European Electricity Prices and the EU Emissions Trading System: Lessons from the UK Carbon Price Floor

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Executive Summary

Efficient regulation is required in order to reduce carbon emissions and achieve the goals of the Paris Agreement. The EU Emissions Trading System (ETS) is currently the most important regulatory instrument implemented for this purpose. Under the EU ETS, companies need European Emission Allowances (EUA) in order to emit CO2. The permits are allocated by means of grandfathering as well as auctions and can subsequently be traded. As the total amount of allowances distributed is fixed, a market price for CO2 permits is created. The main advantage of an ETS is that the policy instrument provides certainty with regard to the total emissions in the short run. However, a cap-and-trade system introduces uncertainty concerning the costs of emitting and the benefits of abatement.

In theory, carbon prices are expected to be passed through to electricity prices. This carbon to electricity price pass-through is important to reduce emissions in the electricity sector in two ways. Firstly, the increased electricity prices are expected to reduce electricity demand. Secondly, the costs of generation increase relatively less for cleaner means of power generation. Hence, changes in the merit order can be induced if carbon prices are high enough. The latter entails that emissions are lower under the same demand.

EU carbon prices have fallen significantly in the wake of the 2008 financial crises. Carbon prices should be high enough to foster investments in low carbon solutions in order to achieve long term environmental goals. A Carbon Price Floor (CPF) can ensure that carbon prices never fall below a certain threshold regardless of market developments. Moreover, if carbon prices are passed through to electricity prices, it is likely that this introduces additional uncertainty and volatility in electricity markets. This may impede investments in abatement and complicate electricity price forecasts. A CPF might also reduce long term uncertainty regarding electricity and carbon prices.

The UK is the only country that is part of the EU ETS that has implemented a CPF. The UK CPF was implemented in 2013 and charges power producers for emitting by means of a Carbon Support Price (CPS). The CPS is meant to charge the difference between the price of permit prices and the minimum price of emissions set by policymakers. Hence, the CPS is supposed to be zero when permit prices exceed the floor price. The CPS is fixed for each year and is based on the EUA price forecast three years in advance.

This thesis aims to answer the following research question: *Can a Carbon Price Floor enhance the EU ETS and how should it be implemented?* In order to answer this question the relation between carbon and electricity prices is analyzed as well as the relation between carbon price shocks and short term spikes in electricity price volatility. Econometric time series methods are employed to quantitatively analyze these relations. Two seperate analyses are conducted that are both based on the same method. An AutoRegressive (AR) Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model with exogenous factors, ARX-GARCHX, is used for both analyses. Electricity prices are the dependent variable in both analyses. The model allows for the variance to change over time and for estimation of what exogenous factors influence uncertainty.

The first analysis evaluates the relation between carbon and electricity prices as well as electricity price volatility using hourly day-ahead prices from 2015 to 2018 in nine countries. Poland (PL), the Netherlands (NL), Italy (IT), Czech Republic (CZ), the United Kingdom (UK), Germany (DE), Denmark (DK), Spain (ES) and France (FR) have been incorporated in this analysis. The second analysis uses daily volume weighted average wholesale electricity prices in the UK from 2011 to 2016. The UK CPF was introduced in 2013 and dummy variables are incorporated in the model to account for possible changes in the relation between carbon and electricity prices. A second set of dummy variables is added to account for the first big increase in the CPS in 2015.

The data used for the the multi-country analysis has been divided in two: data from 2015 to 2017 and the observations from 2018. Carbon price levels increased significantly in 2018 and therefore the possibility of different dynamics between carbon and electricity prices is considered. No significant relation between carbon price shocks and electricity price volatility was observed in both samples. A significant positive relation between carbon and electricity prices was found in 10 out of 27 time series using the 2018 data. This relation was only observed in 2 out of 27 time series in the data from before

carbon prices increases. This non-linear relation indicates that carbon to electricity price pass-through only occurs when carbon price levels are above a certain threshold value.

Daily average wholesale electricity prices from the UK have been modelled to analyze the change in the relation between carbon and electricity prices after the introduction of the UK CPF. Prior to introduction of the CPF, no significant relation between carbon and electricity prices was found. A significant positive relation between carbon and electricity prices was observed after introduction of the CPF. Moreover, the parameter estimates concerning electricity price volatility induced by carbon price shocks increased strongly, but remained insignificant. Although EUA price levels remained the same during the evaluated period, carbon to electricity price pass-through was only measurable by the model after introduction of the CPF.

The same conclusion can be drawn from both analyses. The results indicate that carbon prices are only passed through to electricity prices when the total costs of emitting exceed a certain threshold value. The carbon price pass-through is of importance to foster investments in abatement and achieve long-term environmental goals. Although carbon price levels are currently relatively high, this provides no guarantee that carbon prices will not collapse again. The introduction of a CPF as an addition to the EU ETS can guarantee that the costs of emitting never fall below a threshold value and can therefore ensure the carbon to electricity price pass-through. Therefore, it is concluded that the introduction of a CPF would enhance the current EU ETS.

Although the UK CPF seems to achieve some of it goals and increases the total costs of emitting, some shortcomings have been identified. The UK CPF reduces some uncertainty with regard to the minimum costs carbon emissions, but it also introduces new uncertainties. Since the CPS is fixed per year and selected three years in advance, the price floor appears to be an annually changing carbon tax rather than a lower bound for the total costs of emitting. Therefore, the UK CPF does not solely provide certainty by introducing a lower bound for the emissions costs. Market participants are now dependent on EUA prices, the selected minimum price and the annually changing CPS. These uncertainties can be addressed by introducing a dynamic CPF. EU-wide introduction of a CPF is likely to have the most impact and would reduce the risk of carbon leakage. However, the proposed dynamic CPF can also be implemented on a national level.

The dynamic CPF is similar to the UK CPF, but the CPS is adjusted dynamically. The CPS can be adjusted based on the daily weighted average carbon prices obtained from public trading records. Therefore, the selected price floor is a fixed lower bound for the costs of emissions. If EUA prices are below the price floor, the total costs of emitting will remain fixed until EUA prices exceed the threshold value. Once EUA prices exceed the threshold value, the dynamic CPS will be zero. This is unlike the CPS in the UK, which is selected three years in advance and is based on highly uncertain carbon price forecasts. Collection of daily emissions records poses the biggest challenge with regard to the implementation of a dynamic CPF. This thesis identifies three possibilities for the collection of daily emissions data. Firstly, emissions authorities can continue using the same methodology, but increase the frequency of data records. Secondly, the data collection methods used in the UK CPF can be used. In the UK, the CPS is charged based on the quantity of fuels used and the system assumes a fixed amount of emissions for each fuel type. Transaction records are used for data collection and the delivery moment is considered the point in time at which the tax becomes due. Lastly, data with regard to power generation per plant provided by the European Network of Transmission System Operators for Electricity (ENTSO-E) can be used to calculate emissions on a daily basis.

The dynamic CPF reduces the uncertainty introduced by the UK CPF and sets a lower bound for the total costs of emitting. The latter is essential for the pass-through of carbon to electricity prices. This contributes to the affordability of long term environmental goals and creates an environment that fosters low-carbon investments. Moreover, the introduction of a CPF would provide a clear signal with regard to the commitment of policymakers to achieve environmental goals. The proposed CPF can be implemented EU-wide or on a national level. Regardless of the scope of the CPF, a minimum price for carbon is essential for the pass-through of carbon prices in the event of another carbon market crash.

Keywords: EU ETS, Carbon Price Floor, Volatility, Price Modelling, Time Series

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This thesis concludes my MSc Complex Systems Engineering & Management at the Delft University of Technology. Throughout the MSc I have mostly focused on the analysis and design of electricity systems. As there are many interesting developments in this sector as a result of the liberalization of the electricity markets and ambitious environmental policy, I am glad that I have gained a deeper understanding of this sector. Due to this interest I decided to continue researching these developments during my thesis. Moreover, electricity time series data allow for analysis using econometric modelling techniques. Over the years I have grown fond of econometrics and quantitative modelling and it has been a pleasure to combine this with the methodology taught at the TU Delft Faculty of Technology, Policy and Management (TPM).

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1 Introduction

The threat posed by global warming has forced society to find means to reverse or mitigate climate change. The most important way to do this is by reducing the emissions of Greenhouse Gasses (GHG) worldwide. As climate change affects every living being on this planet, although some regions are likely to be affected worse (Tol, 2014), global leaders have ratified multiple treaties with regard to this issue. One of the most important goals of the Paris Agreement is to keep the increase in global average temperature below 2°C above pre-industrial levels (European Commission, n.d.-c). The Paris Agreement is the most recent treaty related to climate change and is currently signed by 195 different countries. Therefore, EU has set targets to reduce the emissions of GHG by 40% by 2030 as compared to the levels in 1990.

Efficient policies are required in order to reach these goals. A cap-and-trade system or a general tax on emissions are widely regarded as the two most effective solutions (Tol, 2014; Zapf et al., 2019; Wan, 2012). However, both market-based instruments have limitations. If a tax would be implemented, a challenge in defining how high the tax should be in order to reach the emission reduction targets remains. On the other hand, an Emission Trading System (ETS), in which a capped amount of tradeable emission permits are granted, provides certainty that targets are met. However, the financial gains of abatement are uncertain and this poses challenges with regard to investments.

Taxes are politically harder to implement as the word is 'toxic' and politicians are often afraid to lose support. Moreover, taxing pollution upstream or midstream, i.e. taxing the exploitation and importation of fossil fuels, can be disastrous for a country's export if other countries do not implement the same tax. If taxes where implemented downstream, i.e. consumption of goods and services in which GHG are emitted are taxed, the public is affected directly and this is a tough case to make for a politician. Hence, it is no surprise that a carbon tax is not widely implemented (Tol, 2014).

The ETS was implemented in the EU in 2005 and is currently in its third phase (Wolff and Feuerriegel, 2019). The efficiency and side effects of the system have been widely researched. The design of an efficient cap-and-trade system is complex and represents a challenge for policymakers. The price of emitting should be high enough for the system to be effective. However, if the price for emission allowances becomes to high, it may interfere with economic development. The EU ETS is currently implemented in all EU countries plus Iceland, Liechtenstein and Norway. The system covers power and heat generation, energy-intensive and commercial aviation between the participating countries (European Commission, n.d.-a) .

Theory suggests that carbon prices should be passed through to electricity prices (Jouvet and Solier, 2013). Sijm et al. (2006) and Honkatukia et al. (2006) were the first to empirically confirm this hypothesis. However, others could not find this relation in later stages of the EU ETS (Jouvet and Solier, 2013; Wolff and Feuerriegel, 2019). The carbon pass-through is expected to reduce emissions in the electricity sector in two ways. Firstly, changing the marginal costs of polluting plants relative to their pollution may induce changes in the merit order. Therefore, less CO2 would be emitted under the same load. Secondly, price increases as a result of the pass-through of carbon prices should reduce demand.

Although the EU ETS provides certainty with regard to abatement under the assumption of correct monitoring, it introduces uncertainty with regard to the price of emitting. Therefore, there is also risk with regard to the benefits of abatement. Flora and Vargiolu (2020), using Monte Carlo simulations at the firm level, found that addition of a price stabilization mechanism to the ETS would have a positive effect on emission abatement related investments. As emission prices are expected to be passed through onto electricity prices, this may add to the uncertainty in the electricity market. Electricity price uncertainty may induce investment delays which affect consumers and may lead to capacity inadequacy.

Carbon price levels have been relatively low from 2009 to 2018, despite the introduction of the Market Stability Reserve (MSR). The UK responded by introducing a Carbon Price Floor (CPF) as an addition to the EU ETS, ensuring a minimum price paid for emissions. Such an environment is likely to foster investments in abatement and provides a clear signal from policymakers with regard to their environmental intentions. Although carbon price levels have increased since 2018, there is no reason to believe that another carbon price crash is inconceivable. Hence, a CPF, or another price stability instrument, might be desired in the rest of the EU to avoid the costs of emitting falling below the desired value.

The analysis of a CPF is of particular interest since the Dutch government under Rutte III indicated the intention to introduce a minimum price for CO2 emissions in the electricity sector as an addition to the EU ETS (Rijksoverheid, n.d.). Whereas the Dutch intend to introduce a CPF on a national level, France has emphasized its interest in a EU-wide CPF. Regardless of whether a CPF is introduced on a national level or as a EU-wide price stability instrument, it is important to research how the relation between carbon and electricity prices would be affected.

Therefore, this thesis researches the relation between carbon prices and local day-ahead electricity prices, taking into account the possible increases in volatility induced by shocks in the carbon price. Moreover, it is investigated how this relation is affected by the introduction of the UK CPF using daily average wholesale electricity prices. The former analysis will be conducted in nine EU countries to gain a complete overview of the electricity and carbon price dynamics. Electricity systems require many lump sum investments and the networks are therefore path dependent. This has resulted in very different energy systems and energy sources within the EU. Hence, it is plausible that the effects of the EU ETS on the energy system differ per country.

Based on the findings of this thesis, an adjusted design of the UK CPF is proposed that can be implemented EU-wide or on a national level. The design improves upon the UK CPF by dynamically adjusting for the difference between the current ETS price and the CPF. Currently, this difference fixed per year and is based on a 3-year ahead forecast (Hirst, 2018). Therefore, market participants are dependent on ETS carbon prices and the additional costs chosen by the UK government. This introduces new forms of unnecessary risk.

This thesis commences with a literature review that analyzes the electricity system and discusses relevant literature. Subsequently, a research question is defined based on an identified research gap. Thereafter, the research approach is presented and the quantitative models are discussed. This is followed by an analysis of the results, which leads to a proposed design for an improved CPF. Lastly, this thesis is concluded with a discussion and conclusion.

2 Literature Review

This section provides an overview of electricity systems as well as an overview of relevant literature in order to identify a research gap. The literature has been accumulated using the Scopus database. The focus of the gathered literature is the EU ETS with a connection to energy systems. Hence, the following keywords have been used in the search: "ETS", "Emission Trading System", "Cap-and-Trade", "Energy", "EU", "European Union", "Volatility" and "Carbon Price Floor". The analysis of the literature is structured as follows. In the first subsection, a systems analysis is conducted that focuses on electricity price formation, volatility and the mechanics of carbon pricing. Subsequently, literature with regard to ETSs, volatility in electricity markets and the introduction of a CPF is discussed. Lastly, a research gap is identified and a corresponding research question is formulated. An overview of all literature evaluated in this section is provided in Appendix A.1.

2.1 Overview of the Electricity System

In order to conceptually manage the complexity of the electricity system, it is convenient to distinguish between the physical and the institutional side of the system. The physical layer consists of all aspects through which the electricity physically flows. This entails the power plants where the electricity is generated, the transmission and distribution systems and the actual consumption of electricity, often referred to as load. The institutional layer consists of actors that control aspects of the physical layer, but also other parties such as consumers, households as well as industrial, and exchange operators. A schematic overview is provided in Figure 1 (de Vries et al., 2010).

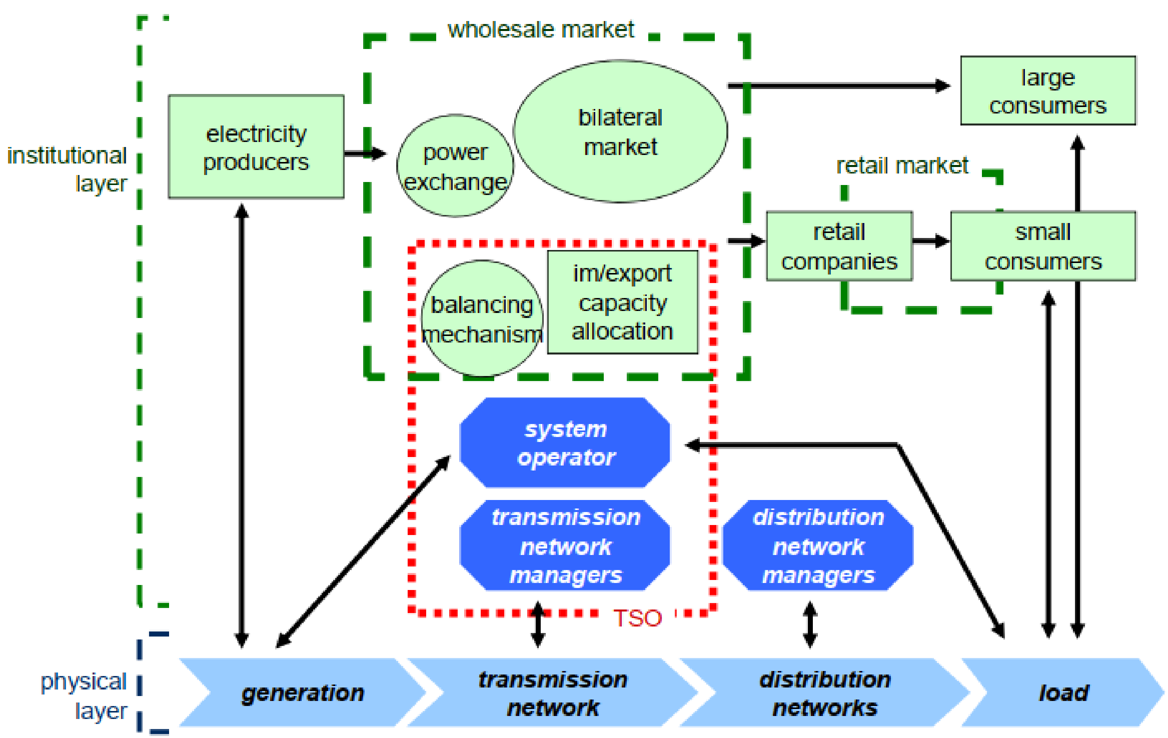

Figure 1: A systematic overview of electricity systems. Image retrieved from de Vries et al. (2010).

The double pointed arrows in Figure 1 indicate ownership of a physical aspect of the power system. Figure 1 is based on the Dutch electricity system, as the Dutch implemented a textbook ideal of a decentralized market (de Vries et al., 2010). Market decentralization is discussed in more detail in the following subsection.

There exist multiple markets when it comes to electricity. Whereas most people often think of electricity prices in the context of the retail market, industry professionals and scientific literature often refer to the wholesale market when electricity prices are discussed. The retail market encompasses the contracts between retail companies and small consumers, which are mostly households and non-energy intensive companies. These retail companies, as well as large/industrial consumers and trading companies, buy electricity in the wholesale market. The wholesale market connects producers to these large customers via either power exchanges or the bilateral market. Most electricity is traded in the bilateral market (de Vries et al., 2010; Ketterer, 2014) and the content of these contracts is confidential. However, volumes traded on energy exchanges are increasing and are considered as an important benchmark for bilateral contracts (Ketterer, 2014).

The Transmission System Operator (TSO) has three main tasks: balancing, management of the transmission network and management of import/export capacity. The transmission system transports electricity across relatively large distances often using high voltages. Balancing entails the balance between electricity injected into the system and withdrawn from the system. As energy can not simply be stored in the network, energy injections and withdrawals have to be in a constant equilibrium. The other two tasks consist of providing transmission capacity, operating it and managing congestion for national transmission capacity as well as international connections.

The distribution networks, operated by the Distribution Network Operator (DSO), connects the transmission network to final consumers. Hence, the DSO is responsible for managing the system that distributes electricity from a central point to scattered consumers. The role of DSOs has become increasingly difficult with the increase of decentralized electricity generation (de Vries et al., 2010). Smaller generation plants often feed-in directly to the distribution networks. Hence, DSOs also have an increased responsibility in transporting this generated electricity.

2.2 Liberalization of Electricity Markets

Liberalization of the European energy markets date back to the early 1990s (de Vries et al., 2010). The goal of liberalization of the energy markets is the introduction of competition where possible. It is expected that competition leads to more efficient markets, which is beneficial to the public. However, competition is not possible in every aspect of the energy system. Natural monopolies occur due to the networked characteristics of energy systems.

Policy is implemented such that the public goals of reliability, affordability and environmental responsibility are reached (de Vries et al., 2010). These goals are also known as availability, affordability and acceptability. Although the policy goals are equal throughout the Europe, the policies that have been implemented vary widely within the continent. This section will first elaborate on the common characteristics of liberalized electricity markets and continues with a more detailed description of the regulation in each of the evaluated countries.

It is no surprise that policies vary in each country, even though the policy goals are equal. Trade-offs have to be made as reliability is often more expensive and environmental responsibility may come at the cost of either of the other policy goals. Moreover, de Vries et al. (2010) describe how governments are constrained by physical, macro-economic and institutional factors. For instance, a country with fossil fuel supplies may be less concerned about varying fuel costs, whereas only few countries have the possibility to build pumped-storage hydro-power plants. Similarly, governments have to consider local political ideology and financing options. These factors as well as different starting points and different speeds of liberalization have resulted in a fragmented European electricity market.

In the process of the liberalization of electricity markets, the value chain had to be unbundled. The unbundling can be approached from a physical and from an institutional perspective. From a physical perspective, the electricity network consists of the layer where electricity is generated, the transmission network as well as the distribution network, and the layer in which electricity is consumed, which is often referred to as the 'load'. The institutional aspect regard the actors that control the physical layers of the system as well as other parties involved.

Based on the new Electricity Directive of 2003 (EUR-lex, n.d.; de Vries et al., 2010), replacing the 1996 Directive, both transport of electricity through the network and system operation are considered natural monopolies. Solely electricity generation, trade and supply allow for competition. This entails that network managers have been appointed for managing and operating the transmission and distribution networks. Network managers are required to allow network access to third parties based on predetermined tariffs without discrimination. Although these activities have to be unbundled from other commercial activities, ownership of vertically integrated companies is allowed as long as independence is guaranteed in terms of legal structure, organization and decision making.

In 2009 the EC initiated the 'Third Energy Package' with net directives regarding the electricity sector as well as new regulations (European Commission, n.d.-e). The Third Energy Package intended to enhance the security of supply, protect consumers and improve market functioning. To improve market functioning, transmission was unbundled from generation, trade and retail. Moreover, it focused on the integration of national European markets by the establishment of the European Network of Transmission System Operators (ENTSO). The ENTSO will enhance integration by establishing standards for network codes and planning network development.

2.3 Market-based Instruments for Emissions Reduction

According to the First Welfare Theorem, a competitive equilibrium is always a Pareto optimum (Tol, 2014). The reasoning is intuitive: why would both parties voluntarily agree to the exchange if both parties would not be at least a well off as without the exchange. GHG emissions are an externality of many common economic transactions in today's world. As exchanges in goods or services that involve the emissions of GHG negatively affect third parties, these exchanges no longer lead to a Pareto optimum. Therefore, government intervention by means of policy is justified since it can increase welfare.

Multiple shortcomings have been identified when it comes to carbon pricing regulation. Zapf et al. (2019) distinguish, carbon leakage, rebound effects, the green paradox and the free rider problem. It is important to note that, as climate change is a global problem, GHG emissions have to be reduced worldwide if the externalities are to be eliminated. Carbon leakage means that if emissions are priced in some places, emitting industries can move to places where the prices are lower/absent. Hence, although the emissions in some countries are reduced, the problem is not. The rebound effect occurs when a decrease in energy use, as a result of efficiency improvements (e.g. improved housing isolation), is canceled out by changes in people's behaviour. Moreover, the green paradox is explained by Sinn (2012). Here, it is argued that owners of carbon resources accelerate production in anticipation of climate policy and reduced demand due to carbon pricing. Hence, climate change is accelerated in expectation of a reduction in carbon consumption in the future. Lastly, the free rider problem in this context occurs due to the fact that it is more beneficial for countries to not reduce their emissions if all other countries do their part. Here, the climate and clean air is a public good and it is to every country's benefit that GHG emissions decrease. However, if all countries would reduce their emissions, each country has incentives to unilaterally stop their emission-reduction efforts.

A common approach is direct regulation. In this type of regulation, the regulators tell companies and households what to do and how to do it. For instance, the European Commission uses this type of regulation by setting limits to the average emissions per kilometer of a car manufacturer's fleet (European Commission, n.d.-d). However, the regulated should be homogeneous and regulation should keep up with innovation for direct regulation to be effective. As this is unrealistic in today's world, market based instruments are required. Tol (2014) shows analytically that subsidies, taxes and tradable permits are cost-efficient in theory. Practical differences exist between the three market-based instruments. The distributional effects of taxes and subsidies differ. Subsidies cause money to flow from the government towards households and companies. Taxes have the opposite effect. Moreover, with both taxes and subsidies it remains uncertain what the cost/reward of emissions/abatement should be in order to reach specific emission reduction goals. Tradable permits, on the other hand, guarantee environmental effectiveness, but with this policy the cost/benefit of emissions/abatement remain uncertain. This section discusses market-based instruments by first elaborating on carbon taxes, subsidies and cap-and-trade systems. Second, existing cap-and-trade systems are discussed.

