Master Thesis

MSc Advanced Economics and Finance (Cand. Oecon)

Effects of Allocation Method on Electricity Firm Behaviour in the EU ETS

Empirical study investigating the effects of auctioning versus grandfathering on Germany's electricity sector.

Student:
Arin Tazeler

Student n°:
S122564

Student:
Markus D. Fritsch

Student n°:
S124358

Supervisor:
Lisbeth La Cour

Page Count: 103
Character Count: 196,433
(15/09/2020)

Abstract

Being a key instrument in fulfilling compliance with the Kyoto-Protocol, the EU Emission Trading System has since its inception in 2005 undergone three phases[1]. Between phases, policy makers adjust initial allowance allocation methods from grandfather in the earlier two phases to auctioning in phase III. As the EU ETS represents a new effort with regards to market-based policy regulation, we investigate: *Does allocation method within a cap and trade system matter for market dynamics? & Does such change market structure influence firm behaviour?*

We find that market structure in terms of allocation method does influence firm behaviour. In line with previous research we find a positive carbon cost pass-through in phase II, yet no further pass through in phase III. This suggests, that market structure can correct some of the distributional rent[2] distortions introduced by grandfathering. On the other hand, we cannot find significant effects of allocation method on energy production in form of input fuel share in Phase III. However, Phase II suggests a rather unexpected response of a proportional increase in carbon intensive electricity production[3] to an increase in carbon prices, as opposed to no effects in phase III.

These are important findings from a policy perspective. Our analysis suggests that system design, and hence policy interventions targeting system design are able to steer firm behaviour. Within the EU ETS the EU directive was successfully able to transfer the rents collected by energy generating firms in forms of auction revenue without making consumers worse off. It is up to member states to re-use these revenues to correct the distortions introduced by grandfathering.

[1]Phase I: 2003 -2005,Phase II: 2005 - 2008, Phase III: 2008-2020

[2]Transfer of economic welfare from non-market participant to EU ETS participant

[3]As defined by: $\frac{GAS\ USAGE}{COAL\ USAGE}$

Contents

1 Introduction

Almost two decades ago, the European Union (EU) started presumably the largest project involving the implementation of market based instruments within a contexts of environmental governance and policy making (Matthes and Neuhoff 2007). With the goal of reaching the carbon emission targets laid out by the Kyoto Protocol, the European Union has been implementing a cap and trade system for carbon emission allowances across currently three phases spanning roughly 20 years (Oberndorfer 2009). Being the market maker, the European Union is the responsible for facilitation, mediation and governance of its newly deployed instrument.

As the term ≫ *cap and trade* ≪ suggest, the market maker, establishes and sets a quota for the commodity being traded. In doing so, the EU artificially creates scarcity in within its system through restrictions on the unit amount. Hence, it allows the EU, or more general any market maker, to control the aggregate amount in circulation - qualifying as a policy instrument in influencing a any trade-able commodity or market based instrument in the economy. Such cap system proves most powerful in limiting the availability or effects of a commodity with negative externalities. Hence, by controlling the aggregate commodity units, or a market based instrument, the market maker indirectly also controls the production of externalities of the commodity in question.

Naturally, within the EU Emission Trading Scheme (EU ETS) the EU takes on the role as market maker. As mentioned, the instrument in question is a Carbon Emission Allowance (EUA), it represents a permission certificate denoted in tons of carbon-dioxide necessary for carbon emitted in industrial production. This allows the EU to directly influence the amount of carbon emissions regardless of its origin, and without any further need for production or sector specific knowledge. By setting the overall aggregate tons of carbon emission in the markets, the EU is able to manipulate the output of carbon emissions over time by changing the cap annually and in accordance with its policy targets. It represents an ideal policy instrument to manage and transfer the cost of the externality between parties. Naturally, the EU ETS system is covering sectors that produce carbon emissions. Among these sectors, the electricity generating sector is the largest one and the main scope of this research.

We have yet to discuss ≫ *trading* ≪ within a cap and trade system. After initial cap-setting, market participants are allowed to freely trade the respective commodity/instrument between market participants (Creti, Jouvet, and Mignon 2012). In doing so, the market still reaches an equilibrium price conditional on the cap set. Naturally, the question arises on the initial commodity allocation methods. Generally, initial allocation is of concern to the market maker, and thus the EU. In cases where the commodity itself is a market based instrument, i.e. EUAs in the of EU ETS, the market maker can simply determine an allocation methods for all participant. The effects of allocation method has been of great debate within research, where no clear consensus is met (Venmans 2016). According to Coase, equilibrium levels are independent of allocation methods. However, Venmans (2016) argues that allocation methods do matter (Neuhoff, Martinez, and Sato 2006). In our case, the EU ETS and the power sector, we argue allocation method does matter for firm-behaviour. Hence, the argument presented within this paper is based on a dynamic relationship between carbon allowance prices and electricity markets, rather than based solely on price-levels.

Looking at the EU ETS market, the first two phases aimed to establish a carbon market and corresponding carbon price (Trotignon and Delbosc 2008). Allocation method and rent transfer were of secondary nature and hence, carbon permissions were allocated to firms for free. Allocation was based retro-spectively by estimating expected carbon output on past firm behaviour (Hepburn et al. 2006). However, due to data restrictions Phase I allocation was plagued by over allocation (Anderson and Di Maria 2011). Combined with non-transferable emission permissions between Phase I & II prices plunged to zero in 2007 (Hintermann 2010). Although, precision improved in Phase II, the financial crisis and the associated recession lead to a persisting over-allocation. Irrespective of over-allocation, a market price was only established in the secondary markets - that is, trading. However, With the introduction of Phase III in 2013 free allocation shifted towards auctioning. As such, roughly 60% of all carbon permits were allocated through an auction based system in 2013. Although initially, the cap and trade system was assumed to be robust to initial allocation mechanisms several scholars suggest otherwise (Venmans 2016; J. Ji, Z. Zhang, and L. Yang 2017; Hahn and Stavins 2011; Goulder, Hafstead, and Dworsky 2010). Therefore, an agent in the markets will adjust its behaviour.

The remainder of the paper proceeds as follows. The background section elaborates on the EU ETS system, and the specific case of the electricity sector. The following literature review presents existing literature and their findings regarding practices in modelling carbon prices. The problem statement concludes our background work and lays out the research question and corresponding hypotheses. Consequently, we present our estimation strategy linking our hypothesis to our empirical approach. As such, the methodology section technically present the methodological framework indicated in our estimation strategy. Next to that, the data section describes our data used in the analyses and transformations applied. We conclude with our data analyses and results section as well as an appropriate discussion to put our findings in the context of current research and events. We finalize our paper by offering a conclusion with corresponding policy implications, and limitation of our chosen research setting.

2 Background & Motivation

In line with the Kyoto Protocol's environmental measures, the European Union established the European Union Emission Trading System (EU ETS) in order to control Europe's emission output (Convery 2009). Initially the system was only concerned with carbon emissions but later extended to several other greenhouse gases (GHGs) (Convery 2009). In essence, the EU ETS represents a cap and trade system that limits the overall carbon output in the markets that are subject to it. Since its inception in 2005, the EU ETS has so far passed three phases each spanning a distinct time-period, addressing teething problems in the market sequentially (Egenhofer 2007b). The phases of EU ETS corresponds to following; Phase I: 2005-2007, Phase II: 2008-2012; Phase III: 2013-2020 (Creti, Jouvet, and Mignon 2012).

Most generally, Phase I also referred to as the trial period, was concerned with an initial establishment of a carbon allowance market and was mainly concerned with infrastructure, whereas Phase II attempts to consolidate the lessons learned in Phase I, for a full implementation (Trotignon and Delbosc 2008). Phase III on the other hand, represents the first major structural and institutional change aiming towards a more efficient carbon market. That is, a switch from free initial carbon permission allocation to the auctioning as an allocation method (Martinez and Neuhoff 2005).
The following section will briefly lay out the history and structure of the EU ETS as a policy tool, and cap and trade system. We will address each phase individually, and lay out the main challenges, changes and implications for market participants.

