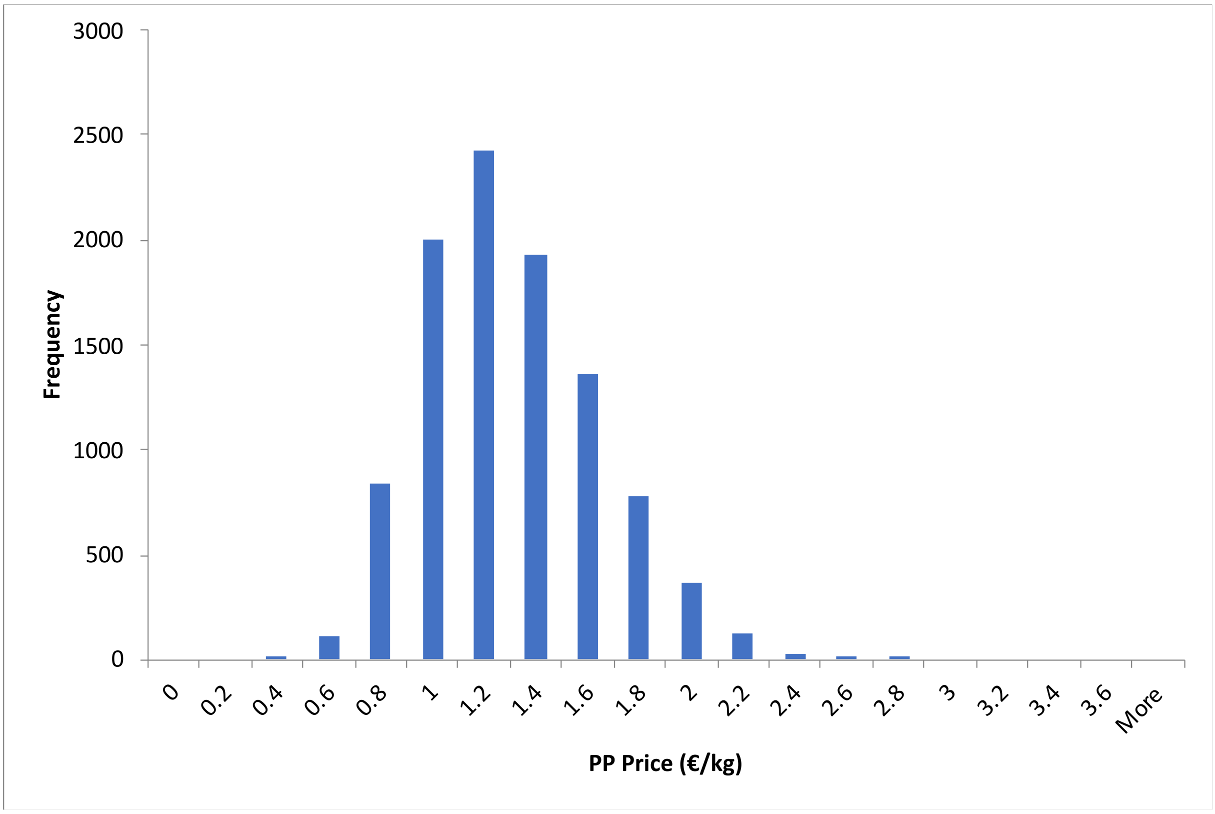

Figure 68 Monte Carlo results of PP price in 2030 using crude oil with the Current Policies Scenario.