2.3.1 Carbon Tax & Subsidies

In case of a CO2 tax, emitters will have to pay a certain amount for each unit of CO2 emitted. In case of a subsidy, a compensation is offered for every unit of CO2 that is not emitted. Tol (2014) argues that both have the same effect in the short run. However, the distributional effects differ. A tax subtracts money from households and private companies while it enriches the government. The opposite cash flow is observed for subsidies. Moreover, taxes make doing business in a certain industry more expensive, whereas subsidies make doing business in certain industries cheaper. Hence, investment flows to emitting industries will shrink using taxes whereas investment flows to clean industries will increase using subsidies.

For both taxes and subsidies the biggest challenge for policymakers is to quantify the price/reward of emitting/abatement. Tol (2014) explains that the Pigou Tax is the best possible market intervention. The Pigou tax sets a price on the externality, it compensates the victim of the externality using the tax revenues and the compensation is such that it offsets the loss of welfare at the margin. However, it is difficult, if not impossible, to determine exactly what the loss of welfare due to climate change is. The biggest disadvantage of taxes and subsidies to reduce carbon emissions is that the results remain uncertain. Although prices/rewards are fixed, it remains uncertain how market participants react. Therefore, it is unclear by how much are emissions reduced and whether societal abatement goals are reached.

2.3.2 Cap-and-Trade Systems

A cap-and-trade system, or tradeable permits system, is similar to a carbon tax but differs as the price of carbon is also determined by a market-based mechanism. The regulator sets a limit to the total number of carbon that may be emitted. Every market participant will need permits before emitting. As a limit to the number of permits exists, a permit market will appear and therefore a price for emissions will appear.

Tol (2014) describes the different ways in which a tradable permits system can be implemented. The biggest differences can be found in the industries that fall under the system and the initial allocation of permits. Permits can be allocated in four different ways. The most popular of these is called Grandfathering. In this system, permits are allocated for free based on emissions in the recent past. However, this system can be considered unfair as historically heavy polluters are rewarded and it becomes more difficult for smaller companies to grow. Furthermore, permits can be granted to the victims of the externality or divided on a per capita basis. These options are both unpractical as it is difficult to identify the victims and the latter option requires close international cooperation and a large transfer of wealth. The last option uses auctions to allocate permits. Auctions were used to allocate 40% of the permits in the EU ETS in 2013 and are planned to be used for 100% in 2020. The main advantages of auctions is that the price of permits are known from the moment they are allocated and that the regulator gains substantial revenue that can be used for compensation of the victims or for relevant subsidies.

Economic theory suggests that, under a cap-and-trade system, the price of emission permits is a marginal costs of electricity production (Freitas and da Silva, 2015). Since the permits can be sold at the current market price, producers have an opportunity cost if used for the purpose of emitting (Pinho and Madaleno, 2011). Hence, producers are assumed to add the cost of carbon to the marginal cost of electricity generation. Policy makers hope to change the merit order of electricity generation by increasing the cost of polluting generation methods. Moreover, as the cost of electricity increases in general, consumers have an incentive to use less electricity. However, for both effects, the cost of carbon has to be passed through to the electricity prices.

The outcome of a cap-and-trade system is fairly certain as the total amount of emissions is set by the regulator. However, uncertainty arises with regard to the price of emitting and therefore the benefits of abatement. This complicates the decision making process for investments in emission reducing technologies. Moreover, if all other market participants invest in reducing their emissions, the price of CO2 will decrease. Hence, it may be more profitable to delay such investments as long as possible.

However, a cap-and-trade system is only environmentally effective if it is monitored and enforced correctly. Tol (2014) argues that enforcement in a cap-and-trade system is only as strong as the weakest link in the chain. That is, if a certain monitoring agent is not reliable, it can have big consequences for the whole permission market. If the occurrence of fraud is likely in a district within the permit market, there is no reason to believe that the actual emissions are equal to the total emissions allowed by the emissions cap.

Multiple variants of the cap-and-trade system are currently enforced (ICAP, 2019). The biggest one is the EU ETS, which is enforced in all EU nations plus Iceland, Liechtenstein and Norway. Moreover, China is currently testing an ETS in some areas and is planning to expand it nationwide. An ETS is also implemented in Switzerland, Kazakhstan, South Korea and New Zealand as well as in parts of Japan, Canada and the United States. It should be noted that an ETS is present in the U.S. only in California and some North-Eastern states, under the title Regional Greenhouse Gas Initiative (RGGI), whereas an ETS is only enforced in the Québec region in Canada. It is noteworthy that the carbon markets of California and Québec have been linked as of 2014 (ICAP, 2019). The different carbon markets also differ in practicalities (ICAP, 2019). What sectors are subject to the carbon market and the threshold size for companies to fall under the regulation differs per country. Moreover, the different markets have adopted different market stability instruments. Some markets work with a price ceiling (New Zealand, California & Québec) or a minimum price (RGGI), while others work with both (South Korea).

The EU Emissions Trading System

The EU ETS was set up as the first international emissions trading system in 2005 (European Commission, n.d.-a). The European Commission (n.d.-a) describes the system as a "key tool for reducing greenhouse gas emissions cost-effectively". The basic principle is simple, European Emission Allowances (EUAs) are distributed and are needed for emitting greenhouse gases. The obtained permits can be traded with other companies when a company emits less than expected and holds a surplus. The tradability of the permits will stimulate that emissions are cut where it costs the least to do so. If a company emits without the equivalent in EUAs, it will receive fine.

The system is divided into phases and is currently in its third phase. Phase I, 2005-2007, was mostly used for testing of the system (Tol, 2014). Subsequently, Phase II lasted from 2008-2012. The system is currently in Phase III and will transit to Phase IV in 2021. The subsequent phases allow for the iterative improvement of the policy design. Hence, the exact rules are adjusted with each phase, where the system is intended to resemble a free market more closely with every phase. The EUAs are fungible within each phase (Tol, 2014). This means that a phase II permit is still valid in phase III, but a phase III permit is invalid during prior phases.

The EU chose to use a mid-stream market for the EU ETS (Tol, 2014). This decision makes sense, solely because there are strong arguments against the other options. In an upstream market, permits would be required for the exploitation and importation of materials with emitting potential. However, the small amount of companies in these sectors would induce market power issues. Moreover, a downstream market would lead to the requirement of the possession of permits for the consumption of goods and services that include the emissions of GHGs. This would be a difficult policy to implement and would be a burden for EU citizens. In mid-stream market it is likely that carbon costs are passed through onto consumers. This effect is also observed by Freitas and da Silva (2015) in Spanish electricity markets.

Currently, the majority of the permits are distributed by auction. However, the EUAs were initially grandfathered (Tol, 2014). Grandfathering entails that permits are distributed for free based on historic emissions. This is clearly not ideal from a free market oriented perspective, as it hinders growth of historically smaller companies and 'rewards' historic emitters. Hence, it is no surprise that since phase III auctioning is described by the European Commission (n.d.-a) as the default method for the distribution of permits and is intended to be used increasingly over time. At the start of phase III, 57% of all permits were auctioned. However, the permits allocated to the electricity sector are 100% auctioned except for a few countries with a far below average GDP per capita (ICAP, 2019).

The EU ETS currently covers 45% of the GHG emissions in the EU (European Commission, n.d.-a). This is due to the fact that not all industries and not all gases are subject to the policy. With regard to CO2 emissions, emissions from power and heat generation, oil refineries, steel works and production of iron, aluminium, metals, cement, lime, glass, ceramics, pulp, paper, cardboard, acids and bulk organic chemicals and flights within the ETS district are covered by the EU ETS.

In order to control the surplus of permits in circulation the European Commission initiated the Market Stability Reserve (MSR) (European Commission, n.d.-b). Emissions decreased as a result of the 2008 economic crisis. This led to a surplus of EUAs and decreased permit prices in the following years. Initially, the European Commission postponed the auctioning of many planned permits until later in phase III. The MSR started in 2019 as a long term solution to the previously described problem. Instead of auctioning the permits later, the allowances are now added to a reserve. The allowances can be released from the reserve in case of a shortage of permits. However, permits not released before 2023 will be labeled invalid.

Other Cap-and-Trade Systems

As discussed before, the EU ETS is no longer the only emissions cap-and-trade system. In total, 8% of all global GHG emissions are covered by a cap-and-trade system (ICAP, 2019). The principle of the systems is the same. However, they vary in detail. Currently, ETSs are in force in the following regions: the EU, Switzerland, New Zealand, the Republic of Kora, Kazakhstan, parts of Japan (Tokyo and Saitama), different regions in the USA (California and part of the Northern East Coast), parts of Canada (Québec and Nova Scotia) and various cities in China are currently running pilots.

The ETSs vary in terms of means to stabilize prices and reduce uncertainty. Policy designers can choose to implement lower price boundaries for emission permits in order to ensure environmental integrity in case of a surplus of allowances. Moreover, it is an option to set upper boundaries in times of high demand in order to keep the program manageable. For instance, New Zealand allows for the purchase of allowances against a fixed price in case of high prices in order to protect local industries. The RGGI on the other hand, sets a floor price for auctions. These stability measures clearly provide more price certainty than the EU's MSR.

The Clean Development Mechanism (CDM) defined in the Kyoto Protocol provides a flexible way to 'trade' permits between different markets (Tol, 2014). A project that reduces emissions, anywhere in the world, can be traded for permits. Certified Emissions Reductions (CERs) units are granted on a per project basis and may be traded with various emission trading schemes. As climate change is a global problem and mitigation anywhere is useful, it makes sense to reward companies that reduce their emissions on the other side of the world. Although the idea makes sense, there is a high risk of fraud and the policy is heavily criticized (Tol, 2014).

2.3.3 Carbon Market Stability Instruments

As mentioned above, some ETSs have established market stability instruments in order to reduce carbon market uncertainty and stabilize carbon prices. Hence, the main goal of a market stability instrument is to provide market participants with additional long-term certainty. Although stability mechanisms can operate in a variety of ways, the most straight forward way is by establishing price limits. Price limits can be established by setting a price minimum, maximum or both.

The EU ETS implemented the MSR, which temporarily removes allowances from the market when the number of allowances in circulation exceeds a certain threshold (ICAP, 2019). The removed allowances are later re-released to the market when the number of allowances in circulation decreases. This system is intended to increase prices when a supply surplus occurs. The RGGI plans to establish a similar stability instrument, which withdraws allowances from the market when mitigation costs, and therefore carbon prices, are found to be lower than expected (ICAP, 2019). The most important difference is that the RGGI removes the allowances indefinitely. Although market reserve systems work in theory, the effects of withdrawing allowances from the market will remain uncertain. A price decrease can be short lived and policy makers will have to quickly decide how many allowances should be withdrawn.

Price limits are implemented in the UK, the RGGI, New Zealand, some of China's ETS pilots and the California-Québec ETS. The UK, the RGGI and ETS pilot's in China implemented a carbon price floor, New Zealand a price ceiling, whereas the California-Québec ETS implemented both. Although both instruments are likely to reduce price volatility, the intentions of price floors and price ceilings are clearly different. A carbon price floor is to intended to provide certainty for investments in mitigation and low-carbon solutions. Hence, price floors are established to ensure the effectiveness of the ETS. The RGGI and California-Québec ETS price floors work by selling no permits at auctions below a pre-defined threshold (Flachsland et al., 2020). Flachsland et al. (2018) argue that carbon price floors in general enhance long-term investment certainty as the policy mechanism directly reduces uncertainty in investment decision calculations. A price ceiling on the other hand, is intended to remove uncertainty in industrial investments. The price ceiling removes uncertainty with regard to unprofitable investments as a result of rising carbon costs. Hence, it serves to protect the local economy and local investments.

A downside of implementing direct price limits, is that these instruments partly remove the price formation by the market. Moreover, setting the price limit(s) poses and additional challenge. However, setting price bounds can clearly provide certainty for investors and market participants as part of the price uncertainty is removed. Moreover, it might reduce price speculations which may result in unrealistic prices.

2.3.4 The UK Carbon Price Floor

The UK is the only country that has unilaterally implemented a carbon market stability instrument. Hence, it is the only country within EU ETS that has implemented such an instrument. The UK established a minimum price for carbon by means of Carbon Price Floor (CPF) on the first of April 2013 (Hirst, 2018). The CPF uses a Carbon Support Price (CPS) whenever carbon prices fall below a certain level to maintain a minimum price. Hence, the CPS is zero whenever the EUA price is above the threshold value and the minimum value minus the EUA price when price of permits falls below the threshold value. The CPS is charged to electricity generators based on the fuels used for generation. The CPF aims to encourage the energy transition by reducing price risk.

The CPF taxes fossil fuels used for the generation of electricity. The corresponding CPS rates are provided for different fuels on a £/kWh basis (Hirst, 2018). The CPS is not dynamic, but fixed for each year. Hirst (2018), in a briefing document for the House of Commons, explains that the CPS rates are set three years ahead of the year in which they apply and announced in the Budget Reports. The CPS rates are calculated based on the (expected) difference between the target minimum carbon price (CPF) and the market price. The market price is based on the average annual ICE-ECX benchmark end of day settlement price for carbon for delivery in the target year. Hence, market prices will remain relevant even if market prices fall below the price floor threshold.

However, the CPS was capped to 18£ per tonne of CO2 emitted in the budget of 2014 in an effort to avoid harming the competitiveness of UK's energy intensive industries (Hirst, 2018). Despite this cap, the CPF has probably aided to changes in the UK energy mix. The share of coal power generation has decreased from 46% in 2012, to only 3% in 2016 (Howard, 2016). It seems that the price of carbon (in combination with the CPS) has increased the marginal cost of coal power generation such that gas power has surpassed coal power in the merit order of production.

2.4 Wholesale Electricity Price Formation

This subsection discusses how electricity prices are formed in the wholesale electricity market. Prices in the retail market react to developments in the wholesale market and are not discussed in detail in this thesis. The electricity wholesale prices are a result of supply and demand, as prices are for all freely traded products or services. However, electricity markets are unique due to multiple physical characteristics (Fezzi and Bunn, 2010). Firstly, electricity cannot be stored in an economically feasible fashion. Therefore, a continuous balance between consumption and generation is physically required for the system to function properly. This need for continuous balancing induced the origination of a balancing market. Moreover, this changes the dynamics of the forward market, as the commodity can not simply be stored over time. Secondly, demand fluctuates throughout the day and year (Ketterer, 2014). As there are limits to how much electricity can be transported feasibly, either due to energy loss or the lack of transportation capacity, demand has to be met locally. Therefore, the local generation apparatus needs different types of plants to cater to this volatile demand. This results in a discontinuous supply function (Bunn, 2003), resulting in even more volatile prices in comparison to the demand.

As mentioned before, most electricity is traded using bilateral contracts that are not publicly available. However, price agreements in these contracts are formed based on prices that are publicly disclosed by power exchanges. On the power exchanges, electricity prices are formed in the derivatives market, the day-ahead market, the intraday market and the balancing market. A systematic overview of these markets is provided in Figure 2. These different markets will be discussed first, followed by a theoretical description of price formation in the day-ahead market and a systematic overview.

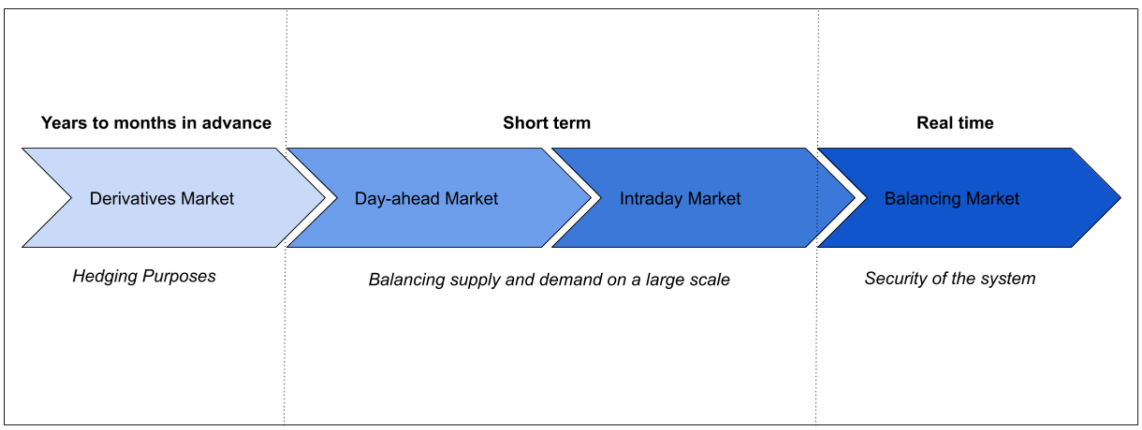

Figure 2: A systematic overview of the different wholesale electricity markets.

Derivatives Market

The derivatives market is mainly used for hedging purposes. Through derivative contracts it is possible to trade for each hour of the day years to months in advance. It can be useful for market participants to use this to hedge price risk or counterparty risk from a bilateral contract. The derivatives market makes it possible to hedge for particular days or weeks in which uncertainty is expected to increase. The derivatives contracts oblige the provider of the contract to deliver the power to the grid at the predefined price.

Day-ahead Market

On the day-ahead market, hourly prices are formed for the following day by means of an auction at noon. Generation companies, retail companies, brokers, traders and large/industrial consumers participate in the day-ahead market. Suppliers place bids for each hour regarding how much electricity they can produce and at what price. Potential buyers correspondingly place bids how much they are willing to buy for each price at each time. The price at each hour is at the intersection of supply and demand. The contracts derived from the auctions are binding and market participants are financially liable for deviations from their energy programs (de Vries et al., 2010). As bids have to be placed one day in advance, generation capacity and consumption have to be forecasted. Generation forecasting becomes increasingly difficult as the share of RE increases. Since RE generation is dependent on weather conditions, deviations from the weather forecasts can impact the cost of a producers obligations for the following day.

Intraday Market

The intraday market is an addition to the day-ahead market to help secure the required continuous balance between supply and demand (Nord Pool Group, n.d.). The intraday market allows for consumers to adjust for unexpected changes in demand and for producers to compensate for outages. Intraday markets are continuously open and offer 15-minute, 30-minute and hourly block products. Unlike the day-ahead market, the intraday market follows a first come first serve principle, taking the best prices into account. The first come first serve principle is not needed in the day-ahead market as all bids are placed at a fixed time.

Balancing Market

Although market participants are financially liable for deviations from their contracts in the day-ahead market, grid balancing is ultimately the responsibility of the TSO. Grid balancing is essential in order to maintain grid frequency within a specific range. The frequency decreases when there is a power shortage, while it increases when there is overproduction. The management of reserve capacity available for the purpose of grid balancing is managed by third parties that offer these so-called ancillary services. The balancing mechanism consists of three reserves (Chang, n.d.). The primary reserve is capacity that is reserved for the occurrence of generation shortages. The TSO reserves this capacity for a specified period and compensates the owner of the capacity for this service. The electricity has to be generated within 30 seconds for a maximum period of 15 minutes. The owner of the capacity is solely compensating per MW of capacity offered during the predefined period. If an imbalance persists for over 15 minutes, the secondary reserve is activated. If the secondary reserve is activated, providers of ancillary services are compensated per MWh. After 60 minutes, the TSO switches to the tertiary reserves. The tertiary reserves are offer to the TSO via contracts and the capacity must be available at all times. This entails that the capacity may not be used for other purposes.

2.4.1 Day-ahead Market Price Formation in Theory

Electricity prices are formed for each hour of the following day on the day-ahead market by means of an auction. Producers submit blocks of how much electricity they can produce at a certain price at each time of the day. This is matched with the demand to form an hourly price.

Imagine a market in which producers have two means to generate electricity, either using renewables or a specific type of fossil fuel. Producing power using renewables is cheaper than using fossil fuels, $C_f > C_r$. However, only a limited amount of renewable capacity is available on each point in time $\bar{Q}$. This is dependent on the total installed capacity as well as weather conditions. Therefore, the marginal cost (MC) of production for this market can be defined as follows (Honkatukia et al., 2006)

$$
\begin{aligned}
MC = C_r \qquad & \text{for} \qquad Q < \bar{Q} \\
MC = C_f \qquad & \text{for} \qquad Q > \bar{Q}
\end{aligned} \tag{1}
$$

In equation (1), Q represents the total demand at a certain time. The market price at each time is set equal to the marginal cost of generation. Hence, the producers of electricity using renewables make a profit for for $Q > \bar{Q}$.

The quantity of renewable electricity that producers can announce to produce, $\bar{Q}$, is not necessarily equal to the quantity that is optimal for producers to generate, $Q*$. This depends on the competitiveness of the market. A competitive generator will try to maximize profit (Honkatukia et al., 2006):

$$\pi = P(Q) * Q - MC * Q \tag{2}$$

Here, P(Q) is the market clearing price, which is a function of demand, Q. π represents the generators profit. In a competitive market, where one cannot influence the output decisions of one's competitors, the marginal revenue is equal to MC=P. Figure 3 shows that if generators produce at $Q^*=\bar{Q}$, with demand level P', they make a clear profit. However, as the generators are price takers in a competitive market, they do not have market power. However, in an imperfectly competitive markets where some generators are able to affect the market clearing price, it might be beneficial for these generators to lower the output size, Q^*. When the offered supply of renewable electricity is exactly equal to demand, $MC = C_f$. Therefore, if a powerful generator is aware of how to obtain this outcome, it might be feasible for this market participant to offer $Q^* < \bar{Q}$.

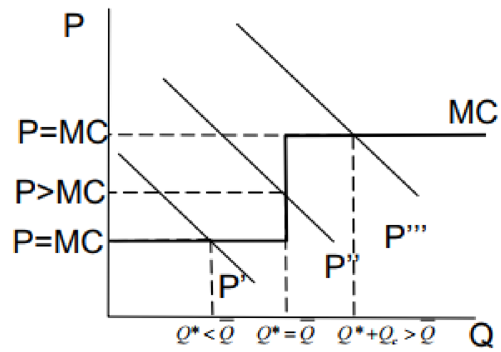

Figure 3: A graphical description of the price electricity price formation. Retrieved from (Honkatukia et al., 2006).

In a real market, price formation is of course less simple. As discussed before, electricity demand varies strongly during the day and throughout the year. Different types of generation are used to cater to different quantities of demand. Bunn (2003) describes how some (often inflexible) plants can offer large amounts of power at low marginal costs to provide the base load. Although the marginal costs of these types of plants are relatively low, the capital costs are typically higher. Hence, these plants have to run most of the time to earn back one's initial investment. Nuclear power plants and coal-fired power plants are examples of power plants often used to cover base load. To adjust for higher demand, flexible power plants are employed. These plants run at high marginal costs, but can be installed for relatively low capital costs. Gas fired power plants are often used for this purpose.

Hence, most electricity markets are dependent on different types of fossil fuel power which are offered at different marginal costs. The order of marginal costs is most often referred to as the *merit order*. Hence, the number of price steps as shown in Figure 3 is a lot higher in reality and market power is a lot more difficult to determine. Moreover, the marginal costs vary over time as commodity prices vary. The commodity prices are formed by other markets, as most fuels are also used for other purposes than power generation. The merit order may change due to variations in commodity prices as a result.

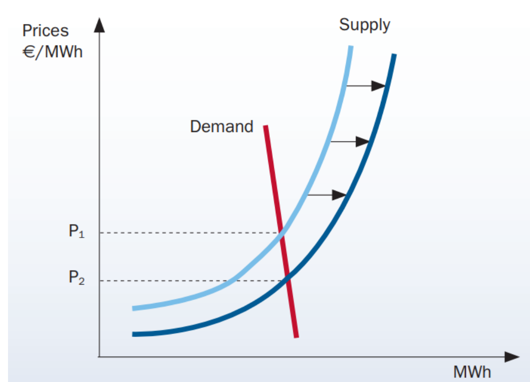

Figure 4: A graphical depiction of the merit order effect. A continuous supply function is shifted to the right if more RE is available. Demand is assumed to be inelastic. Retrieved from (Ray et al., 2010).

Power generated using renewables can be offered at negligible marginal costs. Hence, these power sources come first in the merit order and shift all other sources to the right. This shift in the merit order caused by RES is referred to as the *merit order effect* (Ray et al., 2010). A schematic example of the merit order effect is provided in Figure 4. In Figure 4 one can see that the (continuous) supply function shifts to the right as a result of added renewable power generation. The new price, P2, is lower than P1 as demand is assumed to be inelastic. However, as $\bar{Q}$ is not solely dependent on the installed capacity but also on exogenous weather conditions, $\bar{Q}$ will vary. Ketterer (2014) found that wind energy significantly increases price volatility in Germany.

In a perfect market, the price of emitting should be added to the marginal costs. In case of a cap-and-trade system where allowances are auctioned or in case of taxes on emissions, the actual costs are clear. In case that allowances are grandfathered, there are still opportunity costs. Hence, the costs of emitting are expected to be passed through in a competitive market and the marginal costs of fossil fuel power generation change to:

$$MC = C_f + C_e \qquad \text{for} \qquad Q > \bar{Q} \tag{3}$$

In Equation (3) C_e represents the costs of emitting per unit of production. Note that just like C_f, C_e is dependent on fuel type and other variables such as plant efficiency. Hence, changes in the merit order depend on fuel prices as well as emissions prices.