2.1 EU ETS as a Cap-and-Trade System

The EU ETS represent a classic Cap-and-Trade system that covers some roughly 13.500 stationary installations and with the end of Phase III, and most definitely Phase IV 2000 airline accounts (rewrite more) across the EU-28 (appendix) - and EEA (Norway, Iceland and Liechtenstein) (Ellerman, Marcantonini, and Zaklan 2016). With that in mind, the market covers some two billion tons of carbon-dioxide, representing closely to 4% of the global emissions(Ellerman, Marcantonini, and Zaklan 2016). The cap imposes an absolute limit of carbon emissions in the covered market, by introducing tradeable permits (EUAs). Initially allocated permits are allowed to be freely traded in with market participants.

This forces the market to establish a market price for an allocation permit, irrespective the allocation method. Allowing for trading has a second beneficial effect, it reduces carbon emissions in the market where its least costly to do so. Firms facing high abatement costs, are willing to pay higher carbon prices on the secondary trading market. The EU ETS covers roughtly 30 states, the EU 28, Norway, Iceland and Liechtenstein respectively (Ellerman, Marcantonini, and Zaklan 2016; Olivier, Peters, and Janssens-Maenhout 2012). Nevertheless, when conceived in late 1990 as a response to the first Kyoto Commitment Phase (2008-2012), the market was mostly concerned with the EU15 (Moutinho, Madaleno, and P. M. Silva 2016).

2.1.1 Motivations for a cap and trade system for carbon emissions

Braun (2009) and Egenhofer (2007a) argues several reasons behind the choice for a cap and trade system within the context of emission trading in the European Union: (1) As argued beforehand, the EU agreed on the need for an EU-wide measure addressing emission output in order to be able to address the Kyoto-protocol obligations agreed by the EU15 in late 1990. (2) Closely related to (1), an attempt to introduce an EU-wide carbon tax in the 1990 had previously failed due to the regulatory nature within the EU. More precisely, the EU had failed to introduce a carbon tax as taxation in a fiscal matter under EU law - and thus bound by an unanimous agreement amongst all participating member states. However, a cap and trade system technically is classified as a regulatory measure which in turn is not matter of fiscal policy and as such does not need a unanimous agreement. (3) The EU ETS would not have been the first cap and trade system being successfully implemented. At that time the US had already implemented a promising a cap and trade system on SO_2. And lastly (4) A trial period could be implemented before the actual Kyoto First Commitment Period was starting in 2008. Although fully legally independent, it is no coincidence that the trial period concludes 2007 and the Phase 2 coincides with the First Kyoto Commitment Period.

2.2 From decentralized to centralized

Within the three phases mentioned, the EU ETS has developed from a decentralized system that was simply unified underneath the term EU ETS - to a fully centralized system. Phases I and II were characterised as what was generally referred to as National Allocation Plans (NAPs). NAPs as the name suggest were national level allocation plans - that had to be submitted and accepted by the EU - and thus the total allocation across states was only known once all member states' NAPs were submitted and approved. Or in other words, the EU ETS cap was the sum of the NAPs (Sartor, Pallière, and Lecourt 2014).

NAPs in itself represent sub-allocation plans underneath the EU ETS umbrella - that allocate CO_2 Permissions (EUA) to firms within each nation. The need for firm specific allocation was thought necessary due to the negative effects of CO_2 permission costs on national level industry competitiveness, though often argued more a representation of lobbying strength on EU and nation level. More information can be found in a following section on free-allocation (grandfathering) (Sartor, Pallière, and Lecourt 2014; Egenhofer 2007b).

With Phase III, the NAPs were abolished together with the sought-after auctioning mechanism and centralized allocation rules. NAPs were long criticized for generating wind-fall benefits and competitive disadvantages in some sectors. Regardless the substance behind these critiques, decentralized allocation was necessary in the beginning to ensure participation of member states. With that in mind, the European Parliament, since the beginning has been favouring auctioning as the preferred allocation mechanism (Egenhofer 2007b). As such, the phase in of auctioning was to be harmonized at an EU level. Doing so, industrial sector experienced a different treatment with the electric utility sector facing an abrupt stop of free-allocations in 2013. Reasons being the non-competitive nature of natural electric utility sectors. Next to that, the electricity sector also constitutes roughly 57% of the total EU ETS emissions (Trotignon and Delsbosc, 2008). Such change was especially derogating for member states with particularly coal dependent power generation input mix, some of which were granted exemptions in cases where competition could not be met. Sectors outside the electric utilities facing some international pressure received allocations based on EU-wide sector benchmarks based on data gathered prior to 2013. The benchmark initially started with 80% of the 2013 benchmark and is going to be reduced to 30% in 2020.

2.3 Phases I - II - II

Until today, the EU ETS has evolved significantly from an initial decentralised concept trial in Phase I up to today centralized, full-fledged cap and trade system in Phase III. The following section briefly lays out the significant changes and features of each phase.

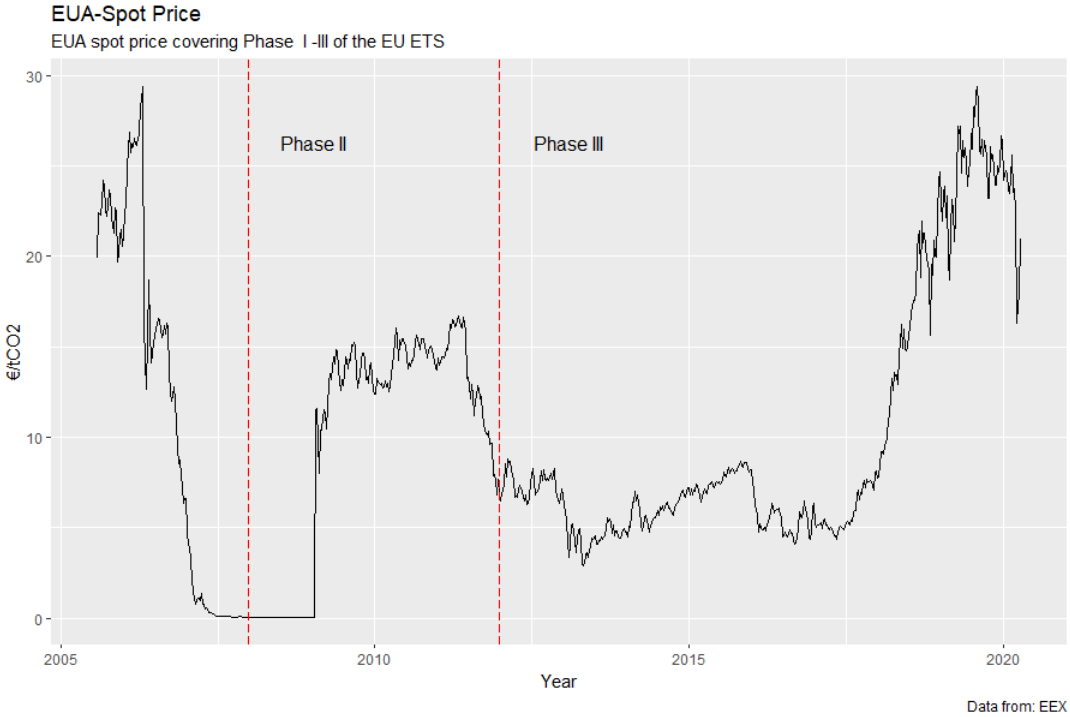


Figure 1: EUA Price per Tonne of CO2

2.3.1 Phase I

As mentioned on multiple occasions Phase I mostly depicts a trial period. It represents a pre-Kyoto Phase before the actual implementation of the system in Phase II (Grubb, Azar, and Persson 2005). It spans three years from beginning 2005 to end 2007. It is fully self-contained. Fully self-contained refers to the fact that with conclusion - no banking or borrowing of excess permits was allowed for Phase II (Hintermann 2010). Consequently, market prices of carbon allowances dropped to zero with conclusion as no permits would expire by the end of Phase I (Hintermann 2010). The main purpose of Phase I was to implement necessary infrastructure, and to gather information on carbon emissions on both firm and sector level (Parker 2008). Data quality on carbon emissions was low prior to Phase I and thus, Phase I granted free allocations of 95% of all permits to firms under the obligation of reporting back their respective carbon output(Parker 2008).