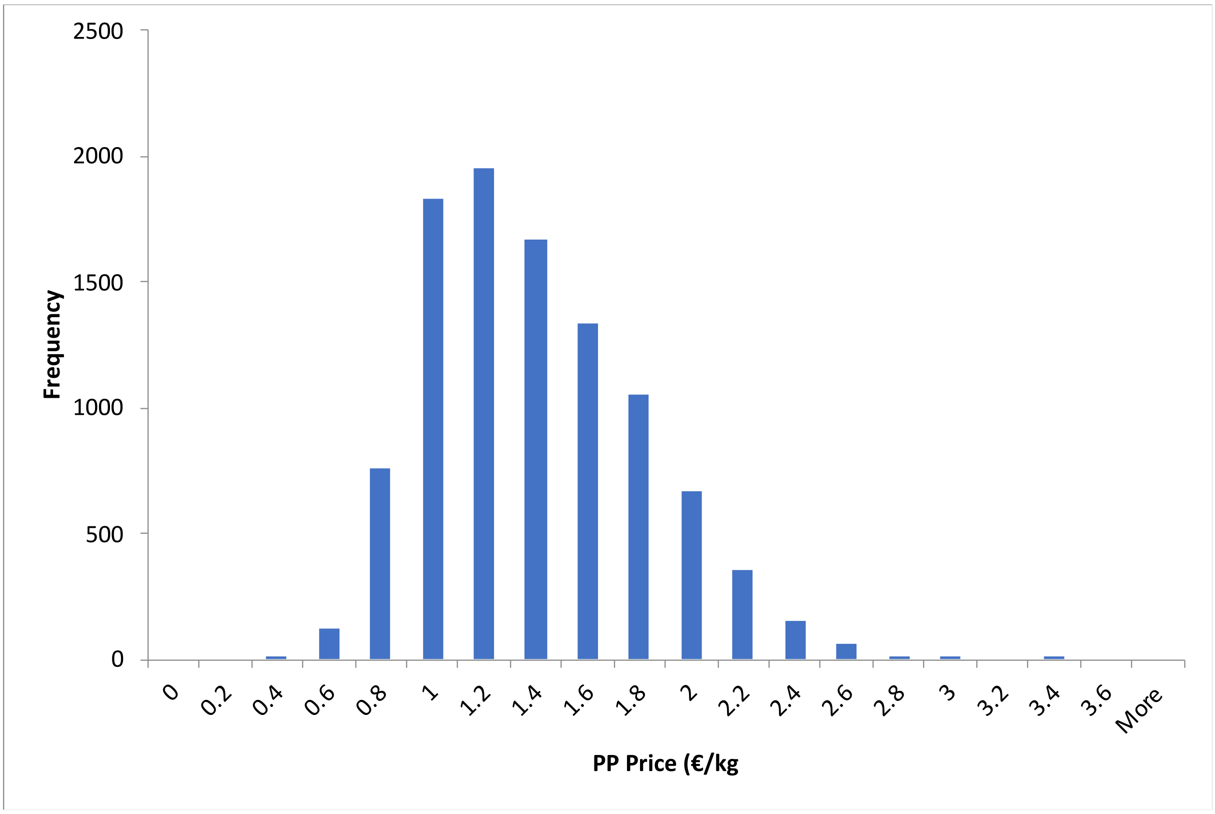

Figure 69 Monte Carlo results of PP price in 2050 using crude oil with the Current Policies Scenario.