Honkatukia et al. (2006) mention three reasons for a possible incomplete pass-through of the cost of emissions to electricity prices in the context of the EU ETS. Firstly, distributors can decide to engage in longer term contracts via the forward/bilateral market in order to hedge the risk of ETS induced price spikes. Second, the price of EUAs is influenced by expected growth of the EU power sector. Third, the prices of fossil fuels interact with prices of EUAs. This interaction is corroborated by Bunn and Fezzi (2007) and Freitas and da Silva (2015). An increase in the price of emission allowances will have a bigger impact on coal power producers than on gas power producers. Therefore, gas power producers may be required to pay a premium due to additional demand.

Connected Markets

Market parties are free to trade across European borders (de Vries et al., 2010). If prices are cheaper in neighbouring countries, it will be more beneficial to import electricity than to buy it in one's own country. Similarly, if prices are higher in a neighbouring country, it is more beneficial to offer your generation capacity on the foreign market. If this would happen in sufficient quantities, electricity price differences within Europe would disappear. However, interconnection capacity is often limited and interconnectors are unable to provide the capacity required for European electricity prices to equalize. Moreover, energy losses endured during transportation may make international trade counterproductive despite advantageous price differences.

2.4.2 Overview

This section provides an overview of the mechanics and factors that influence price formation in the day-ahead market. Understanding the different dynamics of a system is essential before considering possible interventions. It is also useful in order to determine what aspects of the system must be evaluated in more detail. Figure 5 provides a simplified overview of the actors involved in the day-ahead price formation and the exogenous factors that influence their actions.

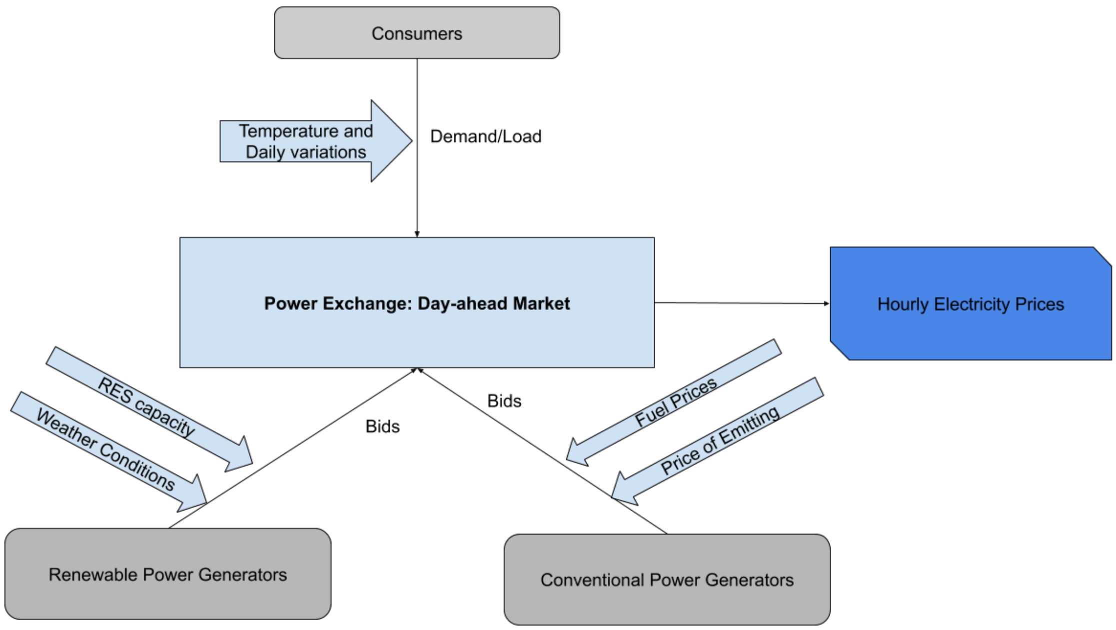

Figure 5: A systematic overview of the most important determinants of price formation in the day-ahead market.

In Figure 5, the grey areas represent actors and the blue area represents the outcome of the process: hourly electricity prices for the following day. The thin lines ending with an arrow represent directional actions. The light blue arrows represent exogenous factors that affect the actions of the corresponding actors.

Consumer demand is often regarded as inelastic. Fezzi and Bunn (2010) found that demand is inelastic in the short run, but that demand responds to high prices in the recent past. Hence, demand/load is mostly determined by seasonal variations and the day of the week (Ketterer, 2014) and temperature (Bunn and Fezzi, 2007).

Renewable power generators will offer all available power they have for negligible prices. However, the size of these bids depends on the available installed capacity and to which extend this can be employed. The latter is dependent on exogenous factors such as wind and sun intensity. The power offered by renewable power generators will shift the merit order to the right and decrease electricity prices (Ray et al., 2010).

Conventional power generators will offer electricity to the market at the marginal cost of production. Plant efficiency and emissions per produced MWh hour are fixed, but the prices of fuel and emission prices vary over time. The latter is especially the case for a cap-and-trade system instead of an emissions tax.

2.4.3 Electricity Prices in Practice

The previous sections discussed the interaction between supply and demand in theory. This section will elaborate on the outcomes of this interaction in practice using France, the Netherlands, Germany and Denmark as examples. These countries provide an overview of the dynamics between supply and demand in European electricity markets as the systems differ in many aspects.

France stands out due to its high share of electricity generation using nuclear power (71%) (Eurostat, n.d.-a). Because of this, France has a low emitting form of electricity that can be generated consistently. Germany is known for its progressive renewable energy policy. The so-called *Energiewende* is the German plan to transform its economy to a low-carbon economy without nuclear energy. Denmark has the highest share of RES in the EU and is therefore an interesting country. The high share is predominantly caused by wind energy which is responsible for 48% of the electriticy generation in Denmark (Eurostat, n.d.-a). Lastly, The Netherlands has the highest share of electricity generation using conventional thermal energy (i.e. fossil fuel generation) in this list (Eurostat, n.d.-a). This dependence on fossil fuels is peculiar, as the Netherlands have a high GDP per capita compared to other EU countries (Eurostat, n.d.-b).

Figure 6 shows the average daily load distribution of each of these four countries. The graphs are generated based on data from ENTSO-E (n.d.). The load for Denmark and the Netherlands are displayed in separate subfigures, as the load values are significantly lower than in France and Germany.

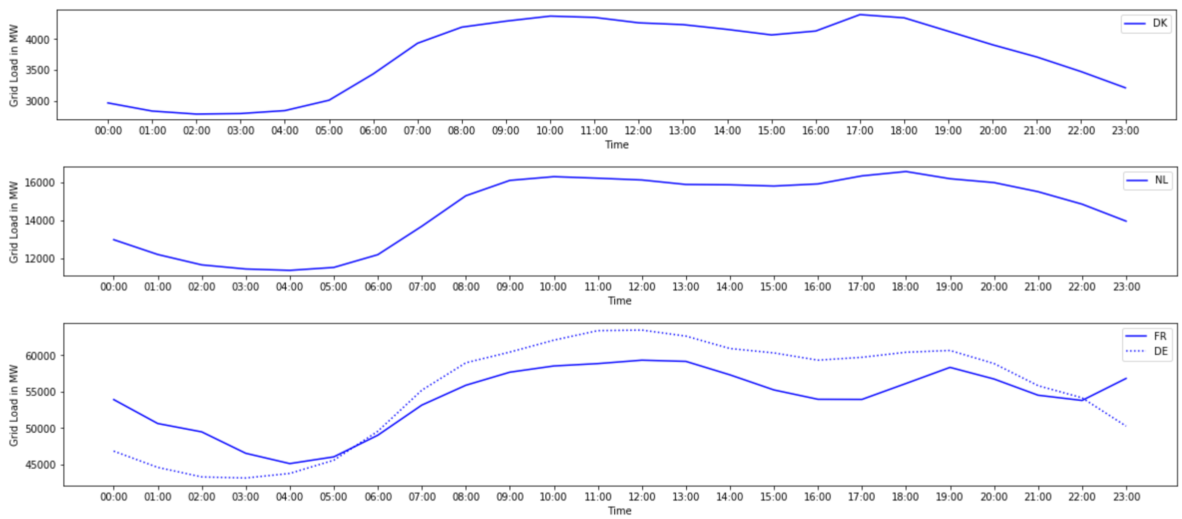

Figure 6: The average daily load distributions of Denmark, the Netherlands, France and Germany.

The load levels in France and Germany are relatively equal. However, it is remarkable that German load levels are lower during off-peak hours, whereas they are higher during peak hours. The shapes of the average load distributions are comparable for all evaluated countries. Load levels start to increase around 04:00 and slowly start decreasing after 18:00.

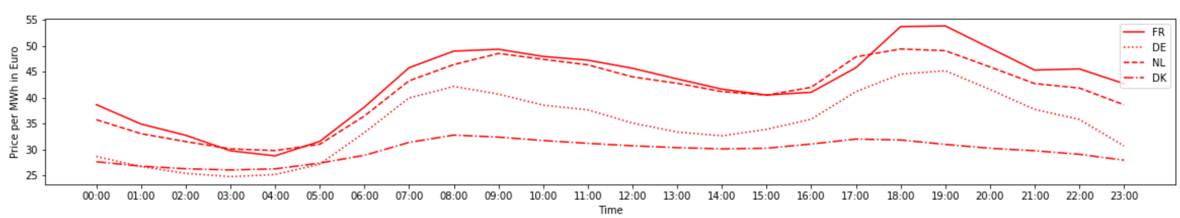

Figure 7: The average day-ahead electricity price distributions of Denmark, the Netherlands, France and Germany.

Figure 7 depicts the average day-ahead electricity price distributions of Denmark, the Netherlands, France and Germany. The graph is generated based on data from 2015 to 2018 from ENTSO-E (n.d). The shapes of the daily price distributions are similar to the load distributions, except for Denmark. The price distribution seems to be relatively flat. Although this effect might be partly amplified by the axis, the data in table 1 confirms the relative flatness of Denmark's price distribution. Even though most of France's electricity is generated using relatively cheap nuclear energy, prices in France are the highest. The average electricity prices in the Netherlands strongly resemble the price levels observed in France. Germany's prices are interesting, as the relative difference between the peak and base prices are the largest. Hence, Germany's intraday electricity prices seem to be most volatile.

Lastly, it is interesting to note that the local minimum between 08:00 and 18:00 is more present in the price distributions than in the load distributions. This is an interesting dynamic between supply and demand and likely caused by the availability of solar power causing the merit order effect during these hours. This effect is less present in Denmark, which is largely dependent on wind power and therefore experiences little merit order effect as a result of solar power during the day-time.

	Avg. Peak Price	**Avg. Base Price**	**Avg. Price**
France	59.82 €/MWh	27.57 €/MWh	42.59 €/MWh
Germany	50.02 €/MWh	21.35 €/MWh	34.87 €/MWh
Denmark	34.55 €/MWh	25.49 €/MWh	29.68 €/MWh
The Netherlands	59.32 €/MWh	28.21 €/MWh	41.03 €/MWh

Table 1: An overview of the average electricity prices per country in Euro/MWh, generated using data extracted from ENTSO-E.

From the figures displayed above it can be concluded that the dynamics between supply and demand vary greatly between European countries. Although the demand curves all have the same shape, the prices differ and have different shape depending on the energy mix. However, all countries have a price minimum around 04:00h. Moreover, these countries all have a price peak between 1700:h and 19:00, although it is less present in Denmark. Lastly, load peaks between 10:00h and 12:00h, but seems to be higher later in the day. Therefore, these hours can be considered intermediate price hours.

2.5 Electricity Price Uncertainty

Electricity spot prices are amongst the most volatile of all financial time series (Jablonska et al., 2012). Volatility complicates the forecasting of a time series. Being able to forecast electricity prices on the long and short term is essential for market participants. Long and short term forecasting are important for different reasons and different market participants require accurate forecasts for different purposes.

Producers of electricity need long term price forecasts in order to make well informed investment decisions concerning the installation of additional generation capacity. Apart from private companies' profit, well informed investment decisions have a broader societal relevance. If investment in new generation capacity becomes too uncertain for producers, this can induce generation inadequacy. De Vries et al. (2010) consider the generation capacity as adequate if it is able to meet demand under all reasonable conditions. Capacity shortages can also induce higher prices and extreme price spikes. Producers are assumed to invest in new capacity if they believe that prices will be higher than the marginal cost for sufficient time to earn back the initial investment costs and hopefully make a profit. On top of price uncertainty, producers are dependent on the investment decisions of competitors. If the total capacity increases unexpectedly as a result of investments by competitors, prices are likely to fall and revenues will fall below expectations. Therefore, the biggest uncertainties for producers is that electricity prices decrease or that the marginal costs of production increase.

Although electricity demand is often regarded as inelastic (de Vries et al., 2010), at least in the short term (Fezzi and Bunn, 2010), consumers are affected by electricity price changes. The latter is especially the case for industrial consumers and retail companies. If electricity prices increase, the profit margins will decrease since the marginal costs of these industrial consumers increase. If electricity prices rise to much, the production processes might become completely unfeasible. If prices rise and retail companies offer electricity for lower prices to households and small to medium sized enterprises, they too will suffer losses. Hence, industrial electricity consumers and retail companies require accurate price forecasts for investment decisions.

It is clear that industrial consumers and retail companies worry about rising prices, whereas producers would be at disadvantage in price increases. Therefore, these parties often engage in bilateral contracts to provide price certainty that both parties benefit from. However, electricity prices formed at the power exchange are often used as a reference for bilateral electricity trading (Jablonska et al., 2012). Hence, accurate prediction of electricity prices throughout the term of the agreement is still required, as neither party will want to be at the losing end of such a trade.

Due to the intermittent character of RE, the increased share of RES in the energy mix has induced an increase in the volatility of electricity prices (Rintamäki et al., 2017; Ketterer, 2014; Woo et al., 2011; Clò et al., 2015). The volatility increases due to the merit-order effect, which Maciejowska (2020) describes as a shift of the supply curve due to an increased availability of low-cost RE generation. Electricity prices decrease as a result. However, the availability of RE power is dependent on weather conditions and therefore increases price volatility. Ketterer (2014) argues that the reduced price in combination with increased volatility caused by RES might delay investment decisions concerning new renewable as well as conventional generation capacity. Woo et al. (2011) even suggest that actors in the electricity market should enhance existing risk management techniques in order to cope with the price risk induced by RES.

A similar case can be made for the increased price volatility induced by the EU ETS. Whereas RE shifts the merit order to the right, an increase in the price of emissions allowances shifts the fossil fuel part of the merit order upwards. Jablonska et al. (2012) show that volatility in electricity prices in the Nord Pool market increased significantly in the first three years of the EU ETS compared to the years prior to introduction of the policy. However, apart from price volatility, carbon pricing introduces additional uncertainty for generators and consumers. Firstly, the EU ETS may change the merit order, differently from the merit-order effect. This adds risk to investments in conventional energy, as the hours that the plant is expected to be running becomes more uncertain. Secondly, the increased price is a burden for consumers, but the uncertainty concerning the degree of the price increase poses an additional challenge. Lastly, this uncertainty also affects investments in RES. Although the increased price can be regarded as a 'premium' for RE generators since they do not need emission allowances, the risk concerning the size of this premium complicates investment decisions.

2.6 Emissions Trading Systems Literature

ETSs have been widely researched to evaluate the effects of introducing a cap-and-trade system. The following section summarizes the literature that concerns cap-and-trade systems. Literature covers topics such as short term policy effectiveness, side effects, effects on investment, macroeconomic effects and dynamics, and different ways to implement the system.

The primary goal of introducing an ETS is the reduction of emissions. The implementation of an ETS appears to have the desired reducing effect on emissions and promoting low carbon development (Forbes and Zampelli, 2019; Zhang and Zhang, 2019; Schäfer, 2019). Forbes and Zampelli (2019) analyzed the electricity system in Ireland and found that CO2 emissions are lower under the same wind intensity since the introduction of the EU ETS. Zhang and Zhang (2019), using the ETS pilots in China as a case study, found that the ETS positively impacted low carbon development with respect to CO2 emissions, energy intensity and energy consumption. Lastly, Schäfer (2019) found that emissions in Germany are lower than in a scenario in which no ETS was introduced. Schäfer (2019) used a linear regression to analyze the decrease in emissions and compared this to a simulated scenario of how the German electricity would have developed without the EU ETS. Although there is a difference, Schäfer (2019) considers the difference to be smaller than expected.

As the reduction of emissions in a ETS system is certain under the assumption of effective enforcement, more research has been conducted with regard to the carbon price pass-through onto electricity prices (Sijm et al., 2006; Jouvet and Solier, 2013; Freitas and da Silva, 2013; Honkatukia et al., 2006; Fell, 2010; Zachmann and von Hirschhausen, 2008; Wolff and Feuerriegel, 2019; Cotton and Mello, 2014). The pass-through of carbon prices is important for two reasons. First, if the costs of carbon are passed through than changes in the merit order may be induced, as more emitting power generation plants become relatively more expensive as compared to cleaner alternatives. Moreover, increasing prices may provide an incentive for investments in RES. Second, increasing electricity prices are expected to reduce electricity demand and therefore reduce emissions in the long term.

The findings with regard to carbon to electricity price pass-through are contradictory to some extent. Honkatukia et al. (2006) and Sijm et al. (2006) both found that carbon prices were largely passed through onto electricity prices in the beginning of the EU ETS. Sijm et al. (2006) concludes that prices are passed through even if carbon permits are grandfathered. Freitas and da Silva (2013) also found a positive significant relation between electricity and carbon prices in Portugal in the beginning of Phase II. Fell (2010) found that electricity prices in the Nordics have a short response to changes in carbon prices, but this effect seems to dampen over time. Jouvet and Solier (2013) conducted the most complete analysis of price pass-through in the EU ETS, by conducting regressions using data from nine countries. They found that carbon prices were passed through in Phase I, but this relation faded after the financial crisis. Jouvet and Solier (2013) blamed the decreasing EUA prices for the absence of pass-through in Phase II. Wolff and Feuerriegel (2019) even found a negative relation between carbon and electricity prices on the EPEX market in Phase III. Cotton and Mello (2014) found that carbon prices were barely passed through in Australia and concluded that the legislation does not have its anticipated effect. Furthermore, Zachmann and von Hirschhausen (2008) found that increases in the carbon price have a stronger effect on electricity prices than a decrease of equal magnitude in the carbon price.

Others analyzed more indirect effects of the introduction of an ETS. This entails topics such as investments in abatement and new capacity, effects on energy consumption and economic development. Lin and Jia (2019) simulated the effects of different carbon price levels in China. Lin and Jia (2019) found that too low prices make the policy ineffective, but higher prices hinder economic growth. Koch and Mama (2019) investigated the relation between the introduction of the EU ETS and Foreign Direct Investments of EU companies to establish affiliate companies outside of the EU. They tested the hypothesis that multinational companies would be willing to go as far as move out of the EU to circumvent EU carbon costs. Although differences were found with the control group, estimation errors were large.

It is of great interest to know what factors drive carbon prices and how carbon prices interact with the prices of other commodities. This is relevant for forecasts as well as being aware of the consequences of policy decisions. Aatola et al. (2013) modelled EUA prices as the dependent variable and found that carbon prices are a function of (German) electricity, gas and coal prices. The cointegration relation between electricity, carbon and other fuel prices has been researched by many (Pinho and Madaleno, 2011; Bunn and Fezzi, 2007; Freitas and da Silva, 2015; Thoenes, 2011). Pinho and Madaleno (2011)'s research covers the energy markets in France, Denmark and Germany and found that the impact of carbon prices depends on the energy mix of the electricity system. Bunn and Fezzi (2007) found that EUA and gas prices jointly form electricity prices in the UK using a cointegrated VAR model. They found that the introduction of the ETS even exacerbates the link between electricity and gas prices. They argue that this increases geopolitical risk with regard to gas and oil prices as the affect on power prices is increased. Freitas and da Silva (2015) researched cointegration relations in Spain. They used a VECM model and modelled electricity, carbon gas and coal prices as endogenous variables and used temperature and RES as exogenous variables. They found long-run stochastic relations between the endogenous variables, though the relation was weaker at some points after the collapse of the carbon prices. Thoenes (2011) found that electricity prices in Germany adapt to commodity prices in a long-run stochastic relation.

Discussions exist with regard to supportive policies as an addition to ETSs. Flora and Vargiolu (2020) researched investments in abatement in the EU using simulations on a firm level and concluded that these investments would significantly increase if a price stabilization mechanism was implemented. This is no surprise, as Jablonska et al. (2012) found that uncertainty in electricity prices increased in the Nord Pool market after introduction of the EU ETS. Wan (2012) as well as Cao et al. (2019) evaluated the advantages of a ETS-tax hybrid. This is in line with the argument of Lehmann et al. (2019), who proposed an ETS-susbsidy hybrid. Cao et al. (2019) and Lehmann et al. (2019) argue that such a system would foster investments in abatement and RES and would therefore reduce the negative impact of climate policy on GDP in the long run. A CPF would provide similar incentives and is discussed later in the literature review.

Zapf et al. (2019) argue in favour of the introduction of a global ETS. A global ETS would be the most efficient mean to achieve global climate goals and solve a number of common issues associated with environmental policy. A global ETS would solve the free rider problem, carbon leakage and the green paradox. Although such a development would be desired from an environmental perspective, it is unlikely that this would be a realistic topic of discussion anytime soon.

To conclude, ETSs seem to be effective in terms of decreasing carbon emissions in the short term. Carbon prices are passed through onto electricity prices, but this effect seems to have faded since carbon price levels decreased significantly. Electricity prices form cointegration relations with the prices of carbon and fossil fuels. Long term investments in abatement could be improved upon if the price incentives are strong enough. It is likely that this would reduce the economic costs of the transition to a low carbon economy in the long run.

2.7 Electricity Markets Volatility Literature

Electricity price uncertainty is undesired as it complicates investment decisions for many actors dependent on electricity prices. This price volatility is partly caused by the interaction between the discontinuous supply curve and inelastic demand that varies strongly during the day and throughout the seasons (Fezzi and Bunn, 2010). This interaction is inherent to electricity markets and makes these amongst the most volatile in financial time series (Jablonska et al., 2012).

Knittel and Roberts (2005) were amongst the first to apply GARCH models to electricity prices. They found an 'inverse leverage shock effect'. This entails that larger increases in volatility are observed in a response to positive shocks as compared to negative shocks of equal size. The opposite relation is often encountered in other financial products. Escribano et al. (2011) improved the application of GARCH models on electricity price time series by accounting for mean reversion, seasonality and price jumps. Koopman et al. (2012) used an Reg-ARFIMA-GARCH model in four different European power markets and found that the day of the week influences spot market volatility. Moreover, they found that dynamic price behaviour differed depending on the market's energy mix. Gianfreda (2010) used GARCH models to research price dynamics in five different power markets and found that the traded volume significantly effects price volatility.

Price volatility in electricity markets is likely to be amplified by the merit order effect induced by intermittent renewable energy power capacity. This relation has been widely researched. Jónsson et al. (2010) used non-parametric models to evaluate how wind energy influences price forming behaviour in the Western Danish day-ahead market. They found that wind power feed-in has a significant effect on electricity price volatility. (Ketterer, 2014) corroborated this finding by employing an ARX-GARCHX model to directly assess the impact of wind power on volatility in the German electricity market. da Silva (2019) found a similar effect for variable RES in the Iberian market, with an especially strong effect on volatility caused by wind power.

It is discussed earlier that Jablonska et al. (2012) found that electricity price volatility increased as a result of the introduction of the EU ETS. They applied regression models to the Nordic Nord Pool market before and after 2005, and found that the variations in the residuals increased after 2005. Daskalakis et al. (2015) found a significant relation between electricity risk premia in futures prices and the price volatility of EUAs. Daskalakis et al. (2015) used data ranging from 2005 to 2011 whereas Jablonska et al. (2012) used data ranging from 1999 to 2008. The relation between a the introduction of a CPF and reduced volatility has not yet been researched.

2.8 Carbon Price Floor Literature

As discussed above, a CPF has been implemented in the UK and in the RGGI ETS. The UK has implemented a CPF as an add-on to the EU ETS, making it the only EU ETS member country that has implemented such a policy unilaterally. This section describes the most important findings from available literature with regard to this topic.

Wood and Jotzo (2011) discuss three ways to implement a carbon price floor in addition to an ETS. Firstly, the government can commit to buy-back permits at a pre-defined price. Hence, maintaining the value of the permits at this price. Secondly, a minimum price at which permits are auctioned can be implemented. This would ensure that new permits will not enter the market below a certain threshold, reducing bearish speculation. Lastly, an additional fee can be added to emitting (as implemented in the UK). Woo et al. (2011) argue that the latter is most compatible with international ETSs.