2.3.2 Phase II

Naturally, Phase II represents the consecutive period following the initial trial period. As indicated on several occasion, Phase II suggests the first full-period of the EU ETS. It spans 5 year, from the beginning of 2008 to the end of 2013.

Phase II was still characterised by free-allocation (90% vs. 10% allocation) through grandfathering, similar to Phase I (González 2006; Betz and Sato 2006). The amount of allowances allocated were slightly adjusted compared to Phase I to account for over-allocation. On top of that, Phase II allows for banking of EUA allowances to be used in Phase III (Betz and Sato 2006). Unlike Phase I, this allowed the EUA prices to stay positive by the end of Phase II (Chevallier 2010). The choice for free-allocation is many-fold and contains economics as well as political arguments - yet similar to Phase I still on a national-level (NAPs) (González 2006). A more detailed consideration can be found in a following section regarding auctioning and grandfathering. The main purpose of Phase II was to reduce the carbon footprint amongst firms in the covered market in order to align Europe's Emission trajectory with the trajectory laid out in the First Commitment Period of the Kyoto Protocol, as well as simplifying the NAP procedure. Hence, the overall cap was reduced by 6.5% compared to the level in 2005, and for the first time the non-compliance penalty reached 100€/tCO_2 (Rickels et al. 2007).

2.3.3 Phase III

The EU ETS is currently about to conclude its third phase. Spanning 7 year, 2013-2020, Phase III depicts the longest phase thus far. The distinctive feature between Phase II and the prior two is the reduction of free-allocation and the corresponding increase in the use of auctioning as the preferred allocation method (Parker 2008). For the most part, in Phase III no permits are allocated for free within the electricity and power producing sector (Benz, Löschel, and Sturm 2010). There are several exceptions for member states that are subject to the electricity modernisation or excessive carbon leakage under EU 10c of the EU ETS Directive (Benz, Löschel, and Sturm 2010). However, this generally mostly concerns newer member states, generally small economies with non-competitive,and domestic electricity sectors (Benz, Löschel, and Sturm 2010). Overall more than 50% of the market are subject to auctioning of carbon allowances, as the electricity sector alone demands around 45% of all carbon permits (Ellerman, Marcantonini, and Zaklan 2014; Trotignon and Delbosc 2008; E. D. Delarue and D'haeseleer 2007).

For the remaining, harmonized EU rules on free-allocation are introduced, thereby abolishing the use of national allocation plans under the Benchmarking Decision (Walker 2008). More specifically, the Benchmarking Decision lays out the benchmark of sectors against the top 10% of firms in that respective sector, EU-wide (Benz, Löschel, and Sturm 2010). In line with the centralised registry system, (EU Registry) a single EU-wide cap was introduced with a linear reduction factor of 1.74% annually (Ellerman, Marcantonini, and Zaklan 2014).

Due to excess allocations banked in Phase II the EU Directive introduced the Market Stability Reserve in 2016. The market stability reserve is closely related to what is often referred to as frontloading and backloading (Fitch-Roy, Fairbrass, and Benson n.d.; Perino and Willner 2016). Frontloading refers to the pre-sale of auctions prior to 2013 in order to accommodate the electricity's forward looking market price. On the other hand, backloading refers to the fact that due to excess supply stemming from an economic downturn in Phase II the market was faced with over 2 billion excess permits in 2015 (**burtraw2014price**; Perino and Willner 2016). Consequently, the market price for carbon permits was too low to provide an appropriate incentive for firms to reduce their emission levels. In order to maintain credibility, the EU ETS Directive decided on re-distribution of permits over time as opposed to reducing the permit count. Hence, the term backloading. Practically, backloading meant a reduction of permissions in 2014, 2015 and 2016 to increase the EUA price in the short-run (Chaton, Creti, and Peluchon 2015). These permissions were to be auctioning in 2019-2020. However, the EU later decided to introduce a Market Stability Reserve which simply holds the backloaded EUAs instead allowing such to re-enter the market(Chaton, Creti, and Peluchon 2015). Therefore, it is no surprise that the market reacted with an increase in EUA prices in late 2018.

2.4 Germany specific climate and energy policies

Although a major part within the EU's climate change objective - the EU ETS is by no means the only policy instrument. Famously labeled 20-20-20 by 2020, the EU imposes a 20% GHG emission reduction from 1991, 20% renewable energy consumption, and 20% energy efficiency improvements (Abrell and Weigt 2008). The latter two especially have particular effects on member states with carbon intensive energy generation. As such, Germany as a coal reliant energy producer had strong incentives to develop wind and solar energy capacities within the electric utility sector. Which are having significant effects on energy production from carbon emmitting fossil fuels.

On top of that, Germany has adopted, as part of its national level climate policy referred to as ¿¿Energywende¡¡, the quick phase out of nuclear power as a response to 2011 Fukushima accident (Smyrgała 2017). Which lead to an immediate shutdown of eight nuclear power plants and the directed closure of all remaining plants by 2020. Given the seasonal behaviour of renewables such as wind and solar power, Germany's energy mix inevitably became more carbon intensive through the substitution of nuclear power with natural gas and coal.

2.5 Allocation Method

As indicated beforehand, across all three phases permit allocation went through different means. Although allocation in both, Phase I & II was based retrospective based on past emissions, Phase II profited from more accurate data gathered in Phase I itself. During such, most prominently energy consumers have been accusing producers of windfall profits stemming from free allocation. It is precisely Phase III where auctioning was introduced as the main allocation method. Almost 100% of EUAs within the electricity producing sector are auctioned.

Nevertheless, the choice for either allocation method has not only political but also economic motivation. The following sections will first lay out the effects of either allocation method, that is auctioning or grandfathering on the following pillars (Hepburn et al. 2006) (1) Effects on distribution of rents, (2) Effects on Competition, (3) Effects on Dynamic Incentives, and lastly (4) Effects on Economic Efficiency and Transaction Costs. Having argued for the effects of either allocation methods on pillars 1-4 we will present the implementation of each within the context of the EU ETS.

2.5.1 Effects on distribution of rents

From an economic perspective, rent distribution is often referred to as "splitting the pie" (of profits) (Dyer, Singh, and Kale 2008). Within the setting of the EU Emission Trading Scheme rent distribution is concerned with the splitting the profits of the revenues introduced by the carbon price.

As discussed many times before, the main aim of the EU ETS is to introduce a positive carbon price in order to internalize the negative externality of polluting the environment (Hepburn et al. 2006). Naturally, the market participant bearing the costs of such carbon price will be the one "left-out". Hence, within the particular context of grandfathering or auctioning as the EUA allocation method - this equally implies the allocation method of EUA costs. Thus, allocation method matters in terms of distribution of rents within the EU ETS.

More specifically, phase I and II employed grandfathering as the preferred allocation method - meaning firms in the EU ETS did not bear the cost of a positive carbon allowance price. At the very least not for the vast maturity of their respective EUA demand. More controversially, receiving a positively paying market asset for free (Woerdman, Couwenberg, and Nentjes 2009) - firms redirected the associated carbon price with the free received EUAs to the consumer of the final good - thus passing through the carbon prices to consumers. Hence, the rent transfer goes from consumers to firms (Hepburn et al. 2006). Although, under grandfathering marginal costs are unaffected - the grandfathering certainly benefits firms' balance sheets through the pass-through of the opportunity costs of practically zero-cost EUAs.

On the other hand, auctioning shifts the initial cost of carbon to firms - such that their marginal production costs increase by their respective carbon demand. Naturally, firms would need to push such costs to consumers as they now face higher production costs. However, given that firms already passed-through a hypothetical carbon opportunity cost on consumers - it is ambiguous whether firms would be able to pass-through a carbon price a second time with the introduction of auctioning. Regarding passing-through carbon costs on electricity prices, (Hepburn et al. 2006) argue that changing from grandfathering to auctioning as the initial allocation method will have little impact on electricity prices. In either case, rents in form of firm profits stemming from a carbon price pass-through are now redistributed in form of auction revenues to EU ETS member states. On a second note, the shift to auctioning will allow governments to recycle the auction-revenue in ways to combat detrimental interactions between the carbon price and other taxes.