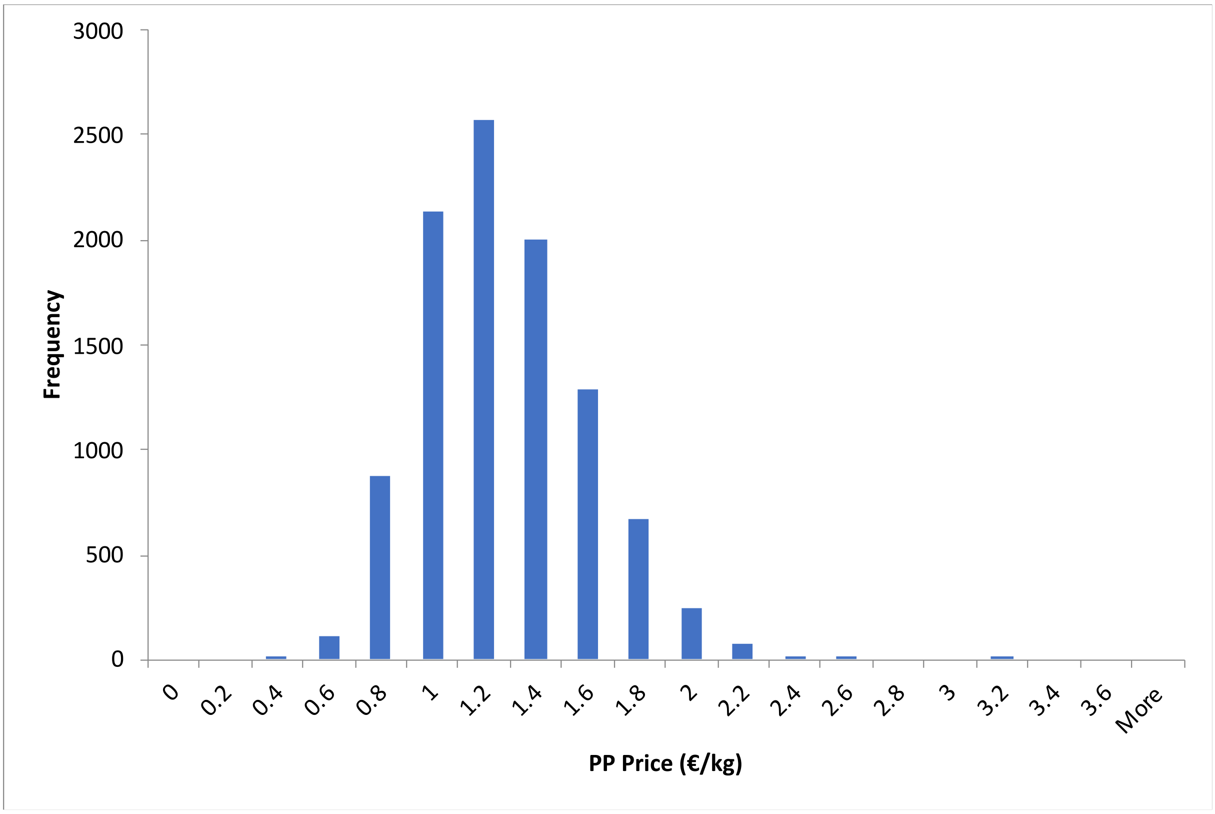

Figure 70 Monte Carlo results of PP price in 2030 using crude oil with the New Policies Scenario.