Philibert (2009) assessed carbon price caps by simulating the environmental and economic consequences of different price floors and ceilings. Philibert (2009) found that price caps reduce the uncertainty with regard to long term environmental policy effectiveness and reduce costs. Although price floors increase some costs, they contribute to keeping costs low for achieving long term environmental results. This is corroborated by Wood and Jotzo (2011), who argue that price floors guarantee minimum abatement effort when ETS prices fall. However, Franco et al. (2015), using simulations in the UK, found that a CPF had little effectiveness in achieving long term climate goals. However, they acknowledge that combinations of different policies provide non-linear outputs.

Newbery et al. (2019) describe a CPF as a 'low regret' policy solution since it addresses the risk of carbon prices falling too low and it provides a signal to investors. However, Eglia and Lecuyer (2017) found that a CPF of 40 €/tCO2 would increase median wholesale electricity prices by 37 €/MWh. A price increase of such proportions would take a heavy toll on consumers and it is hard to argue that this can be considered a 'low regret' policy. Eglia and Lecuyer (2017) simulated electricity prices in Germany using different price floors. It has to be noted that Eglia and Lecuyer (2017) used a fixed supply side and have therefore observed higher prices. Moreover, they argue that a CPF should replace FiT. This would partly compensate consumers for the increased prices.

A base price of 40 €/tCO2 would of course be relatively high, as it is currently capped at 18 £/tCO2 in the UK (Hirst, 2018). Choice of the price floor would be dependent on a Nation's or the System's climate ambitions. Newbery et al. (2019) argue that a EU wide CPF would help re-affirm the EU's position as a climate leader and contribute to achieving abatement goals. Staffel (2017) argues that the UK's Electricity Market Reform has achieved impressive results with regard to decarbonising so far. Emissions in the electricity sector have decreased by 46% between 2013 and 2016. Staffel (2017) attributes this to falling demand, gas power surpassing coal power in the merit order as a result of the CPF and decreasing gas prizes, and the increase of RES. The latter is confirmed by Hu et al. (2019), who found that renewable power generation is economically superior in the UK since the introduction of the Electricity Market Reform.

Weng et al. (2018) and Wang et al. (2020) researched pricing stability mechanisms for China's ETS. It has to be noted that China's cap-and-trade system works slightly different than the European version. China's ETS works with a flexible CO2 cap that allows for CO2 emissions to increase in parallel with economic growth (Weng et al., 2018). Hence, Weng et al. (2018) argue that a CPF is required to maintain a clear carbon price signal when permits are abundant as a result of economic growth or technology improvement. Wang et al. (2020) also argue that a CPF and ceiling are the most effective mechanisms to stabilize the intrinsic CO2 price trend. Moreover, they argue that different mechanisms should be implemented to stabilize intrinsic price trends and restrain daily price volatility.

Flachsland et al. (2020) identify four different objections to a CPF and refute them. Firstly, opponents of a CPF argue that the MSR removes the need for a CPF, as carbon prices have recently increased. However, causality and duration of these price increases are yet to be determined. Secondly, a CPF would transform the EU ETS from a quantitative policy into a pricing instrument. According to Flachsland et al. (2020), policy makers are expected to compel more abatement if emission reductions turn out to be cheaper than expected. Moreover, the EU ETS is becoming a special case as the only cap-and-trade system without some sort of price floor. Thirdly, Flachsland et al. (2020) refute the argument that a floor price would not be legally feasible as an addition to the EU ETS. Lastly, it is argued that finding consensus regarding a common price floor would be difficult and that unilateral price floors would fragment EU climate policy. Flachsland et al. (2020) argue that the UK has implemented an effective CPF unilaterally. Moreover, France has stated to be a proponent of an EU wide price floor. Recently, similar signals have come from the Netherlands, Sweden, Portugal and Spain.

In short, most researches conclude that a CPF enhances cap-and-trade systems by providing certainty and additional incentives for abatement. However, there is little empirical research conducted with regard to the effects of a carbon price floor. Especially the dynamics between ETS prices and electricity prices in combination with a CPF remain unaddressed.

3 Research Question

This section combines the insights obtained in the systems analysis and from analyzing existing literature to identify a research question. The research problem is defined and elaborated on first, followed by a discussion concerning the research gap with regard to this problem. Subsequently, this section is concluded on by defining a Research Question and corresponding subquestions.

3.1 Problem Definition

The main advantage of a cap-and-trade system such as the EU ETS is its certainty with regard to abatement. Since the amount of available permits is capped, it is certain that emissions will not exceed this limit. That is of course, as long as emissions are monitored correctly. Since only the amount of permits is fixed, the price of permits is formed by free market mechanisms. This introduces uncertainty and price risk for emitters and actors that plan on investing in abatement.

As carbon prices are expected to be passed through to electricity prices, this uncertainty will likely affect electricity markets (Jablonska et al., 2012). Flora and Vargiolu (2020) argue that more price certainty would significantly increase investments in abatement. However, electricity price uncertainty does not only affect emissions related investments. Electricity price forecasting is required for many market participants, from producers to consumers. They require forecasts for long term contracts, but also with regard to investments in generation capacity or energy intensive industries. Electricity prices are already very volatile without the introduction of the EU ETS. Additional uncertainty could lead to delays in investments in additional generation capacity and affect all types of consumers. Hence, added electricity price uncertainty due to the introduction of the EU ETS is a potentially undesired effect.

Carbon prices in Europe have fallen below 10 €/tCO2 from 2009 to 2018, likely in a reaction to the 2008 financial crisis. However, the reasons for the price decreases are still heavily debated (Flachsland et al., 2020). Low permit prices can decrease confidence in the commitment of policymakers with regard to their climate goals. Moreover, minimum prices are required to foster investments in abatement and low carbon solutions. A CPF might increase confidence in the climate ambitions of policymakers and assure a minimum price that encourages investments in low carbon solutions. Moreover, a CPF might reduce electricity price volatility by reducing market uncertainty. Currently, a CPF is only implemented in the UK and it might prove valuable to the EU ETS as a whole when permit prices fall once more.

3.2 Research Gap

Daskalakis et al. (2015) and Jablonska et al. (2012) researched the relation between the EU ETS and volatility in electricity markets. Daskalakis et al. (2015) evaluated the price risk premium in forward markets, where the dynamics differ from the electricity spot markets. Jablonska et al. (2012) used regression models from before and after 2005 and evaluated the distribution of the errors. However, the share of intermittent RES also increased during this period and these are known to affect volatility (Ketterer, 2014). Moreover, Jablonska et al. (2012) only researched the Nordic Nord Pool market, whereas Koopman et al. (2012) argues that dynamic price behaviour clearly differs depending on the energy mix. Lastly, both Daskalakis et al. (2015) and Jablonska et al. (2012) use data prior to 2011. Hence, no relevant research has been conducted using data from Phase III of the EU ETS.

The option of a CPF as an addition to the EU ETS has been widely discussed (Flachsland et al., 2020; Newbery et al., 2019; Wood and Jotzo, 2011) and its effects have been simulated (Hu et al., 2019; Franco et al., 2015; Philibert, 2009). The UK implemented a CPF unilaterally and Staffel (2017) argues that the results with regard to decarbonisation have been impressive so far. However, no empirical research has been conducted with regard to how the dynamics between electricity prices and ETS prices change as a result of the introduction of the UK CPF.

This thesis will expand on existing research in four ways. 1) This research will employ methods similar to those proposed by Ketterer (2014). This allows for an estimation of the direct relationship between the time varying volatility and price behaviour of the EU ETS. 2) Data from phase III will be used in order to analyze the most current electricity price dynamics. 3) This research will conduct the same analysis in multiple European markets to account for differences in dynamic pricing behaviour as a result of the energy mix. 4) This thesis will evaluate how the introduction of the UK CPF changed the dynamics between carbon permit prices and electricity prices.

The third addressed research gap is relevant as dynamic pricing behaviour is likely to differ per country (Koopman et al., 2012). Being aware of how the EU ETS and local electricity prices interact and how these relations potentially differ per country may prove valuable to policymakers for further adjustments to the EU ETS and complementary regulation on a country level. It is plausible that differences in the effects of the EU exist between different countries, as electricity systems, regulations and other exogenous variables vary widely. With regard to energy systems, differences exist predominantly in the sources of electricity generation (Eurostat, n.d.-a) . France, for example, is predominantly dependent on nuclear power, whereas Luxembourg generates over 60% of its electricity using hydro-power. Similar differences can be found with regard to regulation (Ecofys, 2014).

3.3 Research Questions

This thesis will evaluate the relation between the EU ETS, electricity prices and electricity price volatility using the same metrics for multiple EU countries that differ either in sources of energy or regulation to answer the following research question:

Can a Carbon Price Floor enhance the EU ETS and how should it be implemented?

The subquestions that will contribute to finding a comprehensive answer to the research question are listed below:

1. How does the EU ETS affect electricity prices and price volatility in local day-ahead electricity markets?
2. How does a Carbon Price Floor affect the dynamics between ETS prices and electricity prices?
3. If the EU ETS is expected to benefit from a Carbon Price Floor, how should it be implemented?

The first subquestion is important in order to identify why possibly different relations are encountered in different markets. Koopman et al. (2012) found that dynamic price behaviour differs per market and it may prove relevant to obtain an overview of important characteristics of each market. Moreover, electricity systems are path dependent networked systems. Therefore differences exist between the physical and institutional aspects of electricity systems within Europe that may be of influence to dynamic price behaviour.

By answering the second subquestion, it is possible to evaluate how the dynamics observed in the first subquestion may be affected by the introduction of a minimum price for carbon. Empirical data from the UK will be used to answer this question, since the UK is the only EU country that has currently established such a stability mechanism.

The third subquestion is at the core of this research and is answered by combining the results of the first two subquestions. Findings from existing literature will be combined with the findings from this research in order to provide coherent policy advice. A design for the implementation of a CPF as addition to the EU ETS will be provided if proven relevant based on the results of this research.

4 Methodology

This section elaborates on the methods used in order to answer the previously defined subquestions that will, eventually, lead to a substantiated answer of the research question. First, the evaluated countries are grouped on the basis of characteristics of the energy system. Subsequently, the used models are discussed in detail and clear argumentation for their use is given.

4.1 Grouping European Countries

Electricity systems are networked systems that require lump sump investments for the development of the system. Therefore, electricity systems are path dependent and it is rarely economically feasible to adjust decisions made in the past. Moreover, the possibilities with regard to development of the electricity network depend on geographical characteristics. For instance, hydropower plants such as dams and pumped-storage offer reliable clean energy for low marginal costs. However, development of these types of plants is not possible for every country due to geographical constraints. Furthermore, some countries have fossil fuel resources available. Therefore, these countries are less dependent on macroeconomic developments with regard to their energy supply if they decide to depend on fossil fuels for power generation. The combination of path dependency and geographical differences has resulted in many different electricity systems within Europe.

As a result of the physical differences within Europe, policies differ as well. Different physical systems require different regulatory interventions. Moreover, institutional and economic factors also affect policy decisions (de Vries et al., 2010). A country's economic growth rate may affect capacity investment decisions and policy makers are dependent on the strength of their economy with regard to financing options. Similarly, the locally dominant ideology may strongly influence regulatory decisions. Hence, it is no surprise that electricity systems differ strongly physically and institutionally even within European.

This thesis will incorporate nine countries in its analysis in order to account for differences in the electricity systems and provide results relevant to policy makers all across Europe. The following countries have been selected: Poland (PL), the Netherlands (NL), Italy (IT), Czech Republic (CZ), the United Kingdom (UK), Germany (DE), Denmark (DK), Spain (ES) and France (FR). These countries are representative for electricity systems in the EU as they vary widely in terms of energy mix, geographic location and degree of market liberalization. The lack of hydro-capacity in the selection of countries is on purpose, as a large share or hydropower generation would require adjusted modelling techniques. Moreover, there are few options left for the creation of new hydropower installations.

As it is complicated to obtain a comprehensive overview of a large quantity of European country's energy systems, it is beneficial to group the evaluated countries based on physical and institutional characteristics. Jouvet and Solier (2013) do this in their evaluation of the carbon pass-through rate in eleven European countries. They divided the eleven countries into four groups, mainly based on the degree of market coupling and marginal fuels. The energy mix and the degree of market liberalization may prove to be useful grouping factors with regard to electricity price formation and price volatility.

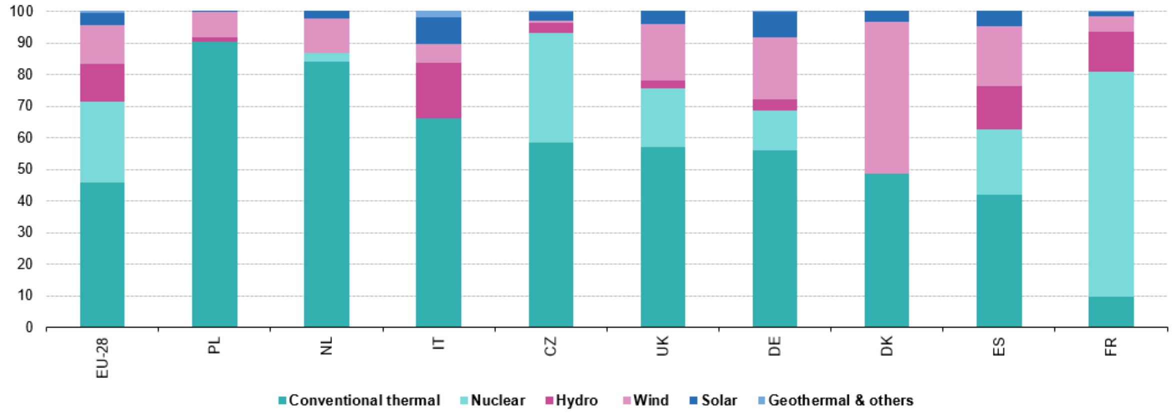

Figure 8: A breakdown of the relative electricity production by source in 2018. Data retrieved from (Eurostat, nd a).

Figure 8 provides an overview of the electricity generation by source in the evaluated countries. Poland and the Czech Republic stand out with regard to the lack of renewable generation. Moreover, both countries are primarily dependent on coal power (IEA, n.d.). Although the Czech Republic has a relatively large share of nuclear capacity, this is likely to only affect base-load generation. A comparable similarity can be observed for Spain and Italy, where both countries are primarily dependent on oil. Lastly, the Netherlands and the UK are both heavily dependent on natural gas for their energy supply. Moreover, de Vries et al. (2010) discuss how the UK has the 'market most similar to the Netherlands'. Based on the described similarities, four groups have been formed and depicted in Table 2. The results of the country grouping are similar to those of Jouvet and Solier (2013).

Group 1	**Group 2**	**Group 3**	**Group 4**
Germany (DE)	The Netherlands (NL)	Italy (IT)	Poland (PL)
France (FR)	The United Kingdom (UK)	Spain (ES)	Czech Republic (CZ)
Denmark (DK)			

Table 2: Subsets of countries based on energy mix, market coupling and degree of liberalization.

Group 1, consisting of Germany, France and Denmark, is the most diverse group. Germany and France are both large markets, whereas Denmark is relatively small. Moreover, France stands out due to its large share of nuclear power generation. Similarly, Denmark has a relatively large share of wind power. However, Germany and France both use Feed-in-Tariffs (FiT) to promote renewables and both countries took a passive stance with regard to liberalisation of their electricity markets (de Vries et al., 2010). France and Germany are interconnected via a relatively large interconnector CRE (2016) and Germany is connected to both markets in Denmark IEA (2017).

4.2 Quantitative Modelling

This section elaborates on the quantitative models used to answer subquestions 1 and 2. This thesis will employ econometric time series models to provide accurate analysis of electricity price formation. The parameter estimates with regard to the effects of the EU ETS are only relevant in the context of an accurate model. This section will first discuss some important properties of time series that may be relevant to a reader with little background on the subject. Subsequently, the electricity pricing model is discussed. Lastly, an extension that allows for testing of the effects of the CPF in the UK is elaborated on.

4.2.1 Theoretical Framework for Time Series Analysis

Time series analysis is conducted in this thesis in order to gain new insights into different European electricity markets. Time series models improve upon '*regular regression models*' by including the order of the observations. Therefore, less of the available information is omitted. It is expected that recent observations directly contribute to the prediction of electricity prices. Moreover, time series methods allow for the analysis time varying volatility (Higgs and Worthington, 2010; Koopman et al., 2012; Ketterer, 2014) and mean reversion (Escribano et al., 2011) observed in electricity price time series.

Some of the basic concepts have to be defined first in order to comprehensively draw conclusions from the conducted analyses. This section will cover the concepts of stationarity, order of integration, cointegration and Granger Causality. These concepts will prove to be important for the understanding of the steps and models discussed in the methodology and conclusions drawn based on parameter estimates.

A random sequence, x_t, is called stationary if its mean, variance, and j-th order autocovariances (for $j > 0$) are all equal over time. Moreover, x_t is strictly stationary if the joint distributions for all collections $(x_t, x_{t+1}, ..., x_{t+k})$ with $k > 0$ is the same for all t. If non-stationary time-series are used for analysis, this can result in spurious regressions. Therefore, it is often most convenient to transform the sequences to stationary series. An Augmented Dickey-Fuller (ADF) test can be used in order to test for stationarity (Dickey and Fuller, 1976). The Dickey-Fuller test tests for a unit root in an AR1 model, which would imply non-stationarity.

A non-stationary time-series can be transformed to a stationary time series by taking the differences, that is $x_t - x_{t-1}$. The order of integration of a time-series, denoted $I(d)$, provides information with regard to how often the differences have to be taken to make a time-series stationary. Hence, a series that is $I(d)$ is integrated of order d and the differences have to be taken d times to make the series stationary. A stationary time-series is said to be $I(0)$.

A linear relation between non-stationary time-series often exists such that the combined time-series is stationary. For example, if y_t and x_t are non-stationary time series, there may exist a relation $\beta_1 y_t + \beta_2 x_t = z_t$, where z_t is a stationary time series. Hence, y_t and x_t are driven by a common stochastic trend. Formally, considering the [m x 1] vector $y_t \sim I(1)$, y_t is said to be cointegrated if one or more vectors γ exist such that $\gamma' y_t \sim I(0)$. Therefore, one can test for a cointegration relation by testing for a unit root in the residuals, z_t in the previously discussed example. However, one has to apply the Mackinnon (1991) critical values, in order to guarantee consistency. The Mackinnon (1991) critical values have to be used as the distribution of the residuals is different from the Dickey-Fuller distribution. The values of the Mackinnon (1991) values depend on the number of variables tested for in the cointegration relation.

Granger Causality, first discussed by Granger (1969), proposes a distinction between mere correlations between time series and causality. Although causality is a difficult concept and often impossible to prove, Granger Causality is often referred to as predictive causality. The formal definition of <u>no</u> Granger Causality between y_t and z_t is as follows:

$$P(z_t | Y_{t-1}, Z_{t-1}) = P(z_t | Z_{t-1}) \tag{4}$$

This can be interpreted as follows: y_t is said to <u>not</u> cause z_t if knowledge of y_t does not contribute to the prediction of z_{t+j} for $j > 0$.

4.2.2 Modelling Electricity Prices

Electricity prices are modelled using an approach similar to the methods proposed by Ketterer (2014). Ketterer (2014) used an ARX-GARCHX model to investigate the relation between wind energy and volatility in German electricity prices. The Xs in ARX-GARCHX represent the exogenous variables added to the model. This model will be expanded using findings from literature and other variables proven relevant based on the systems analysis.

The *generalized conditional heteroskedasticity* (GARCH) model was developed by Engle (1982) and Bollerslev (1986) and is used in time series where volatility varies over time. Higgs and Worthington

(2010) show that GARCH models are useful for explaining price performance in liberalized electricity markets. Moreover, Koopman et al. (2012) found strong evidence of conditional heteroskedasticity in electricity power prices. Hence, the application of a GARCH model is required. Furthermore, modelling volatility of electricity prices using a GARCH model allows for direct estimation of the impact of exogenous factors as shown by Ketterer (2014). The basic GARCH model is described in Equation (5) below:

$$\begin{aligned} u_t &= \sigma_t \epsilon_t, \qquad \epsilon_t \sim N(0,1) \\ \sigma_t^2 &= \omega + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \end{aligned} \tag{5}$$

Here, u_t represents the observed shock at time t and σ_t^2 is the variance of the returns. Note that the volatility in Equation (5) is a stochastic process of error sequence $\{u_t\}$ and itself. The model is usually initialized using the unconditional variance, $\sigma_1^2 = \frac{\omega}{1-\alpha-\beta}$, although the effects are insignificant as the filter is invertible.

Escribano et al. (2011) found evidence of mean reversion in electricity price behaviour. Hence, it is relevant to add an *AutoRegressive* (AR) aspect to the model. The basic AR(p) model is given in Equation (6) below:

$$y_t = c + \sum_{i=1}^{p} \phi_i y_{t-i} + u_t \tag{6}$$

In AR(p), p represents the number of lagged values incorporated in the model. The model explains the electricity price, y_t, using a constant c and p lags of y_t. As mean reversion is expected in the electricity prices, it is expected that the sum of $(\phi_1, ..., \phi_p)$ is less than 1. In context of the AR-GARCH model, the error term u_t is dependent based on the mechanics described in Equation (5).

Figure 5 from the systems analysis clearly shows that some important variables may be omitted if a basic AR-GARCH model would be used to model electricity prices. Figure 5 shows that the electricity price is a function of supply and demand. Where demand is influenced by seasonality, temperature and daily variations, the supply function is defined by RE generation and the conventional power bids. The RE generation is dependent on the available capacity and relevant weather conditions, whereas the bids from conventional power generations are dependent on fuel prices, the price of emitting (EUAs in the EU) and available capacity. Therefore, exogenous factors should be added, creating an ARX-GARCHX model.

Ketterer (2014) expanded the AR-GARCH model by adding *wind penetration*, the share of wind power compared to the total load at a point in time, in the observation as well as the volatility equation. Using wind penetration was proposed by Jónsson et al. (2010) in order to account for the correlation between demand and wind power forecasts. This approach can easily be expanded to *var-RES penetration*, as the merit order effect holds for all forms of var-RES and da Silva (2019) found that all var-RES influence volatility. It provides another advantage, as it reduces the amount of parameters that need to be estimated. Nicolosi and Fürsch (2009) proposed using the residual load, which represents the load that has to be met using conventional power. However, var-RES penetration seems to be more practical as it uses relative measures.

Although demand does need to be modelled using the var-RES penetration approach, seasonality and the day of the week may still affect electricity prices due to the discontinuous supply function. Ketterer (2014) corrects for seasonality by running the following auxiliary regression:

$$y_t = c + \sum_{i=1}^{7} v_i d_i + \sum_{j=1}^{12} \zeta_j m_j + \varepsilon_t \tag{7}$$

The parameters in Equation (7) can easily be estimated using Ordinary Least Squares (OLS). This approach removes any seasonality that is encountered throughout the dataset and improves modelling performance. Moreover, Koopman et al. (2012) found that volatility depends on the day of the week. Therefore, the day of the week will be incorporated in the volatility equation, even though it is corrected for in the prices.

The only exogenous variables displayed in Figure 5 left for discussion are carbon prices and fuel prices. Bunn and Fezzi (2007) show that the gas price and permit price are both positively related to electricity prices in the UK. Hence, both prices should be added to the AR equation. Due to the specific interest of this thesis in the effects of the EU ETS on volatility, the returns of the EU ETS will be added to the GARCH equation. Although gas prices might be most important during peak hours in the UK and the Netherlands, the prices of other fossil fuels might prove relevant in the other evaluated countries. Therefore, oil and gas prices are also added to the AR equation.

Based on the variables and models discussed above, the following ARX-GARCHX is formulated:

$$\begin{aligned} y_t &= c + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{l} \rho_j p_{ETS,t-j} + \sum_{j=1}^{q} \zeta_j p_{gas,t-j} \sum_{j=1}^{m} \gamma_j p_{coals,t-j} + \sum_{j=1}^{k} \psi_j p_{oil,t-j} + \theta w_t + u_t \\ u_t &= \sigma_t \epsilon_t, \qquad \epsilon_t \sim N(0,1) \\ \sigma_t^2 &= \omega + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 + \sum_{j=1}^{l} \lambda_j p_{ETS,t-j}^2 + \tau w_t + \sum_{j=1}^{7} \kappa_j d_j \end{aligned} \tag{8}$$

In Equation (8), w_t represents the var-RES penetration. w_t represents the var-RES penetration at time t. A dummy variable is added to the volatility function representing the day of the week, based on the findings by Koopman et al. (2012). Moreover, p_x represents the price of time series x. If the price time series turn out to be *I(1)*, they will be transformed to stationary series by calculating first differences in order to avoid spurious regressions. This will be tested using the ADF test for stationarity. If the time series turn out to be stationary, the regular prices will be used. The squared value returns of the EU ETS are used in the volatility function to ensure that volatility remains positive. To manage the number of of variables used in the analysis, parameters are removed such that it optimizes the Bayesian Information Criterion (BIC). The BIC (depicted in Equation (9)) penalizes the obtained LogLikelihood for the amount of parameters used.

$$BIC = ln(n)k - 2LL \tag{9}$$

Here, n represents the number of observations and k the number of parameters in the model. LL represents the Loglikelihood value that is obtained from optimizing the LogLikelihood function. The Loglikelihood function is numerically optimized using the constrained version of the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm. Based on the characteristics of the data and fitting results it will be decided whether a Gaussian or a Student's T distribution for the errors is assumed. If a Gaussian distribution is assumed, the following LL function is optimized:

$$LL_{Gaussian} = -\frac{n}{2} log(2\pi\sigma_t^2) - \sum_{t=1}^{n} \frac{u_t^2}{2\sigma_t^2} \tag{10}$$

A Student's T Distribution is less affected by large outliers in the data and is therefore likely to be more suited for the analysis of electricity prices time series. The LL function of a univariate Student's T distribution is given by:

$$LL_T = \sum_{t=1}^{n} \left[ln\Gamma\left(\frac{v+1}{2}\right) - ln\Gamma\left(\frac{v}{2}\right) - \frac{1}{2} ln(\pi(v-2)) - ln(\sigma_t) - \frac{v+1}{2} ln\left(1 + \frac{u_t^2}{(v-2)\sigma_t^2}\right)\right] \tag{11}$$

Here, $\Gamma(\cdot)$ represents the Gamma distribution and v represents the degrees of freedom. The latter has to be estimated.