2.5.2 Effects on Competition

Introducing a positive initial carbon price through auctioning potentially also affects international competitiveness of domestic firms and sectors. This stems from the fact that an increase in marginal production costs will increase the break-even product price the firm is able to charge among its international competitors.

With international competition we specifically must refer to the competitors that lie outside the jurisdiction or coverage of the EU ETS scheme. Such firms face different marginal costs structures as they do not incur carbon emission costs. Hence, the add on of a carbon emission costs to EU ETS firms will decrease their price competitiveness on international markets. This, was a loud argument in the inception of the EU ETS and one of the reasons that favoured grandfathering at the introduction of the system.

From an auctioning perspective, (Hepburn et al. 2006) argue that it is firms that (a) face significant cost increases, and (b) are subject to non-EU competition that are at increased risk, ie. steel, non-ferrous metals or the chemical production. Having argued the different effects of grandfathering and auctioning on competitiveness we need to point out the the switch from grandfathering does not effect competitiveness in the long-run. Grandfathering more so depicts a subsidy for the time being that allows for higher operating costs, or price dumping. It is however true, that auctioning will increase marginal costs when compared to pre-EU ETS.

2.5.3 Effects on Incentives, and Economic Efficiency

Comparing free-allocation with auctioning it is easy to see why there might be differing responses toward the incentive to reduce carbon emission. The need for aligning the incentives to reduce carbon emissions is not only a necessary need for compliance with the Kyoto Protocol but inherently necessitated by what economics and international law often refers to as the "polluter-pays" principle.

Already Gaines (1991) describes the fundamental "Polluter-Pays"-Principle (PPP) as the principle of polluters having to bear the cost that is inflicted by the harmful pollution on the environment. Or put differently, the costs for polluters to bear needs to reflect the costs necessary to keep the environment in an acceptable state (Gaines 1991). This statement very much so hinges on the principle that the right to a clean environment is owned by the public, and thus the right to pollute must be bought by the polluter.

On a first glance, free-allocation might simply not provide enough incentives to reduce carbon emissions if the amount of allocated permissions are sufficient. Opposite to that, auctioning might simply give an incentive for carbon emission reduction through the introduced cost of carbon emissions, although certainly subject to the price itself. However, this difference between allocation method on carbon emission reduction incentives also depends on the method of determining the amount of EUAs to allocate.

Within Phase I and II the allocation amount was determined in retrospect. As such firms had incentive today to increase emissions in order to receive larger EUA amounts in the future. Similarly, if free allocation is based on current installation's CO2 output then naturally firms have an incentive to increase the lifespan of such plants in order to maintain their carbon allowance reception. this effect is sometimes also referred to as the ratchet effect (Demailly and Quirion 2006) which inevitably reduced the efficiency of the EU ETS market.

2.5.4 Effects on Administration and Transaction Costs

Determining the optimal allocation amount under grandfathering can be time- and resource- consuming. When determining the allocation amount, both parties affected, that is businesses/sectors and the government, bear a certain amount of risk. In a nutshell, firms bear the risk of being "caught short" with regards to receiving allocation - which incentivized firms and sectors to lobby on a political level to receive the largest share of rents. On the other hand, the government also bears the risk of unfair allocation or over allocation of permits in a specific sector, which in turn reduces the system's efficiency.

Hence, either party has an incentive to spend a significant amount of time and resources in order to mitigate and minimise their corresponding risks. (Hepburn et al. 2006) argue significant costs incurred of the former mentioned processes by the EU and affected sectors/firms. With regards to Phase 1, the EU attempted to increase participation and improve information asymmetries by delegating the allowance determination to a national level. Although this certainly decreases the efforts necessary by the European Directive, it increased efforts on a national level, and specifically lobbying on a national political level.

With regards to auctioning, it internalized the allowance allocation on a firm level, thus reducing the risk of being "left-out". Where firms are unable to obtain a needed EUA level in one auction, the respective firm can simply engage in a following auction. And hence, auctioning helps firms manage their real and perceived risk (Hepburn et al. 2006). On the other hand, auctioning a significant share of overall allocations on the market also reduces the amount of permits to be freely allocated and thus, the amount that is subject to lobbying.

Concluding briefly, allocation by auctioning not only reduces administration costs by centralizing and internalizing allocation amount determination, but is also simultaneously reduces risks born by governments and firms. As such, it enables firms to more effectively mitigate their CO_2 emission exposure, but also reduces the risk of unfair as well as over allocation of EUA permits in the market.

2.6 Allocation Method in the EU ETS market

As indicated beforehand, permit allocation method differs between each phase of the EU ETS. From the initial grandfathering in Phase I & II up to auctioning in Phase III. The upcoming paragraphs will briefly introduce in more detail how each allocation method was implemented in the market including its objectives, and challenges.

Within Directive 2003/87/EC the European Union adopted free emission right allocation as the allocation method for Phase I and II. Meaning that polluters received permits free of charge. Allowance quantities back in Phase I/II were estimated based on historical emissions. This process of free allocation, determined exogenous by the EU is also generally referred to as *grandfathering* (Grubb and Neuhoff 2006).

2.6.1 Grandfathering in Phase I

More specifically, under Article 10 of Directive 2003/87/EC Phase I was to allocate at least 95% of all allocation for free, and 90% in Phase II (Woerdman, Couwenberg, and Nentjes 2009). The corresponding 90%-95% percent of grandfathered emission permits were allocated according to the historical baselines. Especially Phase I faced allocation difficulties due to a lack of emission output data. Consequently, allocation was based on some estimated baseline rather than actual emission output data. Ultimately, the discrepancy between the rough estimate and actual emission data led to a significant over-allocation in Phase I (Ellerman and Buchner 2008). Such difference in estimated and actual values led to a zero carbon price at the end of this phase. It is however important to mention, that such zero carbon price stems from the inability to bank excess permits to be used in a subsequent phase.

2.6.2 Grandfathering in Phase II

The rough estimated baseline of Phase I was replaced by actual emission data in phase II that was gathered during the previous phase. On top of that, the overall cap was lowered by around 6.5% when compared to 2005 (EC.Europa 2020; Rickels et al. 2007). Nevertheless, the Financial Crisis hitting in 2007 and the subsequent economic downturn, once again led to an over-allocation of the EUA permits in the market. Despite the over-allocation, prices did not plunge to zero in Phase II as excess permits were allowed to be taken over to Phase 3. Nonetheless, carbon prices were still lower than expected (Chevallier 2010).

2.6.3 Auctioning in Phase III

With the introduction of auctioning in 2013 (Phase 3) the electricity sector was almost solely subject to the switch to auctioning. The reason for subjecting the electricity and power producing sector to auctioning but not all other sectors had several reasons. (1) Within the EU ETS market the electricity and power producing sector is by far the largest sector covering approximately 57% of overall allowance demand (Christiansen et al. 2005). More so, the sector represent a single market to consider but covering more than 50% of the overall market. Second (2), within the EU, electricity markets are mostly domestic player with limited international competition, especially international competition with regards to outside the EU (Eikeland and Skjærseth 2019). Thus, as introduced in the previous section there is limited impact of a positive EUA auction price on marginal production costs and thus, international competitiveness. Nonetheless, auctioning was to be incrementally increased throughout the span of Phase 3 to include up to 70% of the market in 2020 (Benz, Löschel, and Sturm 2010)

With regards to the freely-allocated EUAs; these were for the first time in the market's history, centrally coordinated and based on each sectors top 10% best performing firms (Benz, Löschel, and Sturm 2010). The intention was to allow for carbon reduction incentives that were based on sector specific estimates. Doing so would simply emphasize and encourage innovation in order to catch up to outperforming peers.