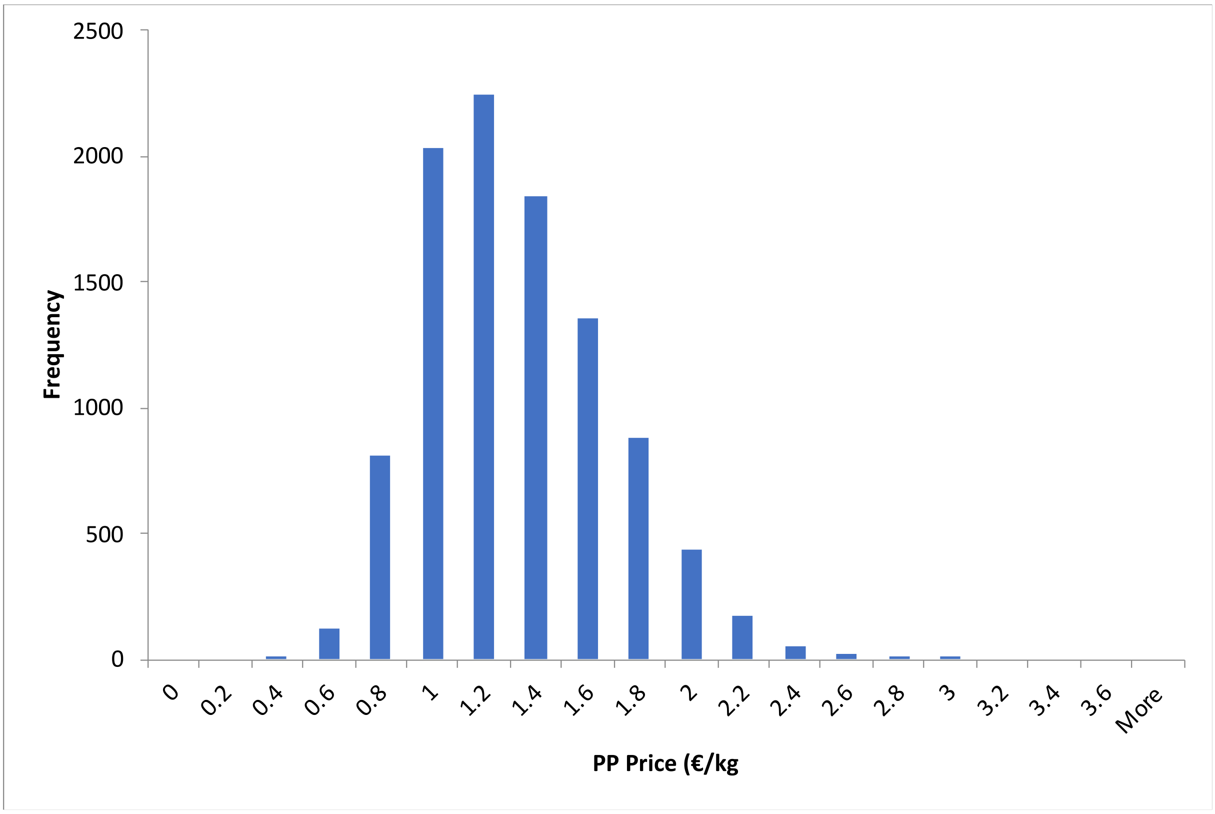

Figure 71 Monte Carlo results of PP price in 2050 using crude oil with the New Policies Scenario.