This research will use daily electricity prices, as all other variables have daily observations. As some of the distinctive features observed in electricity prices may be lost by taking taking daily averages, the model in Equation (8) will be used for base, intermediate and peak prices. This is also done by Wolff and Feuerriegel (2019), who executed the same analysis for three different times of the day. This thesis will evaluate the dynamic price behaviour for the hours 04:00h, 11:00h and 18:00h, (h= 4, 11, 18);. These times represent base, intermediate and peak prices respectively. The choice of hours is based on the analysis conducted in section 2.4.3.

As described by Ketterer (2014), outliers in the electricity prices are removed recursively: all observations that are more than three times the standard deviation of the dataset are replaced by the threshold value. Subsequently, the deterministic part of the electricity prices is removed using Equation (7). Ketterer (2014) used the log values of the de-seasoned electricity prices for further analysis. This has the advantage that the obtained results become relative, which makes them more interpretative. However, this can not be used in this research as negative prices occur in many of the used time series samples. Ketterer (2014) found that the de-seasoned log electricity prices are stationary in Germany. This will be tested using the ADF test for each country and the differences of the de-seasoned electricity prices will be used if the time series is found to have a unit root.

Data ranging form 2015 to 2018 are used for this analysis. As it is the most important variable in this research, it is important to note how the carbon price evolved in the evaluated period. This development is graphically depicted in Figure 9.

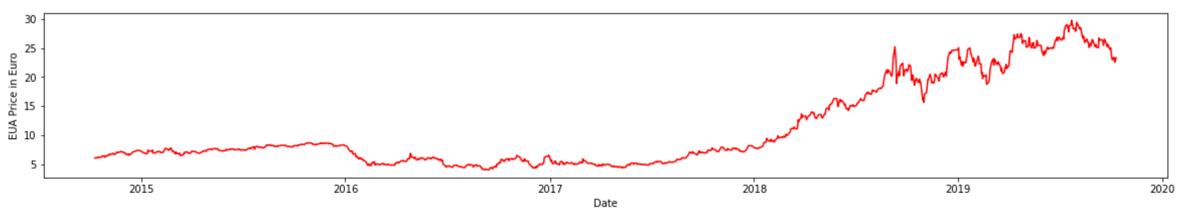

Figure 9: The development of the EUA price between 2015 and 2018.

Figure 9 shows how carbon prices remain relatively stable and low from 2015 to 2017, but start to increase rapidly in 2018. Due to this change in the EUA prices, the relation with electricity prices may be different in the two periods. Therefore, the model discussed in Equation (8) is fitted for 2015-2017 and 2018 separately. An alternative option is to use dummy variables for the two periods. However, this would be computationally unfeasible as it would further increase the number of parameters that have to be estimated in a single model.

4.2.3 Measuring the Impact of a Carbon Price Floor

This thesis researches how a Carbon Price Floor influences the relation between ETS prices and electricity prices. Unfortunately, such an instrument is only introduced in the UK. As of April 1st 2013 a CPF was introduced in the UK. The CPS changed yearly, but the changes varied in size. The biggest change following the introduction of the CPF was in 2015, when the CPS was set to 18£ per tonne CO2, whereas they were half that in 2014 (HM Treasury, 2012; HM Treasury, 2013). This is where the price remained for the following years, partly due to the cap set on the CPS.

The same model as described in Equation (8) is used to analyze the effects of the Carbon Price Floor. Dummy parameters are used to model the change in the interaction between carbon prices and electricity prices after introduction of the CPF. Hence, dummies are created for after April 2013 (when the policy was implemented), and after April 2015 (when CPS rates doubled). Dummies are used to evaluate the effect that EUA prices have on electricity prices, how EUA price shocks affect electricity price volatility and how price mean levels change in each of the periods.

$$
\begin{aligned}
y_t &= c + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{l} \rho_j p_{ETS,t-j} + \sum_{j=1}^{q} \zeta_j p_{gas,t-j} + \theta L_t + u_t \\
\sigma_t^2 &= \omega + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 + \sum_{j=1}^{l} \lambda_j \Delta p_{ETS,t-j}^2 + \tau L_t \\
u_t &= \sigma_t \epsilon_t
\end{aligned}
\tag{12}
$$

As the added dummy variables greatly increase the number of parameters that have to be estimated, some of the variables are omitted. The reduced model is depicted in Equation (12). Coal and oil prices are omitted from the equation, as the UK is mostly dependent on natural gas with regard to its power supply. Moreover, data concerning power generation using renewables is unavailable prior to 2015. Hence, load is used as a variable instead of RES-penetration. Load is indicated as L_t in Equation (12). Lastly, daily volume weighted average wholesale prices are used instead of hourly prices. Therefore, some of the price dynamics may be lost. On the other hand, it might reduce some of the volatility observed in electricity pricing data which would make it more suited for econometric modelling.

4.3 Data Description

In most of the evaluated countries, day-ahead electricity prices could simply be obtained in hourly or 15-minute intervals using the ENTSO-E Data Transparency Platform (ENTSO-E, n.d.). However, the markets in Denmark and Italy are split up and have multiple day-ahead prices for each hour within the country.

The Danish electricity market is divided in two (IEA, 2017). DK1, the western grid, is connected with Germany and continental Europe. DK2, the eastern grid, is connected with the Nordic region. The two markets are connected by 600MW interconnection capacity. This results in similar prices most of the time. This thesis uses data from the DK2 market, as it is the market that is most different from the other evaluated countries.

The Italian wholesale market is divided into six geographic zones and a 'pole of limited production' (GME, n.d.). The zones are Central Northern Italy, Central Southern Italy, Northern Italy, Sardegna, Sicilia and Southern Italy. Although prices are converging (IEA, 2016), differences remain. The prices are aggregated in a hourly national single price (PUN, prezzo unico nazionale), but these prices might miss some important nuances in the data. Hence, this thesis will use data from the Northern Italy market, which is by far the largest within the country in terms of volumes traded on the day-ahead market (GME, n.d.). The ENTSO-E Data Transparancy Platform offers prices, expected load and day-ahead expected var-RES generation per bidding zone.

Data type	**Frequency**	**Region**	**Method**	**Source**
Electricity Prices	Hourly	Each Country	Volatility Analysis	ENTSO-E
RES generation	Hourly	Each Country	Volatility Analysis	ENTSO-E
Grid load	Hourly	Each Country	Volatility Analysis	ENTSO-E
Permit Price	Daily	EU	Volatility Analysis	Factset
Oil Price	Daily	UK ICE	Volatility Analysis	Factset
Gas Price	Daily	NL TTF	Volatility Analysis	Factset
Coal Price	Daily	NL IFEU	Volatility Analysis	Factset
Electricity Price	Daily	UK	UK Carbon Price Floor	ICE
Grid load	30min	UK	UK Carbon Price Floor	NationalGridESO
Permit Price	Daily	EU	UK Carbon Price Floor	Factset & BusinessInsider
Gas Price	Daily	NL TTF	UK Carbon Price Floor	Factset

Table 3: An overview of the used data. All data are extracted directly from the indicated source. ICE stands for the Institution of Civil Engineers

An overview of all the data used for this thesis is provided in Table 3. Table 3 indicates the data type, frequency, region, source and the method it is required for. Different sources are used for the electricity price, grid load and RES generation for the analysis of the UK Carbon Price Floor as ENTSO-E data only goes back to 2015. Unfortunately, this also means that no data is available with regard to renewable power generation in the UK prior to 2015.

4.3.1 Stationarity of the Data

The used time-series data are tested for stationarity using the Augmented Dickey-Fuller (ADF) test. The ADF test tests for a unit root under the null hypothesis, which would indicate that the process is non-stationary. All results are depicted in Table 4 and Table 5. This section briefly summarizes the results.

	P-val	Stationary	P-val of Δ	Stationary
EUA	0.970	FALSE	0.000	TRUE
Oil	0.410	FALSE	0.000	TRUE
Gas	0.220	FALSE	0.000	TRUE
Coal	0.801	FALSE	0.000	TRUE
EUA$_{CPF-Analysis}$	0.324	FALSE	0.000	TRUE
Gas$_{CPF-Analysis}$	0.176	FALSE	0.000	TRUE
Load$_{CPF-Analysis}$	0.025	TRUE	0.000	TRUE
Electricity$_{CPF-Analysis}$	0.001	TRUE	0.000	TRUE

Table 4: The results of the ADF test for the commodity price time series and the time series used in the UK CPF analysis. For readability purposes, only the p-values and the outcome of the test are depicted for the original time series and the first differences. Below the line the results of the ADS tests of the time series used in the UK CPF analysis are depicted.

All time series are found to be either *I(0)*, i.e. stationary, or *I(1)*, which indicates that the first differences are stationary. If time series are found to be *I(1)*, the first differences are used for further computations during this research. The differences of a time series are subsequently referred to as Δ[Name series].

	Electricity Prices				RES Penetration			
	P-val	Stationary	P-val of Δ	Stationary	P-val	Stationary	P-val of Δ	Stationary
ES 4h	0.007	TRUE	0.000	TRUE	0.000	TRUE	0.000	TRUE
ES 11h	0.033	TRUE	0.000	TRUE	0.000	TRUE	0.000	TRUE
ES 18h	0.023	TRUE	0.000	TRUE	0.000	TRUE	0.000	TRUE
DK2 4h	0.483	**FALSE**	0.000	TRUE	0.000	TRUE	0.000	TRUE
DK2 11h	0.434	**FALSE**	0.000	TRUE	0.000	TRUE	0.000	TRUE
DK2 18h	0.038	TRUE	0.000	TRUE	0.000	TRUE	0.000	TRUE
FR 4h	0.013	TRUE	0.000	TRUE	0.000	TRUE	0.000	TRUE
FR 11h	0.000	TRUE	0.000	TRUE	0.000	TRUE	0.000	TRUE
FR 18h	0,002	TRUE	0.000	TRUE	0.001	TRUE	0.000	TRUE
NL 4h	0.362	**FALSE**	0.000	TRUE	0.002	TRUE	0,000	TRUE
NL 11h	0.020	TRUE	0.000	TRUE	0.018	TRUE	0.000	TRUE
NL 18h	0.071	**FALSE**	0.000	TRUE	0.002	TRUE	0,000	TRUE
CZ 4h	0.052	**FALSE**	0.000	TRUE	0.000	TRUE	0.000	TRUE
CZ 11h	0.000	TRUE	0.000	TRUE	0.163	**FALSE**	0.000	TRUE
CZ 18h	0.019	TRUE	0.000	TRUE	0.200	**FALSE**	0.000	TRUE
IT-N 4h	0.026	TRUE	0.000	TRUE	0.000	TRUE	0,000	TRUE
IT-N 11h	0.000	TRUE	0.000	TRUE	0.021	TRUE	0,000	TRUE
IT-N 18h	0.000	TRUE	0.000	TRUE	0.088	**FALSE**	0.000	TRUE
PL 4h	0.682	**FALSE**	0.000	TRUE	0,000	TRUE	0.000	TRUE
PL 11h	0.015	TRUE	0.000	TRUE	0.000	TRUE	0,000	TRUE
PL 18h	0.134	**FALSE**	0.000	TRUE	0.000	TRUE	0.000	TRUE
UK 4h	0.318	**FALSE**	0.000	TRUE	0.008	TRUE	0.000	TRUE
UK 11h	0.229	**FALSE**	0.000	TRUE	0.003	TRUE	0.000	TRUE
UK 18h	0.001	TRUE	0.000	TRUE	0.001	TRUE	0.000	TRUE
DE 4h	0.041	TRUE	0.000	TRUE	0.000	TRUE	0.000	TRUE
DE 11h	0.002	TRUE	0.000	TRUE	0.000	TRUE	0.000	TRUE
DE 18h	0.047	TRUE	0.000	TRUE	0.000	TRUE	0.000	TRUE

Table 5: The results of the ADF test for the electricity price and RES penetration time series. For readability purposes, only the P-values and the outcome of the test are depicted for the original time series and the first differences.

All commodity prices, i.e. coal, oil, gas and emissions allowance prices are found to have a unit root. However, the first differences are all stationary. Nine of the electricity time series are non-stationary, whereas only three of the RES Penetration processes are found to be non-stationary. These outcomes are indicated in bold in Table 5.

4.3.2 Data Characteristics

This section briefly discusses the basic characteristics of the data used in this research. The number of observations, mean, variance, skewness and kurtosis are considered to be the most important data characteristics. The characteristics of the time series used in the UK CPF analysis are depicted in Table 6. These time series are displayed graphically in Figure 10. Due to the abundance of time series used in the multi-country analysis (54 in total), the characteristics are depicted in 13 in Appendix A.2.

Data	**# obs**	**Mean**	**Variance**	**Skewness**	**Kurtosis**
$P_{electricity}$	2192	45.058222	53.720972	0.280138	0.500598
Load in GW	2192	33.793419	21.112668	0.213054	-0.455325
ΔP_{CO2}	1228	-0.006653	0.058896	-0.255216	5.472619
ΔP_{Gas}	1343	0.000851	0.340874	-3.279205	76.400450

Table 6: The basic characteristics of the data used in the UK CPF analysis. Electricity prices are measured in £/MWh. Load is measured in GW. CO2 prices are measured in £/tCO2. Gas prices are measured in £/MWh.

There are fewer observations concerning the commodity prices than concerning the electricity time series (load, RES-penetration and prices). Unlike power exchanges, many other exchanges are closed during weekends. These 'missing observations' are filled in using backfilling. This entails that the last observation is duplicated in the following missing observations. For instance, during a weekend in which there are no observations, the observed value on Saturday and Sunday will be set equal to Friday's observation. This same method is used for missing observations in the electricity time series.

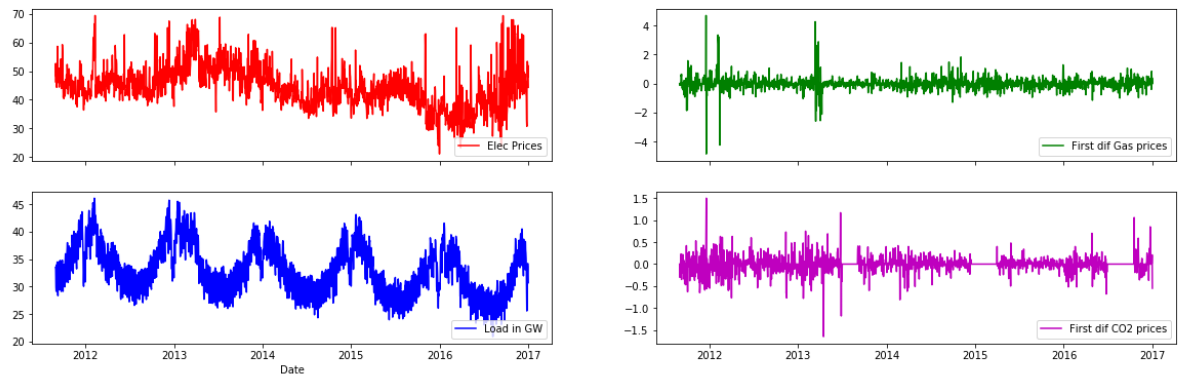

Figure 10: A plot of the time series used in the UK CPF analysis over time. The (deseasoned) electricity prices are displayed in the top left. The load time series is displayed in GW in the bottom left. The top right subfigure displays the first differences of the Gas prices. The bottom right figure shows the first differences of the EUA prices.

Most of the used time series seem to differ from a standard Normal Distribution, which would have zero skewness and a kurtosis of 3. This implies that the errors of the model are also likely to deviate from a Gaussian distribution. Hence, it is likely that the Student's T likelihood function, as described in Equation (11), will be used for the modelling of the electricity prices.

Lastly, it is important to note that the variance of the electricity prices used for the UK CPF analysis is lower than the variance of the other electricity price time series relative to their respective means. This meets expectations, as the prices used for the UK CPF analysis are daily averages instead of hourly prices. As electricity price time series are amongst the most volatile financial time series available, the prices used for the UK CPF analysis might be easier to model due to the lower volatility.

5 Results

This section examines the results obtained in this thesis and reflects upon them. The relation between carbon prices and electricity price dynamics is discussed first, followed by an analysis of the Carbon Price Floor in the UK. Subsequently, conclusions are drawn based on the combined results of both analyses. These conclusions are used to provide a preliminary design for a CPF as an addition to the EU ETS.

5.1 The Relation between Electricity and Carbon Prices

This subsection provides and reflects on the results of the analysis regarding the dynamics between electricity and carbon prices in nine EU countries. Data from three different times of the day are used and the data have been divided in two samples, one spanning from 2015 to 2017 and one using data from 2018. Therefore, a total of 54 models have been fitted. Due to this abundance of obtained results, only the most relevant parameter estimates will be discussed. A complete overview of all parameter estimates is provided in Tables 14 and 15 in Appendix A.3. It should be noted that not all parameters discussed in the model depicted in Equation (8) are used. The fossil fuel parameters and the volatility dummies for each day of the week (as proposed by Koopman et al. (2012)) proved to barely increase fitting results whilst complicating the parameter estimation process.

This analysis evaluated the effect that changes in carbon prices have on the mean price levels and short term price volatility. A significant increase in volatility as a result of carbon price changes at the 0.05 confidence level is observed in two time series in the 2015-2017 analysis in only one in the 2018 analysis. In the 2015-2017 analysis a parameter estimate significantly different from zero was obtained for the 4h prices in France and 11h prices in Denmark. In 2018, a similar parameter estimate is obtained for the 18h prices in the Netherlands. Hence, a total of three significant parameters are estimated with regard to the relation between short term electricity price volatility and changes in carbon prices in 54 regressions. If no relation would be assumed, then it is expected that approximately 3 (2.7) estimates would be significantly different from zero as a result of noise using a 95% confidence interval. Hence, the results obtained in this research provide no proof of a relation between electricity price volatility and EUA prices. This is contrary to the findings by Jablonska et al. (2012), who found more variation in the errors of price estimates after introduction of the EU ETS. This might be due to the data sample used (Jablonska et al. (2012) used pre-crisis data) or the increase of the share of RE in the energy mix in that period. Ketterer (2014) found that the share of RE increases electricity price volatility in Germany. This relation has also been found in 14 of the regressions in this research.

The most interesting results obtained from this analysis regard the relation between carbon prices and electricity price mean levels. The estimate represents the expected change in the electricity price in EURO/MWh when EUA prices increase by one EURO/tCO2. This estimate can be regarded as an indication of the carbon price pass-through to electricity prices. However, it should be noted that this measure is not relative and that it does not indicate what percentage of carbon costs are passed through. The parameter estimates of the fits using the 2015-2017 are depicted in Table 7 and the estimates using data from 2018 are depicted in Table 8. Moreover, a summary of the total amount of significant parameters obtained per time period, time of the day and per country group is provided in Table 9.

2015-2017 Data	4h			11h			18h		
	Est.	Std. Err.	p-val.	Est.	Std. Err.	p-val.	Est.	Std. Err.	p-val.
ES	-0.845983	1.267720	0.504704	-1.609172	1.009190	0.111109	-0.223347	0.971848	0.818277
DK2	0.359152	0.345112	0.298254	-0.092961	0.478180	0.845894	0.570417	0.411278	0.165745
FR	0.572859	1.115175	0.607570	1.089975	1.354130	0.421038	1.503085	1.463327	0.304569
NL	0.189588	0.693034	0.784473	2.494846	1.711558	0.145226	3.283438	1.448229	**0.023573**
CZ	0.264853	1.056201	0.802047	1.433600	1.617423	0.375625	2.050412	1.456792	0.159567
IT-N	1.173010	0.968198	0.225951	2.030003	1.493301	0.174299	1.914020	1.383762	0.166887
PL	-0.054728	0.340397	0.872299	0.350110	1.339364	0.793833	0.441023	1.044974	0.673078
UK	1.195099	0.714948	0.094895	0.586583	1.138338	0.606451	0.429271	1.779908	0.809465
DE	-2.005196	1.030868	0.052013	3.546872	1.482628	**0.016912**	2.105721	1.207843	0.081550

Table 7: Parameter estimates of the relation between changes in the carbon price and the electricity price mean equation using the 2015-2017 data. The p-values of estimates that are significantly different from zero at the 0.05 level are indicated in bold.

Most of the estimates displayed in Table 7 are positive as expected. However, only two of the parameter estimates depicted in Table 7 are significantly different from zero at the 0.05 confidence level. These are the parameter estimates for the 11h time series in Germany and the 18h time series in the Netherlands. Assuming no relation between carbon prices and electricity prices, one would still expect one (1.35) estimate to be significantly different from zero. Hence, the results obtained indicate no clear relation between the price of carbon and electricity prices from 2015 to 2017.

2018 Data	4h			11h			18h		
	Est.	Std. Err.	p-val.	Est.	Std. Err.	p-val.	Est.	Std. Err.	p-val.
ES	1.059124	0.516155	**0.040890**	0.825027	0.462867	0.075513	0.536319	0.423989	0.206703
DK2	0.891321	0.292203	**0.002453**	0.225280	0.294482	0.444764	0.273617	0.254145	0.282363
FR	0.389191	0.542859	0.473877	1.952679	0.647033	**0.002725**	1.463315	0.265677	**0.000000**
NL	1.212094	0.480692	**0.012110**	2.299361	1.164174	**0.049012**	0.604386	0.979789	0.537717
CZ	1.134248	0.477421	**0.018029**	1.879858	0.900793	**0.037593**	0.298980	0.889553	0.736988
IT-N	-0.862085	0.531137	0.105435	0.961816	0.890043	0.280573	-0.281173	0.900659	0.755078
PL	0.085408	0.300492	0.776399	0.092160	1.417062	0.948181	-0.557502	0.745709	0.455176
UK	0.639391	0.597210	0.285045	2.139936	0.779609	**0.006353**	1.383789	0.948155	0.145302
DE	0.237827	0.704967	0.736041	1.253377	0.797319	0.116822	1.727952	0.714795	**0.016122**

Table 8: Parameter estimates of the relation between changes in the carbon price and the electricity price mean equation using data from 2018. The p-values of estimates that are significantly different from zero at the 0.05 level are indicated in bold.

Table 8 shows the estimation results of the relation between electricity and carbon prices in 2018. Most of the parameter estimates are again positive as expected. In contrary to the data from 2015-2017, more parameters are found to be significantly different from zero at the 0.05 confidence level in 2018. This might be a consequence of the rising carbon prices in this year (displayed in Figure 9). Significant parameter estimates are observed in the time series of each of the evaluated times of the day. However, fewer were found in the 18h time series. The 18h time series are also most volatile (see Table 13 in Appendix A.2) and might therefore be more complicated to fit to a model.

	2015-2017 Data					2018 Data				
	Group 1	Group 2	Group 3	Group 4	All	Group 1	Group 2	Group 3	Group 4	All
4h	0/3	0/2	0/2	0/2	0/9	1/3	1/2	1/2	1/2	4/9
11h	1/3	0/2	0/2	0/2	1/9	1/3	2/2	0/2	1/2	4/9
18h	0/3	1/2	0/2	0/2	1/9	2/3	0/2	0/2	0/2	2/9
Total	1/9	1/6	0/6	0/6	2/27	4/9	3/6	1/6	2/6	10/27

Table 9: The number of parameter estimates that are significantly different from zero at the 0.05 level per group and per time of the day for both datasets. Group 1 consists of Denmark, Germany and France. Group 2 is made up of the Netherlands and the UK. Group 3 is composed of Italy and Spain, and Group 3 consists of Poland and the Czech Republic.

Table 9 summarizes the results depicted in Tables 7 and 8. What stands out most in Table 9 is that a significant relation between electricity and carbon prices is found more often in the 2018 data compared to the 2015-2017 data. This is graphically depicted in Figure 11, where the total of significant parameters for each time are compared by means of a bar chart. This observation holds for all groups and all times. Hence, it seems like the carbon prices were only passed through to electricity prices after the EUA prices started to increase in 2018. This indicates the presence non-linear relation between electricity prices and carbon prices, where carbon prices are only passed-through to electricity prices after a certain carbon price threshold is passed.