EU Auctioning Regulation is governing the auctions of the allowances. As mentioned previously, twenty-eight countries are auctioning their allowances on the common auctioning platform. The auctioning platform currently is the European Energy Exchange (EEX). Member states determines the volumes to be auctioned by their own state. During Phase III, 88% of the allowances are auctioned to EU member states based on the member states' verified emissions from Phase I. 10% is allocated to least wealthy EU member states in order to help them invest to reduce carbon intensity of their economies. Finally the remaining 2% is allocated as "Kyoto bonus" to nine following EU member states; Bulgaria, Czechia, Estonia, Hungary, Latvia, Lithuania, Poland, Romania and Slovakia. This "bonus" is given for reducing their GHG emissions by at least 20% compared to their base year.

Auctions are held three days a week for twenty-five EU member state and three EEA states for the days Monday, Tuesday and Thursday. For Germany the auctions are held weekly on Fridays and for Poland the auctions are held bi-weekly on Wednesdays. The auction design is a single round, sealed bid format. Participating firms submit their bids during the single bidding window without being able to see other participant's bids. These bids are then sorted in descending order. Starting from the highest bid, the volumes are summed. The price where the volumes bid and the volumes auctioned matches is considered the clearing price of the auction. All bidders that were above the clearing price pays and obtains the volume of allowance they bid. The auctioned allowance is delivered the following day of the auction and is valid for the Phase III of EU ETS. (European Energy Exchange 2020)

2.7 Electricity Sector

Focusing more on the electricity and power producing sector; Given the initial free allocation, electricity consumers have long been criticizing the system for generating windfall profits (Ellerman and Buchner 2007) in electricity producing firms. Several scholars have assessed this issue by investigating the pass through rates of EUA market value of free-allowances to consumers (Sijm 2005). There seems to be a general consensus towards, at least partial pass-through of EUA opportunity costs that are obtained through grandfathering. What is generally referred to as "Cost-pass through" will be further discussed in the following section. Nevertheless, it is important to distinguish between over-allocation and grandfathering. Whereas grandfathering enables windfall profits through the pass through of opportunity costs to consumers, over-allocation stems from leniency in cap setting (Woerdman, Couwenberg, and Nentjes 2009). Thus, over-allocation in fact reduces potential windfall profits by eroding the market price. Thus, when talking about windfall benefits we must keep in mind that these stem from the fact that allocation is free of charge, and that windfall profits are not exaggerated by over-allocation.

Under grandfathering polluters incorporate freely allocated permits as opportunity costs in their respective mark-ups on electricity prices to seek rent. Thus, EUAs essentially represent a cost-less-asset with positive payoff (Woerdman, Couwenberg, and Nentjes 2009). We label these as opportunity costs, as from an economic stand-point the firm-could have hypothetically sold its permits at the market price instead of using the permits for their carbon emissions. Thus, by serving its customers it incurs the opportunity costs that comes with polluting and thus, needing to use its freely allocated permits. It is widely acknowledged that opportunity costs must be included in any economic decision (Varian 2014).

2.8 Opportunity-Cost Pass-through

Opportunity-cost pass-through refers to the phenomena of actors passing on non-incurred costs to consumers. More generally, opportunity costs represents lost potential benefits from an alternative usage of a resource (Varian 2014). Within the EU ETS market, opportunity costs arise from selling permits instead of using such to cover carbon emissions. The extend of a pass-through of opportunity costs certainly depends on the elasticity of demand. Inelastic demand is generally unaffected by a price increase, and thus we could expect firms to pass through a higher share of opportunity costs to consumers than under elastic demand (Sijm, Neuhoff, and Chen 2006). Markets with generally inelastic demand functions are electricity markets, - where overall aggregate electricity demand is rather unresponsive to price changes in the short-run. More so, electricity markets are generally domestic markets with little international competition - that not only make demand more inelastic, but also represent a perfect opportunity for any policy response analysis (Eikeland and Skjærseth 2019).

2.8.1 Opportunity Cost within Electricity Markets

In the next section we will first elaborate opportunity cost pass-through within electricity markets in general, before continuing with Germany as an electricity producer within the EU ETS market.

At a first glance, one would expect electricity producers to fully reap the benefits of the imposed opportunity costs. Nevertheless, in practice we see several differing pictures. I.e. the Netherlands depicts an almost 100% pass-through rate in its spot-market, however, only about 50% in its respective forward market (Economics 2006). In case of Germany, a much more coal dependent nation, pass through rates vary between 60% up to 117% (Sijm, Neuhoff, and Chen 2006). As hinted, this stems from the high coal dependency and the implied benefits from higher peak power prices in forward contract resulting from expected peak gas electricity generation. Most generally, pass through rates depend on (1) Oligopolistic nature of the market, (2) market factors (i.e. demand, supply), and (3) institutional limitations (Sijm, Chen, and Hobbs 2012).

Looking at wider pass-through research efforts, we often see almost 100% of pass-through of opportunity costs (Sijm, Neuhoff, and Chen 2006; Fabra and Reguant 2014). Within such research stand there are three main channels to consider (1) strategic mark-up adjustments to shocks (2) non-traded costs, and lastly (3) price rigidities (Fabra and Reguant 2014). All three are proposed to influence the degree of pass-through. The general consensus is non-traded costs are the main cause of incomplete pass-through, whereas price rigidity's simply delay pass-through (Nakamura and Zerom 2010; Koujianou Goldberg and Hellerstein 2013). Sijm, Chen, and Hobbs (2012) argues almost one-to-one price-emission cost movements due to the highly inelastic nature of aggregate demand, and the resulting low incentives for mark-up adjustments. More so, market rigidities are generally considered small within electricity markets, as firms naturally auction on the liquid auction market (Fabra and Reguant 2014), where bid preparation costs will likely be marginal.

2.9 The Role of Germany in the EU ETS

In order to study the effects of carbon prices on firm behaviour we choose Germany, and specifically Germany's electricity sector.

Germany plays not only a crucial part within the EU ETS for its electricity output - and carbon usage, but also due to its crucial reliance on carbon emitting fossil fuels in its electricity generation mix. In 2012, Deloitte reports a 55% reliance of coal and natural gas in Germany's net electricity production mix (Deloitte 2015). Hence, the country's electricity mix is carbon intensive and thus very much subject to carbon prices.

Another reason that makes Germany interesting to investigate in terms of carbon and electricity markets is its share of carbon emissions in within EU. More generally, Germany represents the largest economic within the EU, with roughly 3.5 billion €in GDP. As mentioned beforehand, Germany is the largest pollution in terms of green house gases (GHG) within the European Union. In 2012 Germany accounted for roughly 20% of the EU-28 carbon output (Deloitte 2015). Although Germany's carbon emission output has been steadily decreasing since the early 1990's it has recently regained some momentum. The recent increase in carbon emission was a natural consequence of the sudden decrease of nuclear power electricity production as a response to the 2011 Fukushima accident. within the shortest period Germany decided to almost immediately take 8 of its 20 nuclear power plants offline, with the remaining 12 to be gradually shut down until 2022. The sudden electricity generation deficit was mostly covered by an increase in coal electricity production, and more specifically lignite (brown coal) (Deloitte 2015). Consequently, carbon emission output increased in Germany. More so as mentioned few times before, around 57% of EUA demand stems from heat and electricity producing firms (Christiansen et al. 2005).

Naturally, Germany's carbon emission outputs also play a major part in the Kyoto Protocol's carbon emission reduction. It is thus not surprising, that Phase III foremost targets the electricity sector - and as such, Germany's emissions. Nevertheless, as mentioned beforehand the reasons for targeting the electricity sector are many-fold and very much incorporate the low international competition. The upcoming section discusses Germany as an electricity producer, as well internal policies on the sector itself.

2.10 Germany as an Electricity Producer

With regards to Germany's electricity market; although liberalized in the late 1970s the market structure can still be characterized as oligapolisitic with four large electricity providers covering a market share larger than 73% (Deloitte 2015). Although the electricity-generating sector is less likely to exert market power within the EU ETS, given some amount of market power firms will be able to reap benefits that are higher than under perfect competition. In general terms, Hahn (1984) already argued that given some market power, initial allocation matters for cost-effectiveness. Similarly, Sturm (2008) argues that the European Commissions argument favouring auctioning only makes sense under the assumption of market power, arguing the distribution of rents. In line with that, Hintermann

(2011) found that the largest energy providers in Germany manipulated permit prices upwards during the first 18 Months of the EU ETS. Next to market power, incomplete information plays a crucial role within the EU ETS. Incomplete allocation was especially present under the initial permit allocation method in the grandfathering regime of Phase I. To put different, if under complete information there is no gain of using auctioning as an allocation method as the planner would be able to perfectly allocate and forecast all abatement costs to arrive at the cost-effective solution (Montgomery 1972).