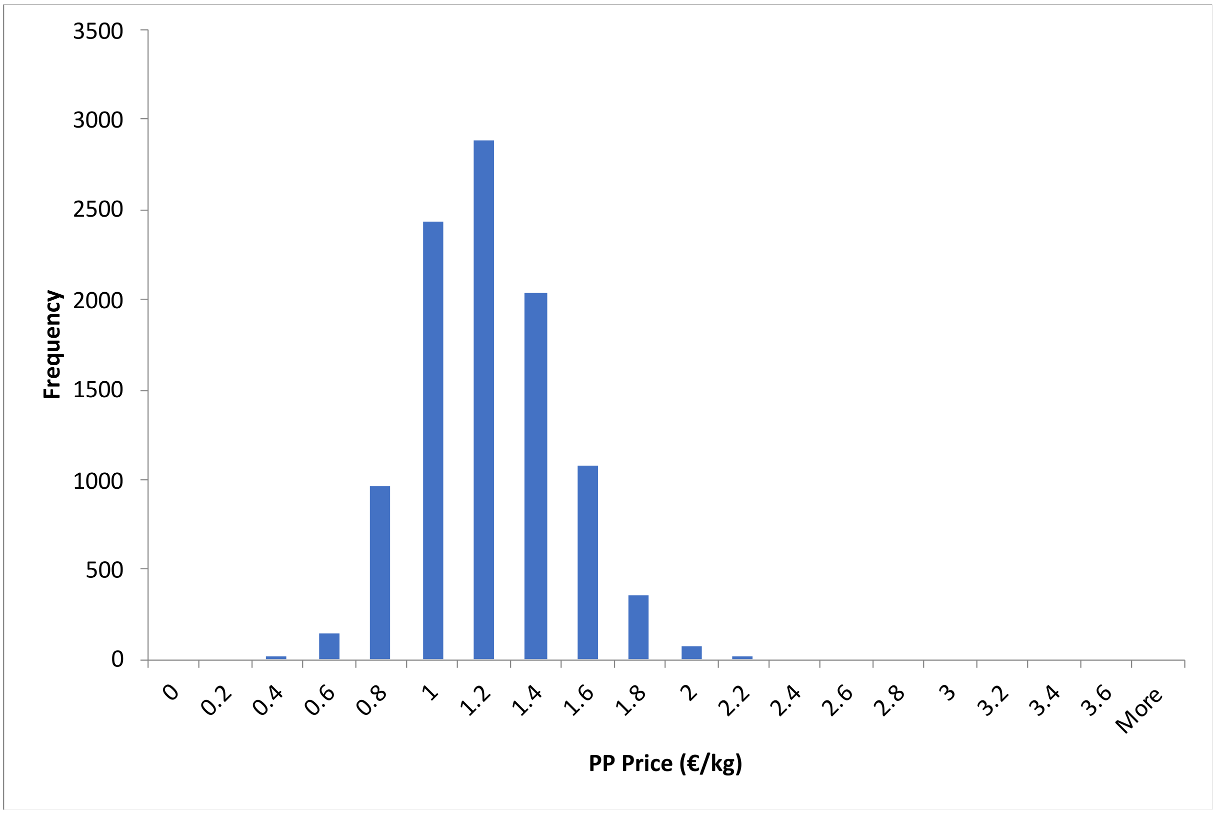

Figure 72 Monte Carlo results of PP price in 2030 using crude oil with the 450 Scenario.

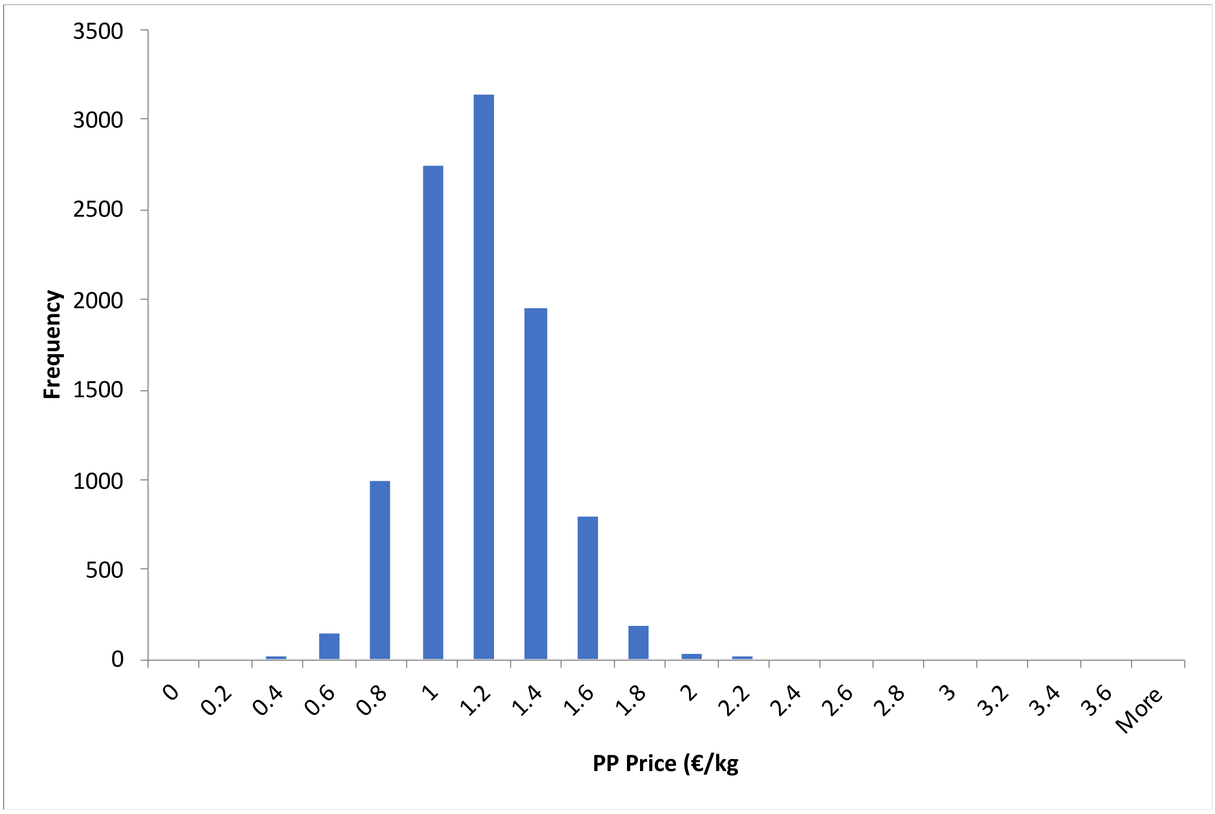

Figure 73 Monte Carlo results of PP price in 2050 using crude oil with the 450 Scenario.