With regard to the 2018 parameter estimations, Group 2 has the most significant parameter estimations relative to the number of time series. This is surprising, as Group 3, consisting of the Czech Republic and Poland can be dubbed the 'coal countries', whereas Group 2, comprised of the UK and the Netherlands can be dubbed the 'gas countries'. As emissions per MWh from coal power are higher than from gas power, one would expect the carbon price pass-through to be more present in these coal countries. This may partly be explained by the free allocation of permits in Group 3. Free allocation of permits for the electricity sector is not allowed in most of the EU member states. However, Poland and the Czech Republic are allowed to grant power plants emission permits for free under article 10c of the EU ETS Directive (Borghesi and Montini, 2015). Poland allocated 31.9 million emission permits to utilities for free in 2018 (Krukowska, 2019). However, Sijm et al. (2006) found that carbon prices are passed through even if permits are grandfathered.

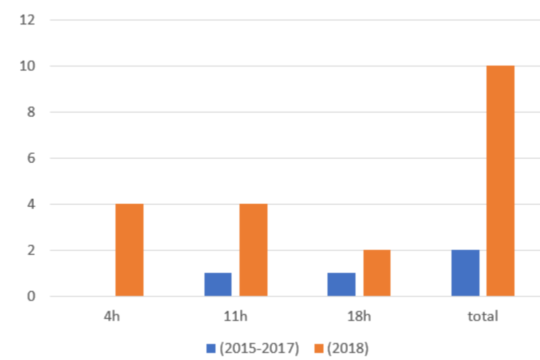

Figure 11: A bar chart comparing the number of significant ETS effect parameter estimates in the 2015-2017 data and the 2018.

5.2 Analysis of the UK Carbon Price Floor

This section discusses the results obtained from the analysis of the UK CPF. The parameter estimates, along with the obtained Loglikelihood values and fitting errors, are depicted in Table 10. A Student's T distribution with $v = 5$ has been used as this provided the best fitting results in terms of LogLikelihood. The fitting results are depicted for the basic model as well as the model including dummy values after the first of April 2013 and the first of April 2015. The 'ETS Effect' represents the effect that a EUA price increase of 1 £/tCO2 (at time $t-1$) has on expected electricity prices in £/MWh at time $t+1$. As prices are formed one day ahead at noon, the most recent EUA price observation is the closing price from the day before. In the dummy model, the parameter 'ETS Effect' covers the period from 2011 until the first of April 2013, whereas it covers the whole period in the basic model.

	Dummy Model			Basic Model		
Parameter	Est.	Std.error	p-val	Est.	Std.error	p-val
c	11.143014	0.813137	**0.000000**	7.640373	0.921947	**0.000000**
ϕ_1	0.680245	0.015707	**0.000000**	0.714021	0.017643	**0.000000**
ETS Effect	-0.003522	0.021622	0.870627	0.412883	0.539104	0.443847
$ETS_{after2013}$	4.192822	1.108974	**0.000161**			
$ETS_{after2015}$	7.233325	1.557924	**0.000004**			
Load Effect	0.095062	0.021368	**0.000009**	0.142336	0.022208	**0.000000**
Gas Effect	-0.125182	0.202481	0.536490	-0.184895	0.191030	0.333223
Constant dummy$_{After2013}$	-0.095060	0.154726	0.539040			
Constant dummy$_{After2015}$	-1.526092	0.260103	**0.000000**			
ω	0.912451	0.358602	**0.011021**	0.616767	0.296748	**0.037801**
α_1	0.062880	0.015571	**0.000056**	0.055436	0.016611	**0.000862**
β_1	0.898768	0.025919	**0.000000**	0.930039	0.022777	**0.000000**
Load Volatility Effect	0.000142	0.001710	0.933620	0.000000	0.001440	1.000000
ETS Shock Effect	0.000000	2.278070	1.000000	0.093657	1.469387	0.949185
ETS Shock Effect$_{After2013}$	7.801413	5.882999	0.184964			
ETS Shock Effect$_{After2015}$	7.233504	9.122613	0.427921			
LogLikelihood	-5749.121784			-5766.306789		
Mean Squared Error (MSE)	27.555348			27.977604		
Mean Absolute Error (MAE)	3.702994			3.716587		

Table 10: The results of the analysis of the UK CPF using 5 degrees of freedom in the Student's T distribution. On the left the parameter estimates of the model using dummy variables after 2013 and 2015 are displayed. The estimation results of the basic model are displayed on the right. The p-values of estimates that are different from 0 at the 0.05 level are indicated in bold.

The load effect represents the expected change in the electricity price by an increase in demand of 1GW. As this model uses weighted average daily prices, the load values are also daily averages. The Gas effect represents the effect that a change in the price of natural gas, as traded on the TTF, has on expected electricity prices. The 'Load Volatility Effect' indicates how much volatility increases by an increase of volatility. Lastly, the 'ETS Shock Effect' stands for how much volatility increases by the squared difference in the ETS price.

The most important results displayed in Table 10 are the estimates of the ETS effect after introduction of the UK CPF. Prior to introduction of the CPF, the estimate of the ETS effect is approximately zero. However, both estimates after introduction of the CPF are positive and significantly different from zero (at the 0.01 confidence level). The effect measured after the first of April 2015, when the CPS was increased to 18 GBP per tonne CO2, is even greater than the other dummy estimate. This result indicates that CO2 prices are only passed-through to electricity prices after introduction of the CPF. The ETS Effect estimate of the basic model confirms this. Although the estimate is positive, it is not significantly different from zero. This is probably the result of the average of the different interactions between the carbon price and electricity prices throughout the period. EUA prices were negligible at first, but were passed through in the second half of the dataset after introduction of the CPF.

The ETS volatility effects also entail interesting results. The shock effect seems to be absent prior to the introduction of the CPF and have higher estimates after 2013. However, both estimates after introduction of the EU ETS are not significantly different from zero at the 0.10 level. Hence, one can not conclude the CPF as employed in the UK affects electricity price volatility in the short term based on these results. However, these results indicate that it is more likely that the UK CPF exacerbates electricity price volatility induced by ETS prices than that it restrains it.

The 'Constant dummies' indicate how base electricity prices change after introduction of the CPF. Prices seem to be slightly lower (only significant after 2015), which can also be observed in Figure 12. Moreover, it is noteworthy that the gas price parameters are not significantly different from zero, even though the use of gas power increased after introduction of the CPF. Even more peculiar is that the estimates are negative, this is likely the result of noise as the estimates are not significantly different from zero. The load effect is positive and significantly different from zero as expected. Lastly, all estimates that are part of the basic AR-GARCH model are significantly different from zero.

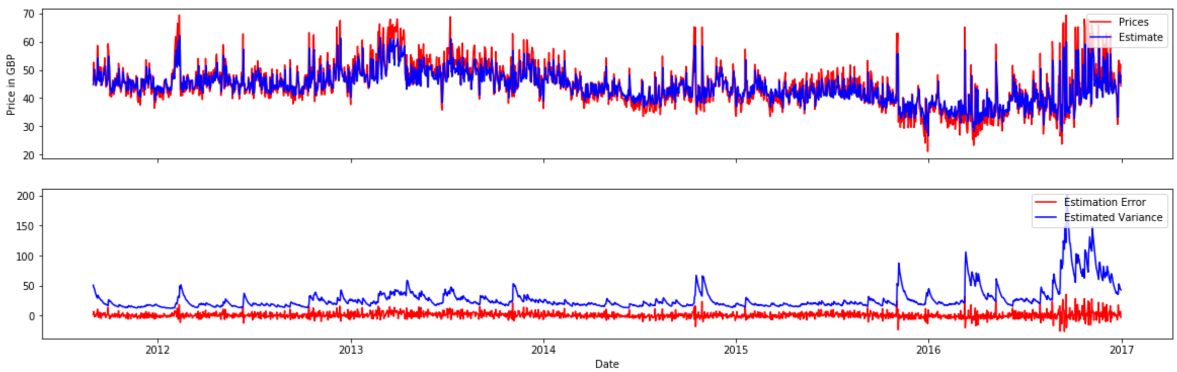

Figure 12: Fitting results of the UK electricity prices and estimated variance using the model including Dummies.

Figure 12 shows the fitting results, dubbed the 'Estimate', along with the actual observed prices. Moreover, it shows the estimated variance along with the estimation error. The estimation error is defined as the difference between the actual prices and the estimated prices. The figure shows that the fitting errors are quite symmetrically distributed and of the same magnitude for most of the time. The size of errors seems to increase by the end of 2016, which can also be observed in the estimated variance.

5.3 Lessons from the Quantitative Analysis

The results from both analyses indicate the presence of a non-linear relation between carbon and electricity prices. This non-linear relation is exhibited in the multi-country analysis by the presence of a significant relation between carbon and electricity only in 2018 after carbon prices started to increase. Although first differences are used, which are a non-relative measure, the differences seem to only significantly affect electricity prices when the carbon prices passed a certain threshold. The analysis of the UK CPF corroborates this hypothesis. As the UK CPF is added to the EUA price when prices are below the CPF threshold, a relation between EUA prices and electricity prices is still present. However, this relation is not present before introduction of the UK CPF. This indicates that when the total price of emitting is too low, it is not (measurably) passed through to electricity prices. The results indicate that a (measurably) relation between carbon and electricity prices is present only when a certain threshold value in the total cost of emitting is passed.

The pass-through of carbon prices to electricity prices is expected in theory and this relation is often empirically validated (Sijm et al., 2006; Freitas and da Silva, 2013; Honkatukia et al., 2006; Jouvet and Solier, 2013). However, the findings of this research are not unprecedented. Jouvet and Solier (2013) found that carbon prices were passed through in nine countries in Phase I of the EU ETS, but this relation could not be verified in Phase II. They provide three explanations for the lack of pass-through in Phase II. First, electricity wholesale markets were heavily impacted by the economic crisis and increased market instability as well as price volatility. Second, electricity demand decreased as a result of the recession. Therefore, generators were less able to pass-through carbon prices in an environment with much excess generation capacity. Third, the lower level of carbon prices made power producers less inclined to pass-through the cost of freely allocated allowances. Moreover, Wolff and Feuerriegel (2019) even found a negative relationship between EUA and EPEX electricity prices on the intraday market in Phase III. Jouvet and Solier (2013) as well as Wolff and Feuerriegel (2019) could not find the expected relationship between carbon and electricity prices when carbon prices were relatively low. Other researches were able to identify this relation when prices were higher during Phase I. This seems to confirm the findings of this thesis that carbon prices are only (measurably) passed through to electricity prices when the total costs of emitting is above a certain threshold.

Honkatukia et al. (2006) discuss three reasons for incomplete pass-through of EUA prices to electricity prices. First, electricity generators and distributors may engage in long term contracts to hedge the risk of price changes induced by the EU ETS. Second, the prices of fossil fuels interact with the price of carbon. If carbon prices increase, the costs of gas power generation increase less compared to the costs of coal power generation. As a result, gas prices may increase in parallel to carbon prices since demand for gas might increase. Third, the price of EUAs is affected by growth of the EU power sector. Yet, these reasons provide no clear explanation as for why prices are only passed through above a certain threshold value. The first reason is irrelevant with regard to the results of this research, as day-ahead market data is used in this thesis. The second reason would be expected at higher carbon prices. Changes in the merit order may be induced by higher carbon prices and this may strongly influence fossil fuel demand and therefore prices. However, this effect is expected to be absent for lower carbon prices. The third reason might be more relevant. Expected growth of the EU power sector is based on speculation and forecasts. If power generators price emissions based on their forecasts, instead of the most recent market price, then signals of regulators' commitment may play a large role in the pass-through of carbon prices to electricity prices. If this behaviour is assumed, then it makes sense that carbon prices were barely passed through in the post-crisis economy. Prices were low and no one would expect policy-makers to make large changes in regulation to the detriment of the economy. Hence, prices were not expected to increase. In the UK after introduction of the CPF, and in the rest of the EU after changes to the MSR (Flachsland et al., 2020), this signal was clearly present.

There are more possible explanations for a non-linear relation between the cost of emissions and electricity prices observed in this thesis. First, it has to be emphasized that the supply curve is discontinuous and that carbon price changes may induce changes in the merit order. As different plants produce different emissions, the pass through may constantly change depending on the marginal plant of production. Second, Zachmann and von Hirschhausen (2008) found an asymmetric relationship between carbon and electricity prices. Price decreases are passed through less than price increases. Hence, the impact on electricity prices in times of rising carbon prices may be more present and more easily measured. Third, it might be easier to hedge against changes in low carbon prices than equivalent changes in higher carbon prices. Small changes in high carbon prices are more likely to induce changes in the merit order. For a coal power producer, it is more complicated to hedge against this risk than equivalent carbon price changes at a lower price level. Last, carbon markets may be less liquid when there is an excess supply of permits. This might make the price signal less reliable and producers will be less likely to pass these changes through to electricity prices. The first two points might also partly explain the more than 100% price pass-through estimated in 2018 and after introduction of the CPF. Changes in merit order might exacerbate the observed electricity price changes induced by EUA price changes. Moreover, the asymmetric price pass-through would complicate estimating a model that does not assume this relation.

Regardless of the real reason for the absence of price pass-through when carbon prices are low, it is important that the costs of emitting remain above certain levels. The MSR was initially unable to assure this until it was reformed in 2018. However, this provides no guarantee that prices remain at their current levels (Flachsland et al., 2020). The introduction of a CPF would guarantee this. Woo et al. (2011), Philibert (2009), Flachsland et al. (2020) as well as Newbery et al. (2019) already argued in favour of the introduction of a CPF in the EU. This research confirms the need for a CPF, since such a stability instrument may guarantee that carbon prices are passed through to electricity prices regardless of carbon market behaviour.

Implementation of a stability instrument would also reduce price uncertainty, which fosters investments. However, a CPF such as implemented in the UK is not without flaws. The UK CPF does not provide the price certainty that a CPF has to offer and could therefore be improved. In the UK, EUA prices are just as relevant when prices fall below the CPF. Therefore, investors and energy consumers are dependent on the development of EUA prices as well as the CPS selected by the government. This adds uncertainty, although in a different way. Price increases become a certainty, but the degree of the price increase becomes more uncertain. The results of this thesis also indicate that the introduction of the EU ETS is more likely to exacerbate short term electricity price volatility rather than reduce it. Moreover, the CPS is established three years ahead. As it is impossible to make such a forecast with great certainty, the CPS is more likely to act as carbon tax on top of the EU ETS than a price floor for EUA prices. A dynamic CPS might improve the UK CPF by increasing prices only when carbon prices fall below a threshold value. This guarantees that the costs of emitting stay above a certain level while reducing some of the uncertainty introduced by the UK CPF.

To conclude, carbon prices seem to be only passed through to electricity prices when the total cost of emitting is above a certain threshold. Although a cap-and-trade provides certainty with regard to the total emissions in the short term, price incentives contribute to lowering long term costs of environmental policy (Philibert, 2009). Staffel (2017) found that electricity demand fell by 1.3% per year and that investments in RES increased rapidly after introduction of the UK CPF. Such developments are important for achieving long term environmental policy goals and are fostered when carbon prices are passed through. Although carbon prices have increased after the MSR reform in 2018, Flachsland et al. (2020) argue that this provides no certainty that prices will stay at their current levels. A CPF, such as the one introduced in the UK, would provide this certainty and would also provide a clear signal of regulators' commitment (Flachsland et al., 2020). Since price uncertainty remains partly unaddressed in the UK CPF, the following section will provide a clear design for a dynamic CPF as an addition to the EU ETS.

5.4 Proposed Carbon Price Floor Design

In the analysis above it is concluded that the costs of emitting have to exceed a certain price level for the carbon price to be passed through to electricity prices. This effect is desired as it may induce changes in the merit order and provides an incentive to consume less energy. Although carbon prices in the EU ETS are currently at a level that they appear to be passed through to electricity prices, there is no guarantee that prices will remain at this level. Therefore, a carbon price stability instrument is required in addition to the EU ETS.

The MSR is currently the only price stability instrument used in the EU ETS (European Commission, n.d.-b). The MSR extracts emission allowances from the market in times of excess supply and places them in a reserve. The reserve can later be released if a shortage of supply occurs. Although the MSR works according to pre-defined rules, it seems to become active only as problems in the market occur. However, "The government's emphasis should always be on prevention, not on active intervention" (Lowenstein, 2001, p. 231). Another price stability instrument, such as a CPF, may completely prevent EUA price crashes, whereas the MSR only intervenes in the event of a market distortion. Hence, Flachsland et al. (2020) argue that the introduction of the MSR did not remove the need for a CPF.

A CPF can be implemented in three different ways (Wood and Jotzo, 2011). First, the administrator commits to buying back allowances at the price floor. Therefore, the opportunity costs of the allowances will never fall below this value. Second, a minimum price can be used for auctions. Third, emitters have to pay an additional fee for each unit of carbon emitted, as is the case in the UK CPF. Wood and Jotzo (2011) argue that the latter is most compatible with an international ETS. The first option implies that the regulator would need a (potentially large) budget to buy back permits at the floor price. This may prove to be an even bigger concern in an international system, as countries of different sizes will be required to contribute. The second method does not guarantee that prices do not fall below a certain value in times of market distortions. Moreover, a reserve price for auctions would only work if it is implemented in all of the EU, as international trade would undermine the effects of a reserve price for auctions. Wood and Jotzo (2011) also argue that a significant share of the permits should be allocated by means of auctions for this policy to be effective. Wood and Jotzo (2011) therefore argue that the third option is probably superior in the context of an international ETS. Moreover, the UK CPF has also been proven to be effective (Staffel, 2017). The main disadvantage is the potential complexity introduced by this instrument.

The UK CPF is used as a starting point for this design, but some of its shortcomings will be addressed. The UK CPF has been successful in reducing electricity demand (Staffel, 2017), reducing the use of coal power (Staffel, 2017) and creating an environment where RE power is economically superior (Hu et al., 2019). The UK CPF ensures that the costs of emitting never fall below a certain level and addresses some uncertainty. However, the UK CPF also introduces new uncertainties. Since the CPS is fixed for a whole year, EUA prices still induce short term uncertainty. Moreover, the yearly fixed CPS increases uncertainty as it is based on expected EUA prices. As the CPS is chosen three years in advance, this decision might have more impact than the CPF itself as EUA prices can change drastically in three years or during the year. Therefore, a dynamic CPS that addresses these issues is desired.

Newbery et al. (2019) analyzed the political economy concerning the introduction of an EU-wide CPF and the introduction of a CPF on the national level. They argue that a EU-wide CPF would ensure that cross-border electricity trade is not hindered by unequal carbon prices. Similarly, an EU-wide CPF would reduce the risk of carbon leakage. Moreover, it would help re-establish the EU's position as a leader in environmental policy. However, it might be difficult to find consensus with regard to a price floor and a EU-wide CPF might therefore be unrealistic in the short term. Newbery et al. (2019) also discuss the possibility of ambitious countries introducing a CPF unilaterally, which might evolve into regional price floors. The political interests involved on this level of decision making are beyond the scope of this research. Therefore, the proposed design will be generic in that it can be implemented EU-wide and on a national level. Hence, the floor price will be disregarded as the ideal price depends much on the local energy market and the policy goals.

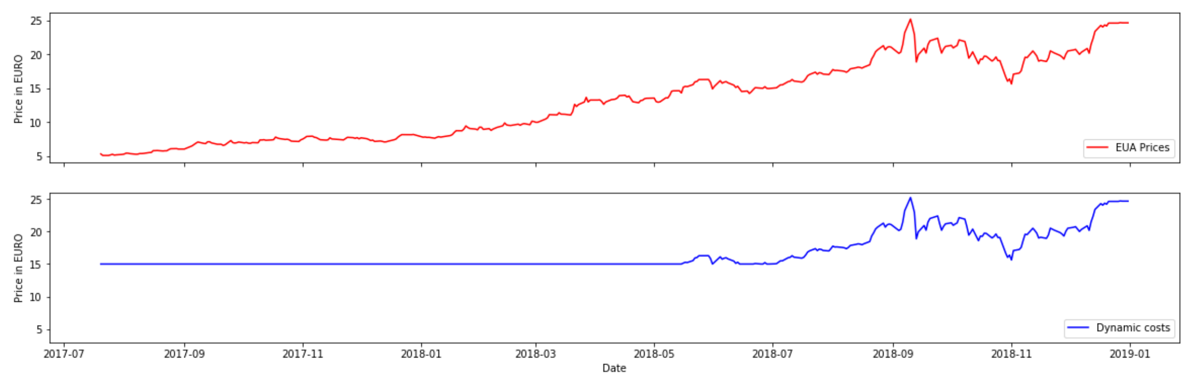

Figure 13: The costs of CO2 emissions under the current system compared to the costs of emissions under a dynamic CPF. An arbitrary price floor of 15 €/tCO2 is chosen for the purpose of illustration.

Ideally, a CPF would complement the EU ETS such that EUA prices form the total costs of emissions unless EUA prices fall below a certain threshold. Figure 13 illustrates this graphically, using a CPF of 15 €/tCO2 for the purpose of illustration. This type of CPF will be referred to as a 'dynamic CPF'. This differs from the UK CPF, as the UK CPF solely pushes the costs of emissions upwards by setting a yearly CPS. Hence, the UK CPF works more like a tax that is based on the expected EUA price, than that it interacts with the EU ETS. A dynamic CPF does not affect the costs of emissions as long as the permit market generates a desired price by itself. Therefore, it is more a stabilization mechanism than an add-on.

A dynamic CPF would ensure the main advantage of the UK CPF, while taking out some of its disadvantages. The main purpose of a CPF is that a minimum price is paid for emitting. This is assured by the UK CPF as well as a dynamic CPF. However, the CPS in the UK CPF is based on forecasts of the price of permits made three years in advance. This forecasts have to be regarded as highly uncertain as everything can happen in the carbon market in the meantime. Hence, market participants are dependent on EUA prices as well as the CPS. Market participants in a market environment where a dynamic CPS is introduced are solely dependent on the development of EUA prices. However, this uncertainty is reduced as the lower bound of the costs of emitting are fixed.

Just like the UK CPF, a dynamic CPF would mainly consist of a minimum price and a CPS. Since the CPF is fixed for a certain period as defined by policymakers, one can also refer to a 'dynamic CPS' system. In a perfect world, the dynamic CPS would adjust in continuous time. However, EUA prices do not change continuously either. Hence, a dynamic CPS should be the difference between the CPF and the last known EUA price. The last known EUA price would in this scenario be based on the price used in the last trade on a public exchange. In such a dynamic, trading practices remain relevant even when EUA prices fall below the threshold price. For instance, if one buys permits for a low price and prices subsequently increase, whilst staying below the price floor, the CPS decreases. Therefore, the CPS decreases and the costs of emitting of the market participant are lower as they bought EUA prices at a lower price. However, the market participant is still expected to pass-through the full price of the emission permits due to opportunity costs. The CPS costs are also expected to be passed through as these costs are actually made.

The dynamic CPS as described above is unrealistic due to practical constraints. Firstly, a dynamic CPS that is calculated solely based on the latest public trade can easily be gamed. Market participants could buy very small volumes for a price above the price floor to artificially keep the CPS equal to zero. Moreover, such a system would require very liquid markets. Therefore, the dynamic CPS should be based on a volume weighted moving average price of the emission permits. A daily volume weighted average that includes auction prices would solve these issues. If a dynamic CPS is calculated this way at the end of each day, the total costs of emitting will resemble the costs presented in Figure 13 with only small deviations based on intraday EUA price fluctuations.

The implementation of a dynamic CPF would also be constrained by the data collection methods used by the monitoring authorities. The Netherlands is the only country that has formally opted for a CPF in the power sector besides the UK (Rijksoverheid, n.d.; Newbery et al., 2019). Therefore, the methods used by the Nederlandse Emissie Autoriteit (NEA), or Dutch Emissions Authority, are used as an example. The NEA has indicated to follow the methodology as described by European regulations (Appendix A.4). Hence, the methods used by the NEA are assumed to correspond to methods used by other emissions authorities in the EU.

The NEA records company emissions on a yearly basis (Appendix A.4). The NEA receives these records directly from the companies, who fill in a verified emissions report annually. This emissions report follows a standardized European format and is therefore assumed to be used in all other EU countries. Although the NEA indicated that other emissions authorities are free to request additional data, the current European standards for emissions data collection do not allow for the implementation of a dynamic CPF. Therefore, three design options with regard to the implementation of a dynamic CPF have been identified.

Firstly, emissions authorities can change their data collection methods by increasing the frequency of the current emissions records. Solely changing the frequency would be the least disrupting as processes would not have to be adjusted. This option would mostly be a burden for the industry as their administrative and monitoring costs would increase. Moreover, the burden on emissions authorities might increase due to additional verification activities. An annual report would still be sufficient, as long as the data frequency within the report is increased to daily emissions. The reports can also be sent more frequently depending on administrative preferences.