An argument used by the Council of Ministers on the decision to use grandfathers is to increase willingness to participate of EU member by making free permits acceptable for their respective industries as a response to potential competition losses. Officially, politicans did not foresee the potential for windfall profits. Such arguments is questionable at best, as it is easy to see how companies can exploit a free asset at market value. The validity of such argument is further put under scrutiny given that already Bohm (1999) raised concerns about the potential for windfall profits under grandfathering. A more reasonable argument for the use of grandfathering is set in lobbying of national level industries, which in turn aligns with increasing participation amongst member states. In fact, the unwillingness of member states has prior been a hindrance in introducing an EU-wide carbon tax in the late 1990s (Woerdman 2004).

3 Literature Review

Carbon emission trading is a relatively new concept as a financial market and paired with recent data-availability it is a popular research topic among researchers. General price and volatility dynamics, determinants and effects of carbon emission market has been heavily researched and modeled with many different methodology. A major gap within the existing research is these dynamics for the Phase III of the EU ETS, due to its recency. We summarize and present some of the the existing research regarding the dynamics of carbon emission markets with other markets. More specifically the aim is to identify potential determinants and dynamics in existing carbon research. We make use of these findings when determining the variables to include in our estimations. More ss, in forming our hypotheses and assisting us in choosing the appropriate methodological approach for our undertaking.

Energy production from fossil fuel combustion accounted for more than 50% of CO_2 emissions in 2017. Fossil fuels are the most common variables when modeling carbon emission price determinants (Greenhouse gas emission statistics - emission inventories, 2019).

Castagneto-Gissey (2014) researches interactions between electricity prices and carbon prices between the period of 2008 and 2012, namely Phase II of EU ETS. The research uses one year ahead forward prices for carbon emissions, coal, gas and electricity for Germany, France, UK and Nordic markets. The author first tests for the causality between electricity and carbon markets in these markets and finds that there is a bi-directional relationship in German and Nordic markets. However, the direction of electricity to carbon appears stronger. He also finds a unidirectional relationship for UK and France but in conflicting order. Additionally, given present volatility clusters the research employ GARCH type models, with electricity as the endogenous variable are used to test volatility dynamics between energy markets. The paper finds that coal prices have the largest impact on electricity prices in terms of both price and volatility.

Hammoudeh, Nguyen, and Sousa (2014) analyzes short term dynamics of emission prices by using Bayesian Structural Vector Autoregressive models. The authors use both daily and monthly data between August 2006 and November 2013 with oil, natural gas, coal and electricity as variables. They use impulse response analyses to estimate the effect of shocks to fuel commodities on carbon prices. Their finding suggests that only oil has a significant effect on carbon prices when electricity is included in the model. However when electricity is not included all energy variables become significant. With the impulse responses they show that a shock to oil first increases the carbon price but then decreases it and its effect persists for 2 years. They find that carbon prices are most affected by natural gas prices and its impulse response depicts a negative and persisting effect. Electricity's impulse responses follow similar patterns to natural gas as well but effects of a shock to coal prices, unlike other fuels, depicts a positive effect. The authors argue that this might be due to coal is a relatively cheap source and a price increase doesn't lead to a substitution in the short run.

Contradictingly, Aatola, Ollikainen, and Toppinen (2013) finds negative coefficients for coal and positive coefficients for natural gas in their empirical analyses. They build a theoretical model based on a profit maximization problem of firms with 2 types of fuels as production input. The theoretical model indicates that higher unit prices for an carbon intensive inputs increases the usage of less polluting inputs. In turn, this decreases the demand and price of the carbon emissions. Vice-versa is valid for higher unit price of less polluting input. In their empirical analysis they use daily futures price data from 2005 to 2010. They use GARCH and VAR type specifications to test the effect of electricity, natural gas and coal prices on carbon. Their findings from the GARCH model backs their theoretical framework. However, when taking the endogeneity of variables into account by using a

VAR model no significant relationship is found.

Fossil fuel and electricity prices have been found to affect carbon allowance prices, albeit inconsistently across different research efforts. The research presented above empirically tests how movements in the determinants affects the carbon allowance prices. Vice versa, there are researches that are trying to capture how movements in the carbon allowance market affect other market prices. Many of these research effort are in the realm of cost-pass-through of of carbon allowances prices on electricity prices.

Sijm, Neuhoff, and Chen (2006) argues that power companies pass on the opportunity cost arising from EU ETS allowances to the electricity prices. They test this by using both forward and spot markets in Germany and Netherlands in their analyses. Using OLS, they estimate how much changes in electricity prices can be explained by corresponding prices of carbon allowance and fossil fuel. Their finding shows 60 to 100% pass-through rate of carbon allowance costs. Additionally, the authors show that, depending on the carbon intensity of the electricity production fuel source, the electricity companies realize windfall profits.

In a similar fashion Fell (2010) investigates the relationship between Nordic wholesale electricity prices and the EU ETS. Using a vector error correction specification with EUA, electricity, gas and coal as variables in the system, he finds that wholesale electricity price reacts significantly to EUA price shocks in the short run which then dies over time. Furthermore, by investigating price of electricity for different hours of the day, he shows off-peak hour electricity prices react more significantly to EUA shocks compared to peak hours.

Similar to our paper's scope, Hoffmann (2007) investigates how EU ETS system is impacting the investment decisions of electricity producing companies in Germany. Having a more qualitative methodology, the author interviews high level employees from five electricity producing companies in Germany regarding how their investment decisions depend on the allowance trading system. It should be noted that Hoffman's analysis took place in 2007, which corresponds to Phase 1 of EU ETS. His findings include CO_2 prices becoming one of the main driver for profitability of power plants and influencing the choice of technology when building new plants in the future. Additionally, he finds conflicting strategies regarding investing into gas power plants between interviewees. While there are claims of high carbon prices leading to more gas power plants, higher natural gas prices seem to be increasing preference towards coal power plants. The author concludes by saying that actual technological changes in electricity production in Germany, driven by EU ETS system are moderate at best.

Aside from fossil fuels and electricity markets, there has been extensive research adressing macroeconomic, financial and weather related effects as potential drivers of carbon allowance and energy market dynamics.

Yu and Mallory (2014) research exchange rate impacts on carbon prices. Their hypothesis is that electricity as the main driver of the carbon prices is produced by either natural gas or coal. Coal market being usually driven by global markets that are denominated in USD while natural gas is mostly imported from Russia therefore is denominated in Euros. Therefore their hypothesis is EUR/USD exchange rate should affect carbon prices through these fossil fuels. The research uses weekly data from 2008 to 2012 and uses Structural VAR model for estimation. Their finding shows that EUR/USD exchange rate is significant, albeit only borderline, and negative.

By arguing and showing the financial time-series properties of EU ETS carbon allowance prices, Chevallier (2009) argues that carbon prices should be highly correlated with stock and bond markets, both in its mean and variance. In order to test this relationship, he uses a TGARCH model specification on carbon futures as dependent variable and dividend yields on daily Euronext 100, junk bond yield, 90-day daily US Treasury Yield Curve Rate, market portfolio excess return, as well as other energy prices as exogenous variables. For the full sample, he finds that only stock market variable among macroeconomic variables have a significant effect on carbon prices which affects it negatively. When he divides the sample into two sub-samples from credit crunch crisis of August 2007, he finds that junk bond variable is significant and positive on carbon prices.

In another research Chevallier (2011) analyzes the impact of global macroeconomic and financial market indicators on carbon prices. He uses Factor-Augmented VAR models on carbon prices and a dataset of 115 variables between April 2008 and January 2010. The rich dataset includes market indicator macro-finance variables and fuel commodities. From impulse response analyses he finds that carbon prices usually responds negatively to a shock that reduces the market indicators. His forecast error variance decomposition analyses shows that the factors used in the model explain close to 50% of the variance, which hints towards a relationship between market indicators and carbon prices.

Mansanet-Bataller, Pardo, and Valor (2007) discusses that carbon prices should depend on energy consumption. Combining this with findings of Le Comte and Warren (1981) and Considine (2000) regarding weather's affect on energy consumption, weather data has been used as a price determinant for carbon emissions.

Mansanet-Bataller, Pardo, and Valor (2007), as one of the earliest research on the topic, analyzes the daily price changes of carbon in 2005 by using both energy and weather variables. They use daily forwards prices for oil, natural gas and coal to explain EUA OTC forward prices. As for the weather variables, they test using both historical weather data for Germany and European weather index. They chose German weather due to few reasons; firstly carbon prices used in their study is mostly traded by German market participants and secondly Germany represents the biggest share of EUAs allocated. Additional to the German weather, the European index used in their analysis is constructed by weighing the temperatures in certain European cities by their population. They use an OLS specification first without the weather variables and then with the weather variables. They both use daily temperature and extreme temperature dummies in their model.

They find that including the weather variables increases their adjusted coefficient of determination. While the mean temperature index is insignificant on the carbon prices, they find that extreme temperatures in Germany have a positive effect on carbon price levels, indicating that extreme hot and cold days increases carbon prices.

Due to the changing regulations surrounding the EU ETS, carbon prices historically underwent different price and volatility regimes. Effects of changes between EU ETS phases as well as other breaks has been researched previously.

As one of the most influential research done on the carbon price determinants, Alberola, Chevallier, and Chèze (2008) investigates the price determinants of carbon allowances during the period between July 2005 and April 2007 by taking the two structural breaks into account. In order to get rid of the influence of different price regimes, the authors split their full sample into sub-samples. As such they test the price drivers' effects in different price regimes. As their dependent variable they use daily spot prices of EUA. For the energy market determinants of carbon they use brent oil, natural gas, electricity and switch price of CO_2. Additionally they use dummy variables for weather in two different specification as extreme weather temperatures and temperature deviation from the mean temperature. They use an OLS model with 5 different samples, divided according to the structural breaks in the full sample.

The results from empirical analyses differ between different sub-periods. For the full period they find that coal has a negative effect while electricity and natural gas have positive effects. However they find no significance of oil and switch prices for the full period. Additionally they do not find any significance of temperature variables for the full period either. Last but not least, they find a significant structural break in April 2006 structural.

The significant variables are differ between two main sub-samples for before and after the structural break. In both sub-samples their findings suggest oil, switch, electricity affects carbon prices positively but they don't find any significance for coal and natural gas variables. For the temperature variables they find that extreme cold weathers are significant in both sub-samples. However its sign differ between sub-samples. The authors contextualize this by mentioning how 2006 winter was very cold while 2007 winter was warmer than average.

Essentially their findings suggest that there are 2 types of drivers; (1) institutional and (2) political drivers, captured by the structural break, energy prices and temperature.
Their main finding is that carbon price fundamentals change over the period that they tested for. The structural breaks identified significantly change the price dynamics in their periods. In a more recent research Creti, Jouvet, and Mignon (2012) analyzes the price determinants of carbon emission for the first two phases of EU ETS, and compares whether the price drivers for different phases holds or not.

Their research covers the period between mid 2005 to end of 2010, which includes Phase I and part of the Phase II. They use futures prices of EU allowances as their dependent variable. For the price drivers they consider Dow Jones Euro Stoxx 50 to control for the financial turmoil as well as brent oil futures and the fuel switching price between natural gas and coal. They also include a dummy variable to account for a structural break arising from a major change in April 2006. In order to test for long run relationship between these variables they utilize Johansen's cointegration test for the whole period as well as the periods covering Phase I & II separately.

They find different dynamics in their variable system between their two sub-periods. While oil price is significant and positive for both sub-periods, they find that stock price variable changes signs between the Phases, becoming positive in the Phase II. Additionally the switch price variable is only significant in Phase II. Their findings suggest that the cointegrating relationship between carbon emission prices and its fundamentals are more apparent in the Phase II.

Two papers presented above highlights the importance of different price dynamics in EU ETS history based on different institutional structures. Alberola et al. by finding different price drivers between their full sample and two sub-samples divided by a break and Creti et al. by showing the drivers change between two Phases. We see that changes in institutional design of the carbon trading scheme have affected the price dynamics of carbon in the past.

Lastly, volatility dynamics between carbon and energy markets has been researched extensively. In order to capture the time varying correlation properties of carbon market, multivariate GARCH model specification has been widely used to model volatility spillovers between carbon and other markets.

Q. Ji, D. Zhang, and Geng (2018) uses dynamic conditional correlation (DCC) GARCH and BEKK-GARCH specifications to explore volatility spillovers between carbon and coal, natural gas and oil prices from 2008 to 2014. They find significant unidirectional spillovers from coal to carbon and carbon to natural gas, while no spillover from oil prices. Additionally their finding suggests an asymmetric relationship where decrease of all three fuels causes more volatility for carbon prices than when they increase.

Koch (2014) uses a smooth transition conditional correlation (STCC) GARCH specification to allow conditional correlation between carbon, oil, gas, coal and EURO STOXX 50 index. The data used is between April 2005 to April 2011. He first tests whether correlations are constant or not with an LM-test and rejects the constant correlations. He uses VSTOXX volatility index as transition variable between low and high volatility regimes. He finds that high stock market volatility leads to high correlation between carbon and fuel prices.

Concluding briefly, we have looked at research within carbon (emission) price determinants to identify potential related variables in our system. The majority of research conduced concludes on the influence of fuel prices, as well as overall productivity. These drivers seem to be consistent across a variety of research settings ranging from mean, up to volatility specifications. Common drivers made out are: Coal, Gas, Oil, and overall economic activity.

4 Problem Statement

The previous section discussed fundamental drivers of carbon prices using prior literature within the field of carbon emission markets. More specifically, we argue for the common effects of energy commodities on carbon prices, that is: *natural gas-, coal- and oil-* prices respectively. The reasoning behind their relationship with carbon emission prices lies withing their carbon emission output during combustion.

Prior research has been able to establish this relationship empirically. However, research has often neglected the effects of the market set-up. The latter is especially interesting in the context of cap and trade systems, such as the European Emission Trading System (EU ETS).

Regarding EU ETS: Within the system, carbon prices are established within *"Cap-and-Trade Schemes"*. As such it represents an artificial market. We used the term artificial market in the sense that the market maker establishes and introduces a set-supply of carbon emission allowances to the market via a preferred allocation method. On top of that, the market maker allows for subsequent trading. Thus, the inert nature of establishment and allocation of such product, we argue, potentially influences market dynamics itself. Between Phase 2 and 3 of the market, the institutional design of the EU ETS system has undergone significant changes. More specifically, the method carbon permit allocation differs substantially between the two phases. Accordingly, allocation method changed from grandfathering to an auction based system. As the design of the EU emission trading system changed we expect to see changes in the dynamics between the carbon price and the market. Particularly, the dynamics between the carbon price and its market participants. Hence, we ask the question:

RQ1: Does Resource Allocation Method matter for Market Dynamics within a Cap and Trade System?

Additionally, we specifically argue that changes in the system's design lead to changes in firm behavior. More specifically, for firms significantly subject to the EU ETS. Firms generally prefer certainty in regulatory frameworks, and thus changes in the EU ETS leave firms vulnerable to new market conditions arising from those policy changes. Given the nature of their respective business, firms differ in their exposure to carbon emissions and their potential to hedge such exposure to carbon prices and policy changes. In practice, firms can change or adapt their production processes, and thus their carbon emissions.

Given their production using carbon emitting fuel inputs, the *electricity generating* sector is substantially affected by changes to EU ETS regulations yet has major carbon-reduction opportunities arising from switching input fuels in electricity generation. By minimizing their carbon emissions electricity firms are simultaneously able to minimize their exposure to policy changes. In fact, the main goal of the EU ETS system is to decrease carbon emissions by incentivizing carbon emitting firms to switch to less carbon emitting or carbon neutral processes. Consequently, we argue that the electricity sector specifically depicts large opportunities arising from switching input fuels in electricity generation as a response to changes in carbon prices. As such, the following question arises:

RQ2: Do Resource Allocation Methods influence Electricity Sector Production Behaviour in a Cap and Trade System?