Second, it is an option to apply the methods as used in the UK CPF. In the UK, the CPS is charged in £/kWh, based on the fuel type used for electricity generation (Hirst, 2018). The CPS is a component of the Climate Change Levy and distinguishes between gas, liquid state or solid fossil fuel types (GOV.UK, n.d.). Therefore, the UK system neglects differences between different types of liquid and solid fuels used for generation. Producers become liable to the CPS when gas passes through the meter at the generating station or other fuels are delivered through the entrance gate at the generating station (GOV.UK, n.d.). This delivery moment is also considered to be the point in time at which the tax becomes due. However, this is not necessarily the point in time in which carbon is emitted. Entities involved in making or receiving fossil fuels are obligated to keep records.

Third, the data provided on the ENTSO-E Data Transparency Platform can be used to obtain more frequent emissions data. The ENTSO-E Data Transparency Platform provides hourly generation data of each power plant. Therefore, the hourly emissions can be calculated based on the type of fuel used for generation and the plant activity. However, calculating the emissions based on generation data requires assumptions with regard to plant efficiency or the use of emissions standards per kWh per plant type. In the latter case, plant efficiency would be disregarded. Moreover, plant efficiency data may be tampered with if it is directly requested from the industry itself.

Based on the underlying principles of the annual procedure of Monitoring, Reporting and Verification (MVR) (European Commission, 2015), the designed system should be feasible, reliable and affordable. Feasibility regards the ease of implementation and to what extent current processes have to be adjusted. Moreover, the designed system would become less feasible if the number of parties involved increases. Increasing the frequency of the records of emissions data concerns an expansion of the current system, the new processes should be the least disruptive of the current system. Reliability concerns the expected accuracy of the data obtained. Most of the MVR principles are related to reliability and cover topics such as accuracy, consistency, and transparency. Lastly, the affordability refers to costs made by monitoring authorities as well as the industry due to the introduction of a dynamic CPF. Although the latter might be of the least importance, the costs of monitoring and enforcement should remain within certain limits. The three design options are scored in Table 11 using the best-of-class method as described by Dym et al. (2014).

	Expanding Current Methods	UK Model	ENTSO-E Data
Feasibility	1	3	2
Reliability	1	3	2
Affordability	2.5	2.5	1

Table 11: A best-of-class chart (Dym et al., 2014) scoring the different design options according to each criterio. The chart provides a relative measure for each criterion and the designs are scored from 1 (best) to 3 (worst).

The design options are scored using a best-of-class chart in Table 11. The best-of-class chart scores each design option from 1 (best) to 3 (worst) with respect to each criterion. Scoring of the design options is the result of a qualitative process. The scoring of each design is relative to the other designs. Hence, a design scoring 1 on a criterion does not necessarily indicate that it is good with regard to this criterion. It merely implies that this design scores better than the other designs with regard to this criterion. If multiple designs are expected to perform equally with regard to a criterion, the average of their positions is used.

The results in Table 11 show that expansion of the current methods is expected to score best with regard to feasibility and reliability, whereas the use of ENTSO-E Data is expected to be the most affordable. Expansion of the current methods is expected to be most feasible as the current processes do not have to be adjusted. Keeping records at a higher frequency will be labor intensive, but this will be the case for each one of the design options. Using the ENTSO-E Data will require the involvement of a new important stakeholder, whereas the UK Model requires the development of processes for new types of data collection and verification. Hence, the latter is expected to be the least feasible.

Expansion of the current methods is also expected to be most reliable. Current methods are assumed to be reliable. If current methods are distrusted, one should also doubt the reliability of the EU ETS as a whole. The use of ENTSO-E Data only adds to uncertainty with regard to plant efficiency. The UK model is assumed to be the least reliable and accurate, as different types of fossil fuels are assumed to induce the same emissions. Moreover, the moment of the fossil fuel use is disregarded since the moment of fuel delivery is taxed. Therefore, the regulator is dependent on transaction records of private companies. In the UK, where the CPS is charged on an annual basis, small inaccuracies concerning the moment of the fossil fuel use are of lesser importance. However, if the CPS is adjusted daily, such inaccuracies may be very relevant. It would be an undesired side effect if power generators buy their fuels in bulk when CPS rates are lower, only to use them at a later point in time. Such a dynamic might also distort commodity markets and strengthen the relation between carbon and fossil fuel prices. Moreover, delivery and transaction data can easily be tampered with if small changes can have a big impact. Such uncertainties would undermine the transparency and integrity of the data.

The design option using ENTSO-E Data is expected to be most affordable. Using this data will only require the testing of plant efficiency once. Both the UK model as well as expansion of the current methods require an everlasting increased effort of the monitoring authorities as well as the industry. Hence, both are assumed to be more expensive than the use of ENTSO-E Data. Using the UK model, fuel transactions and delivery records have to be actively verified on a daily basis by the monitoring authorities. Similarly, increasing the data frequency using current processes will add to the verifying activities of the emissions authorities.

It is notable that the UK model for data collection scores the lowest in the best-of-class chart depicted in Table 11. The UK model is the only method that is implemented in practice and can therefore be considered feasible. However, it should be noted that there is a big difference between collection of annual data and the collection of daily data as required for a dynamic CPF. It is based on this essential difference that the UK model is considered the least feasible and the least reliable.

The use of ENTSO-E Data or an expansion of the current methods are the most viable design options for the introduction of a dynamic CPF based on the scoring in the best-of-class chart. Both designs can be implemented without the development of new methods for data collection. However, the ENTSO-E would have to adjust to its new monitoring responsibilities and it should be questioned whether this is a desired new role for a collective of TSOs. Moreover, dependency of emissions authorities on the ENTSO-E might also prove to be a complication. Therefore, the expansion of current methods seems to be the least complicated design option to implement.

6 Discussion

The results of this thesis confirm the findings by Wolff and Feuerriegel (2019) and Jouvet and Solier (2013) that carbon prices were no longer passed through to electricity prices after carbon prices decreased in the wake of the financial crisis. Moreover, this thesis confirms that carbon prices are (at least partially) passed through if the total costs of emitting are high enough. This pass-through was observed once the UK introduced its CPF and when carbon prices started to increase in 2018. This corresponds with the findings of Sijm et al. (2006), Fell (2010) as well as Freitas and da Silva (2013), who found evidence of the price pass-through using data from before the financial crisis.

These results of this thesis provide a strong argument in favour of a CPF as an addition to the EU ETS. It is important that carbon prices are passed through in order to provide incentives to reduce demand and foster investments in abatement. Although carbon price levels are currently such that they are passed through, this provides no certainty for the future. The introduction of a CPF would provide this certainty, while having limited downsides. Hence, a CPF was referred to as a 'low-regret' policy by Newbery et al. (2019).

Some important limitations have to be acknowledged when the results of this thesis are interpreted. The mathematical models used in this thesis are an attempt to model real behaviour, but they are limited in the extent to which they can do this. Modelling the real world is complicated, especially with regard to the highly volatile electricity price time series analyzed in this research. It has to be noted that the parameter estimates solely represent the best fitting model. This is therefore not necessarily a detailed description of the 'real' interaction between macroeconomic variables. Furthermore, it is likely that ETS prices are correlated with fuel prices (Freitas and da Silva, 2015; Bunn and Fezzi, 2007) and this relation can be picked up by the model. Moreover, the non-linear and discontinuous supply function present in electricity markets complicates modelling. Lastly, Zachmann and von Hirschhausen (2008) found that carbon prices were passed-through asymmetrically. Rising carbon prices impacted wholesale electricity prices more than equivalent carbon price decreases. These non-linear dynamics are not incorporated in the model and might exacerbate or nullify some of the dynamics that are present in reality. The estimation of a more than 100% carbon price pass-through may be attributed to these limitations.

It should also be noted that the GARCH part of the model is only able to capture a specific type of volatility. The uncertainty captured by the GARCH model regards volatility that is mostly of importance for short term electricity price forecasts. The observed volatility does not directly correspond to the uncertainties that are present when one would want to forecast prices years or even months ahead. Moreover, the uncertainty that is captured by the model only reflects on events that did occur and not on (extreme) events that may occur, the so-called Black Swan events. However, if a certain variable is related to increases in volatility in the short run, it is likely that it also increases long term uncertainty.

It is peculiar that a significant positive relation between carbon and electricity prices is found in the UK after introduction of the CPF in the analysis using average daily prices, but that this relation is only found in the 11h time series in 2018 in the analysis using day-ahead prices. These results are slightly contradicting. This may be due to the additional volatility observed in the time series using hourly prices. Daily changes in the marginal unit of production in the time series measured at a specific time have more impact than on the daily averages. This complicates estimation of the model, as the non-linear discontinuous characteristics of the supply curve are more present in the hourly data. Although the results are slightly contradicting, the conclusions from both analyses are the same. As these conclusions are also corroborated by Jouvet and Solier (2013) as well as Wolff and Feuerriegel (2019), the contradicting findings are insufficient to nullify the conclusions of this research.

All results obtained in this thesis are based on numerical optimization techniques. The quantitative models are employed using Python 3.7. The Minimization package from Scipy is used for the optimization of the models and the corresponding hessian is obtained using a package by Numdifftools. As these methods search for local optimums, these techniques are dependent on the initial parameter guesses that are used as input for the models. Adjusting input parameters to optimize all 54 fits modelled in the multi-country analysis required much manual effort. Although considerable effort has been put into adjusting the initial parameter guesses, some local optima may have been found. Similarly, the standard errors of the parameter estimates are based on estimations of the inverse hessian.

It is interesting that the dummy variables used to distinguish between different levels of volatility for different days of the week provided no added value in terms of improving the BIC in the multi-country analysis. This relation was observed by Koopman et al. (2012) and one would expect more volatility on weekdays as compared to days in the weekend due to more industrial activity in the former. Similarly, it is interesting that incorporating the prices of fossil fuels did not enhance the forecasting abilities of the model. Based on theory and the dynamics of the supply curve, it is known that changes in the fuel price of the marginal unit of generation should alter electricity prices. However, the model was unable to detect a linear relation between fuel and electricity prices. This is probably the result of the non-linear characteristics of the supply curve and the fluctuating demand, which changes the marginal unit of generation in each observation. The growing capacity of intermittent RE power also exacerbates the occurrence of changes in the marginal unit of generation between observations. Moreover, the large number of parameters that had to be initially estimated may have complicated the process of numerical optimization.

The findings of this research correspond with the findings of Wolff and Feuerriegel (2019) and Jouvet and Solier (2013). Jouvet and Solier (2013) measured cost-pass through by means of a linear regression, whereas Wolff and Feuerriegel (2019) used an ARX model. This thesis expanded the ARX model by adding a GARCHX part to account for heteroskedasticity in the errors. If one is interested in verifying the quantitative results of this research, it might be interesting using State Space models in combination with a Kalman Filter and Kalman Smoother (Durbin and Koopman, 2012). The use of State Space models with a Kalman Filter would allow for estimation of the unobserved signal in electricity prices and create the possibility to estimate how the unobserved signal is affected by changes in carbon prices. Analysis of the unobserved trend may be an appropriate way to deal with daily changes in the marginal unit of generation as this can be regarded as 'noise'. This methodology distinguishes between the actual signal and noise and would therefore be very useful for the modelling of highly volatile electricity price time series.

If one decides to accept the quantitative findings of this research, it might prove relevant to simulate the impact of the introduction of a CPF as proposed in this research. It is important to be aware of the costs associated with the introduction of a CPF and how investor behaviour would change as compared to their behaviour under the UK CPF. This research can also contribute to the decision making process of the price floor. With regard to deciding on a price floor, it is also important to research what the cost of emitting should be for carbon prices to be passed through to electricity prices. This is particularly important, as price pass-through is important for achieving long term environmental policy goals.

It remains of importance to research the factors that affect the carbon market in the EU. Although the financial crisis is regarded as the cause of the price decrease in 2009, the real cause remains uncertain (Flachsland et al., 2020). As prices have reached higher levels since 2018, it is uncertain whether they will stay there and what kind of macroeconomic events could pose a threat to stability of the price signal. A recession will always commence unexpectedly and such an event should not jeopardize environmental policy goals.

7 Conclusion & Policy Implications

This thesis has applied econometric time series modelling methods to analyze the relation between the price of EU carbon allowances and day-ahead electricity prices in nine European countries. The used models allow for estimation of the relation between carbon and electricity price levels and short term electricity price volatility amplified by shocks in the carbon price. This thesis evaluates how the introduction of a CPF as an addition to the EU ETS affects these relations and whether such an instrument would enhance the EU ETS. The results of this thesis indicate that carbon prices are only passed through to electricity prices if the total costs of emitting are above a certain threshold. These results correspond with the findings from existing literature. Therefore a CPF is recommended in addition to the EU ETS.

Although the UK CPF is likely to have aided to the reduction of electricity demand and carbon emissions, the policy instrument has some shortcomings. The CPS is fixed for a year and set three years in advance based on EUA price forecasts. However, the development of carbon prices over three years, and even within a year, is highly uncertain. Therefore, the CPS acts more like an annually changing tax than an instrument that is charged based on the difference between the EUA prices and the CPF. This introduces a new type of risk for market participants. Therefore, a CPF design that adjusts CPS rates dynamically is proposed. The proposed design can be introduced EU-wide or on a national level.

Carbon to electricity price pass-through is of importance for the long term effectiveness and affordability of the EU ETS. Even though an ETS ensures that emissions do not exceed the pre-defined emissions cap under the assumption of accurate monitoring and enforcement, it does not necessarily provide the right incentives for the investments required for achieving long term environmental policy goals. The pass-through of carbon prices to electricity prices fosters these investments in multiple ways. First, polluting forms of power generation become relatively more expensive as compared to cleaner alternatives. This can induce changes in the merit order and therefore reduced emissions under the same demand. Second, higher electricity prices increase the profitability of investments in RES. Third, increased electricity prices provide an incentive for consumers to reduce demand and invest in energy efficiency.

Two analyses have been conducted in order to research the relation between carbon and electricity prices in the EU. The first analysis, using data from nine EU countries, shows that carbon prices were not passed through to electricity prices when carbon prices were low. The pass-through was only measurably present after carbon prices started to increase in 2018. The second analysis regards the UK CPF. This analysis shows that carbon prices in the UK were passed through to electricity prices once the CPF was introduced. This pass-through effect was present even though carbon price levels were low when the policy was introduced.

Both analyses provide similar conclusions. Carbon to electricity price pass-through only occurs if the total costs of emitting exceed a certain threshold value. Carbon price pass-through is of importance to achieve long term environmental goals. The introduction of a CPF as an addition to the EU ETS would guarantee that emission costs never fall below a predefined value and can therefore ensure that carbon prices are passed through to electricity prices at all times. Moreover, the introduction of a CPF would provide a clear signal from policymakers with regard to their environmental ambitions. Lastly, a CPF would provide long term certainty for investments with regard to the minimum price of carbon. Hence, the EU ETS would be enhanced with the introduction of CPF, especially in the long run.

This thesis corroborates the findings from existing literature that the desired carbon price pass-through has been absent since carbon prices crashed. This thesis shows that carbon price pass-through can be observed if a CPF is introduced despite low EUA price levels. To guarantee carbon price pass-through, the total costs of emitting should exceed a certain threshold value at all times. Hence, the findings of this thesis provide a strong argument in favour of the introduction of a CPF as an addition to the EU ETS. Although carbon price levels are currently high, the future price development remains uncertain and chances of a price crash can never be fully excluded.

The conclusions of this research can be validated using State Space models and the Kalman filter.

This methodology may be applicable as it allows for analysis of the unobserved trend in electricity prices and whether this is affected by carbon price changes. Moreover, it is important to gain a deeper understanding of the factors that affect carbon prices. Lastly, it is important to further research the effects of a CPF with different minimum prices. Simulations may be appropriate to evaluate societal costs and to what extent each price floor fosters low-carbon investments. The latter can contribute to the decision making process of policymakers with regards to the minimum price when a price floor is introduced.

It was initially expected that carbon price shocks would induce electricity price volatility spikes. The additional certainty provided by a CPF was expected to mitigate this volatility effect. However, this volatility effect seems to be exacerbated rather than mitigated due to design of the UK CPF and the yearly fixed CPS. The dependency on the decision of the government with regard to the CPS on top of the still relevant EUA prices also seems to increase long term uncertainty for market participants. However, it is concluded that a CPF is also an important instrument to ensure that carbon prices are passed through to electricity prices. Therefore, this thesis proposes a dynamic CPF that eliminates some of the flaws of the UK CPF. In the dynamic CPF, the CPS is adjusted daily based on daily weighted averages of public carbon trading records. Three different design options are discussed for the introduction of such a dynamic price stability instrument. The proposed design will have the most impact if it is introduced EU-wide, but can also be introduced on a national level by ambitious governments. Regardless of the scope of the CPF, a minimum price for carbon is essential for the pass-through of carbon prices in the event of another carbon market crash.

8 Reflection

This thesis is the result of a collaboration with my supervisors Dr.ir. de Vries and Dr.ir. Kroesen. I have enjoyed working on this thesis and I have learned a lot. This thesis provides new insights into the relationship between carbon and electricity prices and the empirical effects of a CPF regarding this relation. Although the former has been researched before, the analysis concerning the relation between carbon and electricity after introduction of the UK CPF using empirical data was a first. Now that the research has been completed, it is possible to reflect upon the research question and the methods used.

By conducting this research I have improved my understanding of volatility and uncertainty. The research question and subquestions emphasize electricity price volatility and how this is related to EUA prices. As prior research has proven that GARCH models are applicable in the context of modelling electricity price time series, I used this methodology to measure uncertainty induced by the EU ETS. Ketterer (2014) has been an important influence in this way of thinking, as her research used this methodology to directly analyze the relation between renewable power generation and electricity price volatility. Although GARCH models lend themselves well for the modelling of varying volatility in time series models, I have come to believe that this is different from the uncertainty experienced by investors. Short-term price modelling is relevant for some market participants and short term volatility spikes are therefore unwelcome nonetheless. But if one is interested in empirically researching (EU ETS induced) uncertainty experienced by investors and power generators, I recommend using investment data or data concerning hedging activities.

When I started writing this thesis I was mostly focused on volatility and uncertainty. I expected that the introduction of a CPF would reduce investor uncertainty, and therefore reduce electricity price volatility. However, the results indicated that the UK CPF seemed to exacerbate volatility rather than that it reduced it. As the results did not fit this narrative and forced me to shift my focus and evaluate the price pass-through. By analyzing the price pass-through, I found another argument in favour of a CPF. This argument may be even stronger than reduced uncertainty.

Although GARCH models have some shortcomings, as discussed in the Discussion section, I believe that GARCH models are essential to empirically model electricity price time series. The characteristic non-linear discontinuous supply curve present in electricity market is difficult to model with standard linear models. The often frequent price spikes can easily be captured by the time varying volatility and therefore the GARCH aspect is required. By thinking about these dynamics for a stretched period of time, I have come to think that the volatility measured by Ketterer (2014) as a result of wind-penetration might actually be the result of the non-linear supply curve.

This research was constrained by the data available. The EU ETS has been present for over fourteen years and this should provide sufficient data. However, the UK CPF has been introduced less than seven years ago. Moreover, the ENTSO-E only provides extensive data starting from 2015. Especially the latter has proven to be a hurdle. The data provided by ENTSO-E will prove to be valuable for many others interested in researching electricity systems using empirical data. Finding data from the first years of the UK CPF and prior to its introduction was a time consuming practice and price data were obtained by courtesy of the Institution of Civil Engineers. Due to the absence of data I was unable to obtain hourly pricing data for the analysis of the UK CPF. Therefore, some of the nuances in the price dynamics may be missing from the data. On the other hand, the daily averages that are used out of necessity are less volatile and may therefore have provided better results.

I commenced with this research with the use of econometric methodology in mind. Gladly, my supervisors were quickly to point out that this approach is impractical when one intends to write a *Complex Systems Engineering & Management* (CoSEM) thesis. This has been the biggest hurdle that I have encountered while conducting this research. In response to the feedback provided by my supervisors, I restarted with a systems analysis and formulated a problem that I identified in the system. Subsequently, I defined a research question related to the identified problem and devised methods to answer this question. Although I still ended up using econometric methods, the new process was more practical and has resulted in a more coherent thesis.

In hindsight, it might have proven valuable to commence with writing this thesis with a specific design or system intervention in mind. A proposed intervention that would (partly) solve these issues and can be tested using simulations would be ideal for a CoSEM thesis. Luckily, my supervisors pushed me to incorporate the analysis of the UK CPF in this thesis. The latter has resulted in a proposed design of a dynamic CPF in which I was really able to use some of the characteristic skills I have obtained from the CoSEM curriculum.

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A Appendices

A.1 Literature Review Table

Source	Subject	Country	Methodology	Findings
(Tol, 2014)	Climate Economics	Global	Theoratically/analytical derivations	Validation for policy/Pigoux/ same effectiveness as tax.
(Zapf et al., 2019)	Proposal new Global ETS design	Global	Identification of weaknesses	Global ETS solves issues such as the free rider problem, carbon leakage and the green paradox.
(Flora and Vargiolu, 2020)	Variance, pricing & Investment	EU	Identify distributionFirm level monte carlo simulations	Variance Gamma model for distribution of the price A price stabilization mechanism would stimulate investment in abatement
(Wan, 2012)	ETS & Carbon Tax	EU	Literature Review	Carbon tax and ETS should be complementary systems. ETS more space to develop globally, both are cost effective
(Wolff and Feuerriegel, 2019)	Relation ETS & Energy prices (Phase III)	EU	Autoregressive model with exogenous vars	(Surprisingly) Negative relation between the price of allowances and energy prices
(Lehmann et al., 2019)	Externalities in electricity generation Mix electricity from RES-E in energy & ETs	EU	Quantitative	RES-E subsidies in aid in reducing externalities from fossil fuel energy generation. However, RES-E subsidies do not help against energy (coal/oil) dependence on other countries.
Aatola et al.	Price determination of EUA in ETS	EU / Germany	Use daily forward prices of EUA as dependent var	Strong relation with price of electricity, gas and coal.
(Jablonska et al., 2012)	side-effect of emissions trading on electricity spot market price	Nordic Nord Pool	Regression models before & After 2005 Background variables such as temperature, water reservoir levels, carbon prices	More volatility in electricity spot market due to ETS
(Schäfer, 2019)	CO2 abatement in electricity sector	Germany	Linear Regression	ETS has a small effect (6%abatement) and no effect since 2010. suggests: intensity based emission cap
(Koch and Mama, 2019)	FDIs of multinational firms related to ETS	Germany	Difference-in-Differences approach	EU ETS Firms increased the number of their affiliates compared to the control group.
(Bunn and Fezzi, 2007)	mutual relationships between electricity, gas, carbon prices in the daily spot markets	UK	co-integrated VAR model	carbon and gas jointly influence the equilibrium price of electricity
(Forbes and Zampelli, 2019)	Combine wind generation and EUA price with emissions	Ireland	time series analysis	Less emissions due to ETS under same wind intensity
(Freitas and da Silva, 2015)	Commodity price interactions	Spain	VECM for long and short run equilibrium relations	Found long run relation, weaker at some points after the collapse of CO2 prices
(Cao et al., 2019)	ETS-carbon tax hybrid	China	Simulations	Hybrid form reaches same CO2 reduction with lower loss of GDP as compared to only ETS.
(Zhang and Zhang, 2019)	Impact of ETS on low-carbon development	China	empirical	Positive relation ETS and low carbon development
(Lin and Jia, 2019)	Influence of ETS price on economic development	China	Analyses of the impact of the ETS under different price levels	GDP will decrease more with increasing ETS price levels Too low price makes system ineffective, high price has economic impact.
(Koo et al., 2019)	ETS inclusion of smaller companies	Korea	Linkage simulation model	ETS effects would be greater if smaller companies would be included in the ETS
(Zhang and Fan, 2019)	Does ETS improve energy efficiency?	China	Stochastic frontier analysis	ETS is not as effective for energy efficiency improvement as supposed,
(Sijm et al., 2006)	ETS price pass-through	Netherlands & Germany	Numerical Regression Model	Even if the permits are grandparenthed, carbon prices are passed through for 60-100%
(Pinho and Madaleno, 2011)	Relation price electricity, carbon and fuels	Germany, France, Nord Pool	VECM using electricity, carbon, oil, gas and coal Monthly averages from 2005-2009	Impact of Carbon market depends on energy mix
(Jouvet and Solier, 2013)	Carbon Cost pass-through to electricity prices	EU (9 countries)	Ordinary Least Squares using base & Peak prices	Less pass-through in phase II than in Phase I.
(Freitas and da Silva, 2013)	Carbon Cost pass-through to electricity prices	Portugal	Cointegrated VECM using Elec, Carbon, Gas and Coal Exogenous: mix used and temperature Phase 2: 2008-2011	The dynamic pass-through of carbon prices into electricity prices is strongly significant.
(Fezzi and Bunn, 2010)	Interaction electricity demand & Supply	PJM	Asymmetric VECM to estimate demand and supply functions in day-ahead markets	Demand is inelastic in the short run. However, the quantity traded on the market does respond to past disequilibrium in the supply function.
(Honkatukia et al., 2006)	Carbon Cost pass-through to electricity prices	Finland	VECM gas, coal & Power prices ARIMA Daily obs	75-95% of a carbon price change is passed through to electricity prices in finland
(Fell, 2010)	carbon cost pass-through to electricity prices	Nordic	CVAR electricity prices and CO2 allowance prices Using hourly prices	Electricity prices have short-term responses to CO2 price shocks, but this response dampens over time
(Thoenes, 2011)	Relation electricity and fuel prices	Germany	VECM	Electricity prices adapt to fuel prices changes in a long-run cointegration relation.
(Cotton and Mello, 2014)	Effects of ETS and RES allowances	Australia	Generalised forecast error variance decomposition analysis	Carbon price shocks have no lasting effect on electricity prices in Australia.
(Zachmann and von Hirschhausen, 2008)	Carbon Cost pass-through to electricity prices	Germany	autoregressive distributed lag model ECM	Rising prices of emission allowances have a stronger impact on wholesale electricity prices than falling prices
(Eglia and Lecuyer, 2017)	Costs of a Carbon Price Floor	Germany	Simulating the effect of different price floors.	A CPF of 40€/tCO2 would increase median wholesale prices by 37€/MWh. Consumer costs could be partly compensated by reduced EEG costs.
(Newbery et al., 2019)	Power Sector Carbon Price Floor	Europe and UK	Literature Review	An EU-wide CPF for the power sector would constitute a significant improvement to the EU ETS.
(Flachsland et al., 2020)	Carbon Price Floor	Europe and UK	Literature Review & Discussions with High-level Stakeholders	A price floor would make the EU ETS less prone to future revision in case of unexpectedly low prices.
(Hu et al., 2019)	Power dispatch after UK Energy Market Reform	UK	Dynamic Economic and Emission Dispatch (DEED) model	Under the UK CPF renewable power is superior with regards to economics and emissions.
(Wang et al., 2020)	Price stabilization mechanisms	China	Typology & Decomposition Followed by Quantitative Analysis	Price limits are the most effective means to stabilize the intrinsic price trend.
(Weng et al., 2018)	Carbon Price Floor	China	Simulations of different CO2 price paths	CPF needed to guarantee a price signal under China's ETS with a flexible cap.
(Staffel, 2017)	Impacts of Power Decarbonisation	UK	Quantitative Analysis	Power emissions fell 46% from 2013 to 2016: Falling demand, Gas surpassed Coal and increased share of RES.
(Franco et al., 2015)	Electricity Market Reform	UK	Systems Dynamics Simulation	CPF little effective, solely reduced emissions but an unclear signal to investors.
(Philibert, 2009)	Impact of carbon price caps and floors	Global	ACTC simulation model for the cost of climate mitigation policies	Price caps can reduce uncertainty and expected costs Price floors help to maintain the environmental effectiveness of the policy.
(Wood and Jotzo, 2011)	Price floors in an ETS	Global	Literature Review	Price floors guarantee minimum abatement and help manage cost uncertainty.

Table 12: Overview of the reviewed literature.

A.2 Data Characteristics

Data	# obs	Mean	Variance	Skewness	Kurtosis
ΔP_{CO2}	1260	0.013651	0.148533	-0.994146	15.332235
ΔP_{Oil}	1007	-0.003119	1.154296	0.024113	1.122580
ΔP_{Gas}	1005	0.002095	1.986782	-6.620722	339.370859
ΔP_{Coal}	1007	0.019811	0.900593	1.259152	34.989672
$P_{ES,4h}$	1461	40.175702	132.995304	-0.344764	0.343165
$P_{ES,11h}$	1461	53.574168	117.989578	-0.348581	0.332955
$P_{ES,18h}$	1461	52.743669	118.941668	-0.310893	0.505129
$\Delta P_{DK2,4h}$	1455	0.011886	13.145845	0.046936	20.132017
$\Delta P_{DK2,11h}$	1455	0.011760	17.573680	-0.236326	12.116649
$P_{DK2,18h}$	1455	31.805869	147.432033	0.854328	0.478865
$P_{FR,4h}$	1456	28.733379	114.911374	0.136717	0.405208
$P_{FR,11h}$	1456	47.206923	171.633482	0.402418	0.932629
$P_{FR,18h}$	1456	53.684897	358.108830	1.993508	8.387209
$\Delta P_{NL,4h}$	1456	0.006601	27.535999	0.141443	3.632330
$P_{NL,11h}$	1456	46.315357	161.236309	0.661099	0.226151
$\Delta P_{NL,18h}$	1456	0.012938	133.210442	-0.180879	4.810949
$\Delta P_{CZ,4h}$	1461	0.020864	148.469170	0.754031	5.041969
$P_{CZ,11h}$	1461	40.272560	159.751660	0.330651	1.046302
$P_{CZ,18h}$	1461	46.052601	158.925555	0.527816	0.650137
$P_{IT_N,4h}$	1457	40.583459	104.433378	0.424147	0.234624
$P_{IT_N,11h}$	1457	55.504386	181.579714	0.952196	1.483818
$P_{IT_N,18h}$	1457	61.862697	200.015823	0.935873	1.536939
$\Delta P_{PL,4h}$	1456	0.006712	9.193244	0.026125	9.138351
$P_{PL,11h}$	1456	49.074954	213.551738	1.710974	4.016280
$\Delta P_{PL,18h}$	1456	0.011010	64.740648	-0.348198	6.911400
$\Delta P_{UK,4h}$	1445	0.010580	34.292939	-0.242981	6.847520
$\Delta P_{UK,11h}$	1445	0.004638	52.373831	0.090787	3.336138
$P_{UK,18h}$	1445	65.958664	377.705364	2.581757	12.178348
$P_{DE,4h}$	1456	25.132589	117.167490	-0.252339	0.593863
$P_{DE,11h}$	1456	37.621078	168.806566	0.182851	1.001553
$P_{DE,18h}$	1456	44.510591	173.138536	0.479845	0.625118
RES-PEN$_{ES,4h}$	1456	0.240696	0.030181	1.149300	0.939568
RES-PEN$_{ES,11h}$	1456	0.352024	0.019446	0.459875	0.219198
RES-PEN$_{ES,18h}$	1456	0.231489	0.016896	0.779689	0.346856
RES-PEN$_{DK2,4h}$	1456	0.240696	0.030181	1.149300	0.939568
RES-PEN$_{DK2,11h}$	1456	0.352024	0.019446	0.459875	0.219198
RES-PEN$_{DK2,18h}$	1456	0.231489	0.016896	0.779689	0.346856
RES-PEN$_{FR,4h}$	1456	0.240696	0.030181	1.149300	0.939568
RES-PEN$_{FR,11h}$	1456	0.352024	0.019446	0.459875	0.219198
RES-PEN$_{FR,18h}$	1456	0.231489	0.016896	0.779689	0.346856
RES-PEN$_{NL,4h}$	1456	0.240696	0.030181	1.149300	0.939568
RES-PEN$_{NL,11h}$	1456	0.352024	0.019446	0.459875	0.219198
RES-PEN$_{NL,18h}$	1456	0.231489	0.016896	0.779689	0.346856
RES-PEN$_{CZ,4h}$	1456	0.240696	0.030181	1.149300	0.939568
$\Delta RES-PEN_{CZ,11h}$	1456	0.000017	0.018711	-0.201731	1.321855
$\Delta RES-PEN_{CZ,18h}$	1456	0.000120	0.015418	0.053791	1.043394
RES-PEN$_{IT_N,4h}$	1456	0.240696	0.030181	1.149300	0.939568
RES-PEN$_{IT_N,11h}$	1456	0.352024	0.019446	0.459875	0.219198
$\Delta RES-PEN_{IT_N,18h}$	1456	0.000120	0.015418	0.053791	1.043394
RES-PEN$_{PL,4h}$	1456	0.240696	0.030181	1.149300	0.939568
RES-PEN$_{PL,11h}$	1456	0.352024	0.019446	0.459875	0.219198
RES-PEN$_{PL,18h}$	1456	0.231489	0.016896	0.779689	0.346856
RES-PEN$_{UK,4h}$	1456	0.240696	0.030181	1.149300	0.939568
RES-PEN$_{UK,11h}$	1456	0.352024	0.019446	0.459875	0.219198
RES-PEN$_{UK,18h}$	1456	0.231489	0.016896	0.779689	0.346856
RES-PEN$_{DE,4h}$	1456	0.240696	0.030181	1.149300	0.939568
RES-PEN$_{DE,11h}$	1456	0.352024	0.019446	0.459875	0.219198
RES-PEN$_{DE,18h}$	1456	0.231489	0.016896	0.779689	0.346856

Table 13: An overview of all of the most important characteristics of the data used in the multi-country analysis.

A.3 Parameter Estimates Multi-country Analysis

		ES		DK2		FR		NL		CZ		IT-N		PL		UK		DE	
		Est.	p-val	Est.	p-val	Est.	p-val	Est.	p-val	Est.	p-val	Std. error	p-val	Est.	p-val	Est.	p-val	Est.	p-val
	c	35.733018	**0.000000**	0.105653	0.295223	9.692212	**0.000000**	0.001000	0.996437	0.02011	0.939939	10.921448	**0.000000**	0.001000	0.993001	0.0010000	0.995792	19.41859	**0.000000**
	ω	1.228461	0.678744	0.331157	0.626374	21.050604	0.109272	3.552049	0.247797	4.929809	**0.033951**	2.062202	0.418235	0.565869	0.355286	0.357996	0.788321	1.098602	0.748215
	RES Effect	-43.518563	**0.000000**	-2.550476	**0.000001**	-77.081098	**0.000000**	-16.744033	**0.000000**	-29.973754	0.986913	-30.233118	0.980200	-12.085385	**0.000000**	-8.045576	**0.000000**	-34.663895	**0.000000**
	ETS Effect	1.059124	**0.04089**	0.891321	**0.002453**	0.389191	0.473877	1.212094	**0.01211**	1.134248	**0.018029**	-0.862085	0.105435	0.085408	0.776399	0.639391	0.285045	0.237827	0.736041
4h	ϕ_1	0.262024	**0.000000**	-0.250429	**0.000003**	0.733246	**0.000000**	-0.345834	**0.000000**	-0.269643	**0.000004**	0.787198	**0.000000**	-0.338014	**0.000000**	-0.386925	**0.000000**	0.423652	**0.000000**
	α_1	0.222554	**0.03543**	0.547029	**0.000027**	0.302807	**0.016565**	0.485311	**0.000517**	0.519078	**0.001434**	0.101029	**0.037487**	0.184889	**0.010018**	0.328723	**0.000679**	0.184448	0.054502
	β_1	0.504713	**0.009515**	0.48258	**0.000000**	0.289143	0.250788	0.318001	**0.025542**	0.524507	**0.000002**	0.867009	**0.000000**	0.518062	**0.000027**	0.403807	**0.000011**	0.520638	**0.000029**
	ETS Shock Effect	0.562674	0.657729	0.820161	0.413945	0.000000	1.000000	0.085508	0.947665	0.000000	1.000000	0.000000	1.000000	0.431809	0.475667	8.253486	0.164188	0.000000	1.000000
	RES Vol. Effect	78.892844	0.057896	3.219339	0.338432	11.342797	0.932198	70.106869	0.060991	9.99039	0.999727	10.010269	0.999024	32.016957	**0.02234**	39.921038	**0.004139**	109.425584	**0.001039**
	c	23.317705	**0.000000**	0.106886	0.442228	13.806697	**0.000000**	26.342508	**0.000000**	17.813411	**0.000000**	15.284577	**0.000000**	40.82315	**0.000000**	0.0010000	0.997457	34.091891	**0.000000**
	ω	14.060161	**0.00075**	0.063954	0.92044	33.200517	**0.008777**	3.70862	0.491982	51.244827	**0.000013**	11.098379	0.096116	19.32653	0.481159	2.556614	0.562462	0.001	0.999854
	RES Effect	-24.820986	**0.000000**	-6.611476	**0.000000**	-59.316796	**0.000000**	-35.850756	**0.000000**	-56.8798	**0.000000**	4.178648	0.540137	-87.053407	**0.000000**	-24.739871	**0.000000**	-58.243001	**0.000000**
	ETS Effect	0.825027	0.075513	0.22528	0.444764	1.952679	**0.002725**	2.299361	**0.049012**	1.879858	**0.037593**	0.961816	0.280573	0.09216	0.948181	2.139936	**0.006353**	1.253377	0.116822
11h	ϕ_1	0.615876	**0.000000**	-0.252977	**0.000001**	0.750945	**0.000000**	0.530628	**0.000000**	0.644068	**0.000000**	0.752601	**0.000000**	0.305817	**0.000000**	-0.386192	**0.000000**	0.300934	**0.000005**
	α_1	0.406106	**0.003788**	0.224185	**0.004973**	0.1923	**0.026675**	0.099345	**0.037834**	0.362218	**0.003226**	0.203749	0.018573	0.116336	**0.014478**	0.068473	0.161472	0.361017	**0.009382**
	β_1	0.087594	0.431571	0.622078	**0.000000**	0.274873	0.162803	0.865323	**0.000000**	0.000000	1.000000	0.603003	**0.000000**	0.611581	**0.000012**	0.857992	**0.000000**	0.475184	**0.004849**
	ETS Shock Effect	0.000000	1.000000	0.293648	0.597256	0.000000	1.000000	4.960308	0.330168	11.181938	0.883351	9.799775	0.22567	60.427428	0.119277	2.439849	0.41988	0.000000	1.000000
	RES Vol. Effect	14.580487	0.601761	15.83874	**0.04795**	9.715573	0.951394	10.322455	0.905192	9.636694	0.975463	11.360559	0.91357	7.632788	0.990137	10.962293	0.774302	200	**0.022223**
	c	16.262406	**0.000000**	3.854311	**0.000000**	9.712615	**0.000000**	0.177321	0.699356	15.467366	**0.000000**	20.108847	**0.000000**	0.001000	0.997044	44.37585	**0.000000**	28.63072	**0.000000**
	ω	0.001	0.999425	0.001	0.998821	19.285031	0.062589	0.001	0.999676	26.461791	**0.000000**	2.952678	0.333861	0.001000	0.999561	1.614915	0.71096	0.001	0.999613
	RES Effect	-17.809714	**0.000000**	-4.121876	**0.00001**	-34.685106	**0.000408**	-37.590533	**0.000000**	-23.199989	0.557327	-28.254442	0.35023	-41.075024	**0.000000**	-35.849012	**0.000000**	-41.871294	**0.000000**
	ETS Effect	0.536319	0.206703	0.273617	0.282363	1.463315	**0.000000**	0.604386	0.537717	0.29898	0.736988	-0.281173	0.755078	-0.557502	0.455176	1.383789	0.145302	1.727952	**0.016122**
18h	ϕ_1	0.738113	**0.000000**	0.921559	**0.000000**	0.845384	**0.000000**	-0.302169	**0.000000**	0.730742	**0.000000**	0.715098	**0.000000**	-0.351598	**0.000000**	0.408843	**0.000000**	0.502842	**0.000000**
	α_1	0.197639	0.029449	0.201498	**0.000398**	0.214089	**0.008558**	0.01808	0.344624	0.282206	**0.000018**	0.187541	**0.015404**	0.177092	**0.006397**	0.106377	**0.008589**	0.159454	**0.000001**
	β_1	0.481092	**0.000703**	0.775319	**0.000000**	0.511382	**0.000003**	0.976231	**0.000000**	0.317233	0.122304	0.774633	**0.000000**	0.794079	**0.000000**	0.87419	**0.000000**	0.737616	**0.000000**
	ETS Shock Effect	0.000000	1.000000	0.221843	0.525087	0.000000	1.000000	3.589015	**0.000467**	1.279272	0.825874	8.079276	0.23076	3.12384	0.32422	1.085194	0.69116	0.226148	0.897703
	RES Vol. Effect	141.779414	**0.00258**	2.689436	0.562816	10.558103	0.967747	0.000000	1.000000	8.666723	0.993986	9.74142	0.963062	55.271213	0.347457	10.31918	0.869308	82.690977	**0.03104**

Table 14: All the parameter estimates and corresponding p-values of the regressions using data from 2018. The p-values of estimates that are significantly different from zero at the 0.05 level are indicated in bold.

		ES		DK2		FR		NL		CZ		IT-N		PL		UK		DE	
		Est.	p-val	Est.	p-val	Est.	p-val	Est.	p-val	Est.	p-val	Est.	p-val	Est.	p-val	Est.	p-val	Est.	p-val
4h	c	12.476326	**0.000000**	0.001000	0.983608	6.086786	**0.000000**	0.001000	0.991698	0.068032	0.592577	5.661847	**0.000000**	0.001	0.980874	0.001	0.992266	11.439264	**0.000000**
	ω	0.001	0.999553	0.146424	0.543249	1.35718	0.1954	1.282638	0.143491	2.894444	**0.017634**	1.88818	0.083722	0.001	0.989037	0.809149	0.417559	0.282287	0.843159
	RES Effect	-28.617628	**0.000000**	-2.145768	**0.000000**	-63.068038	**0.000000**	-13.524304	**0.000000**	-29.998617	0.927511	-30.190915	0.949103	-1.702551	**0.02996**	-8.330237	**0.000000**	-22.542032	**0.000000**
	ETS Effect	-0.845983	0.504704	0.359152	0.298254	0.572859	0.60757	0.189588	0.784473	0.264853	0.802047	1.17301	0.225951	-0.054728	0.872299	1.195099	0.094895	-2.005196	0.052013
	ϕ_1	0.648159	**0.000000**	-0.232098	**0.000000**	0.759583	**0.000000**	-0.370926	**0.000000**	-0.247071	**0.000000**	0.846881	**0.000000**	-0.203663	**0.000000**	-0.370145	**0.000000**	0.463867	**0.000000**
	α_1	0.190488	**0.004176**	0.372543	**0.000000**	0.190576	**0.000077**	0.307208	**0.000000**	0.253838	**0.000009**	0.127987	**0.000599**	0.154552	**0.000002**	0.357056	**0.000000**	0.15345	0.188134
	β_1	0.707728	**0.000000**	0.524758	**0.000000**	0.71436	**0.000000**	0.496166	**0.000000**	0.681652	**0.000000**	0.806618	**0.000000**	0.79784	**0.000000**	0.438932	**0.000000**	0.805	**0.000001**
	ETS Shock Effect	19.087664	0.425800	0.5731	0.783431	65.412614	**0.033291**	2.627239	0.790868	17.94482	0.423456	7.38822	0.532042	2.892945	0.137121	0.000000	1.000000	8.202722	0.373176
	RES Vol. Effect	50.256056	0.054365	3.059258	**0.006511**	50.935726	0.169208	50.761412	**0.000304**	10.07871	0.995546	10.010454	0.997688	1.873097	0.187704	46.538017	**0.000016**	10.97145	**0.004831**
11h	c	9.297322	**0.000000**	0.001000	0.985567	9.881473	**0.000000**	17.625885	**0.000000**	12.806254	**0.000000**	12.052215	**0.000000**	24.772778	**0.000000**	0.001	0.994761	22.481652	**0.000000**
	ω	22.117013	**0.000000**	0.982405	**0.022082**	6.518578	0.064954	0.458033	0.771733	9.802213	**0.048173**	6.429481	**0.014906**	15.513118	**0.000017**	1.451247	0.53811	0.629467	0.526379
	RES Effect	-23.477446	**0.000000**	-2.436456	**0.000000**	-62.44979	**0.000000**	-30.907945	**0.000000**	-50.470162	**0.000000**	-11.245998	**0.00099**	-39.831856	**0.000000**	-19.49844	**0.000000**	-42.429409	**0.000000**
	ETS Effect	-1.609172	0.111109	-0.092961	0.845894	1.089975	0.421038	2.494846	0.145226	1.4336	0.375625	2.030003	0.174299	0.35011	0.793833	0.586583	0.606451	3.546872	0.016912
	ϕ_1	0.812577	**0.000000**	-0.215988	**0.000000**	0.771992	**0.000000**	0.56006	**0.000000**	0.644669	**0.000000**	0.752805	**0.000000**	0.415865	**0.000000**	-0.404203	**0.000000**	0.344316	**0.000000**
	α_1	0.370818	**0.000004**	0.333732	**0.000000**	0.126477	**0.003258**	0.055593	**0.004358**	0.283616	**0.000167**	0.208086	**0.000001**	0.254053	**0.000001**	0.151954	**0.004835**	0.087659	0.001197
	β_1	0.000000	1.000000	0.491486	**0.000000**	0.752788	**0.000000**	0.940459	**0.000000**	0.619797	**0.000000**	0.711998	**0.000000**	0.439412	**0.000000**	0.722334	**0.000000**	0.896588	**0.000000**
	EST Shock Effect	7.967956	0.841308	11.49989	**0.049345**	8.378465	0.763369	7.966295	0.650947	9.336192	0.807625	8.128009	0.762464	8.07075	0.7499	11.095711	0.596784	8.299677	0.618728
	RES Vol. Effect	12.078139	0.562319	0.534513	0.821323	11.265169	0.865077	9.853584	0.702844	10.718784	0.884752	10.61188	0.758702	10.214396	0.830521	60.437902	**0.006506**	10.144291	0.378661
18h	c	10.893448	**0.000000**	1.442116	**0.000000**	12.649245	**0.000000**	0.160063	0.356815	13.359895	**0.000000**	9.315495	**0.000000**	0.001	0.993743	23.877746	**0.000000**	19.815799	**0.000000**
	ω	0.001000	0.998637	0.436968	0.183662	3.532107	**0.035684**	1.215863	0.23584	2.689457	**0.041282**	11.863403	**0.003002**	1.226692	0.37236	8.341323	**0.025562**	0.001	0.999146
	RES Effect	-18.868685	**0.000000**	-2.251801	**0.000000**	-50.12211	**0.000000**	-38.083729	**0.000000**	-29.39148	0.150141	-29.556166	0.071829	-23.910099	**0.000000**	-23.906372	**0.000000**	-28.962194	**0.000000**
	ETS Effect	-0.223347	0.818277	0.570417	0.165745	1.503085	0.304569	3.283438	**0.023573**	2.050412	0.159567	1.91402	0.166887	0.441023	0.673078	0.429271	0.809465	2.105721	0.08155
	ϕ_1	0.773914	**0.000000**	0.94528	**0.000000**	0.733275	**0.000000**	-0.41936	**0.000000**	0.673199	**0.000000**	0.830542	**0.000000**	-0.376071	**0.000000**	0.59203	**0.000000**	0.497661	**0.000000**
	α_1	0.110482	**0.010613**	0.302946	**0.000000**	0.168618	**0.000002**	0.178394	**0.000002**	0.206721	**0.000014**	0.300863	**0.000188**	0.263876	**0.000008**	0.20482	**0.000278**	0.201179	0.000011
	β_1	0.872278	**0.000000**	0.488501	**0.000000**	0.778591	**0.000000**	0.817213	**0.000000**	0.772264	**0.000000**	0.524267	**0.000005**	0.670378	**0.000000**	0.705096	**0.000000**	0.729081	**0.000000**
	ETS Shock Effect	7.637491	0.465280	2.420161	0.385132	7.147654	0.800335	8.273189	0.722837	8.354644	0.686127	8.091879	0.868877	30.273071	0.164722	8.126565	0.863544	2.468047	0.956484
	RES Vol. Effect	10.656609	0.284578	5.190213	**0.039696**	11.771245	0.817091	10.36379	0.63119	9.881384	0.912117	9.907911	0.966546	38.918536	0.170706	10.417023	0.787067	55.898202	**0.008634**

Table 15: All the parameter estimates and corresponding p-values of the regressions using data from 2015-2017. The p-values of estimates that are significantly different from zero at the 0.05 level are indicated in bold.

A.4 Information from the Dutch Emissions Authority

This section shows the additional information provided by the Dutch Emissions Authority, or NEA, with regards to the methods used for data collection. The information is obtained by means of an e-mail correspondence in Dutch. A translation of the questions and answers is provided below.

Q: At what frequency are emission permit prices recorded and what sources are used for this?
A: The NEA does not keep record of pricing information. The most important trading platform for EUAs is the EEX.

Q: At what frequency are the emissions of power generation companies recorded?
A: The NEA receives emissions data on a annual basis. The total emissions per installation are also actively published. Companies that are incorporated in the EU ETS are obligated to have a current monitoring plan and to report their emissions annually.

Q: How do the methods for data collection used by the NEA differ from the methods used by emissions authorities in other European countries?
A: The methods used in different European countries barely differ. The monitoring of CO2 emissions is based on European regulations that are equal for all EU member states. A standardized European format is used for the annual emissions report that has to be handed in by companies. There may be some differences between different countries, as each member state is free to request additional data. However, the NEA is not aware of these differences.