Moving towards more carbon and electricity markets we argue that electricity firms subject to EU

ETS are reacting to institutional changes in the system through two mechanisms:

1. Effects on Opportunity Costs

2. Effects on Marginal Production Costs

As mentioned previously, we specifically apply our research within the EU-ETS and most importantly the electricity sector. We choose the electricity sector as it is most affected by current policy changes with regards to resource allocation method. An second reason for choosing the electricity sector is that it represents an ideal research setting given its country level setting. Electricity market face low international competition, and operate mostly on a national level. Nevertheless, they are still subject to international fuel-, and to some extend, electricity prices.

Within our research setting we specifically focus on Germany's electricity sector as our local market. We do so, as Germany's electricity input mix consists of coal and gas electricity generation, mostly. Either fuel is carbon emitting during combustion, while being substitutes for each other. From a market perspective, Germany represents the largest energy and carbon producer within the European Union. As a consequence, it also represents a major share of the aggregate allowance demand.

With regards to electricity markets within the EU ETS, previous research argues a historical opportunity cost pass-through of EUA prices under grandfathering. Electricity generation firms have been increasing electricity prices to shocks in carbon prices. Firms did do so, as grandfathered allowances presented an opportunity cost. In contrast, under auctioning firms cannot treat these permits as opportunity costs any longer. The consequence; as electricity prices already incorporate opportunity costs firms can no longer pass-through shocks to carbon prices under auctioning. However, EUA prices now enter marginal production costs of electricity generation. However, as firm cannot increase prices a second time - firms' production mix will have to respond to carbon price movement through switching between coal and gas as input. Given that an electricity sector possess both, coal and gas combustion plants, as well as excess capacity - the sector can adjust its input mix accordingly.

> ***H1****: Auctioning reduces (opportunity-) cost pass-through in German electricity markets relative to grandfathering in the EU ETS.*
>
> ***H2****: Auctioning increases sensitivity to carbon prices in fuel-mix of German electricity generation relative to grandfathering in the EU ETS.*

The argument for *H2* is based on the EU ETS' objective of incentivizing more carbon neutral fuel processes, which largely focuses power generating firms. Given the extend of EUA demand attributed to the power sectors this is only to be expected. By abandoning grandfathering and supplying carbon allowances through auctions the system tries to estrange firms from using carbon emitting technologies. Electricity generating firms can decrease their costs arising from their respective carbon allowance demand by switching to less carbon intensive technologies and hence, reducing their exposure to carbon prices and EU ETS related policy changes.

In order to do investigate *H1, & H2* we model the interactions between world fuel prices, European carbon prices, and electricity markets endogenously. We account for national level electricity policy implications to isolate the effects of a structural break induced by a change in resource allocation method in the European Unions' Emission Trading Scheme. The strategy to test the hypotheses presented are further elaborated in the following section.

5 Estimation Strategy

As elaborated in our literature review section, previous research within energy and carbon markets depict various approaches for modeling theirrelationships. In terms of methodology used, previous research splits into two main research streams: single equation regression analysis , such as ARMA or GARCH type models, or multiple equation regression analysis, such as VAR or VEC type specifications.

For the model type used in the analyses it is important to consider the interactions between different variables of interest, more specifically, the interactions between different energy prices and price determinants. For instance, assuming that EUA prices increase, which we hypothesize leads to higher usage for natural gas in power generation, increasing the price of natural gas. Consequently higher natural gas prices may lead to higher electricity prices due to higher natural gas marginal production costs. Furthermore, Knittel and Roberts (2005), argue that dynamic relationships like the one describes are important in modeling price-setting of electricity markets. Such dynamic relationships are best modeled with simultaneous estimation of multiple equations. In order to account for the a potential endogeneity issue, and as well as long-run and short-run adjustments in our system we consider a recursive VEC model specification.

Our main interest is to investigate the interaction between carbon prices and electricity prices over different periods. Fell (2010) mentions, estimating such a relationship is not straight forward due to time varying response of electricity prices to a change in carbon prices. He argues that such interaction will likely depend on the type of technology used in the electricity production. Therefore including a variable in our system of equations that can depict the fuel usage in electricity production is crucial for our analyses. Furthermore, we are also interested in how fuel usage in electricity production responds to shocks, mainly shocks to carbon prices. On top of that, we aim to tackle the timing mismatch between fuel share shift, and carbon price movements by dividing our electricity variable in peak and off-peak times. Peak hours empirically respond more to spot price movements as peak electricity production is a function of spot electricity demand.

As explained in the background section we know that there are fundamental institutional changes in the EU ETS system between Phase II and III. In order to capture the impact of such changes on energy markets we try implement several model specifications and compare the estimation results over two distinct sub-samples. By comparing the models from different periods we try to assess whether there are differences between interactions of our variables. As we are interested in isolating the effects of EU policy changes, we emphasize the inclusion of national level energy level proxies. More specifically, we account for any effects in national level policy changes by including exogenous variables regarding the change in energy fuel usage from other sources, e.g. uranium, solar, wind, lignite. Which are all, central to Germany's Energy Reforms.

Another issue regarding the electricity prices are different prices for every hour of the day. An average of the day price can be used for the analyses. It is also a common practice in the literature to assess different electricity prices of the day which can be seen in Jouvet and Solier (2013). As indicated before, this makes sense as peak electricity demand employs higher marginal cost production e.g. natural gas. Natural gas production capacity is flexible in the short run, and thus suited for sudden energy demand spikes. Whereas, off-peak electricity demand generally depicts low variation in fuel mix usage.

We explained that using a system of simultaneous equations is the most appropriate way to estimate the interactions in energy markets. For such type of estimation we can either use a VAR or VEC models. Having price variables in our estimations, our results may be spurious if we estimate in levels as price variables are likely to be non-stationary. If our variables are indeed non-stationary we can estimate them by a VAR in first differences and disregard any long-run equilibrium, or by incorporating a potential cointegration relationship using a VEC model. Again, a VECM hinges on the presence of cointegration within our variable system. The VEC model is preferred as by first differencing we are neglecting valuable information on the long-run dynamics between the variables.

The estimation process is as follows; we analyze the data, conducting preliminary tests in order to determine the most suitable model specification. This includes selection of lag length, testing the order of integration and the rank of cointegration in our variable system. After we determine the rank of cointegration we estimate a VECM, comparing short-run and long-run relationships between different phases and different variable systems. Finally, we estimate the corresponding impulse response functions (IRFs) w.r.t. to each electricity specification. IRFs depict how variables in the system responds to shocks in another endogenous variables. By visually comparing the IRFs of our variables of interest between two different phases we can assess the different responds to same shocks. Such analysis will be especially useful when investigating how a carbon price shock affects electricity prices and fuel mix of electricity production.

6 Methodology

Within the upcoming section the procedures and estimation methods to study the relationships between carbon prices, fuel prices, and electricity markets are discussed. In doing so, we will first take a look a closer look a the data analysis with regards to series behaviour that is: (1) Stationarity, (2) Autocorrelation, and (3) Unit-root; before moving onto introducing the concept of (4) Cointegration, (5) Cointegrated Vector Autoregressive Regression analysis(VECM), and lastly (6) Impulse Response Functions. Next to elabroating on the concepts themselves, we will simultaneously discuss the econometric implementation and their respective, adequate testing procedures.

6.1 Stationarity

In most general terms, Lütkepohl, Saikkonen, and Trenkler (2004) and Lütkepohl (2005) define stationarity of a (time) series as the time-invariance of first and second moments of given time-series y_t. To put differently; y_t is defined as stationary if the following two hold:

1. $\mathbb{E}[y_t] = \mu_y$ for all $t \in T$
2. $\mathbb{E}[(y_t - \mu_y)(y_{t-h} - \mu_y)] = \gamma_h$ for all $t \in T$ and $t - h \in T$

Which simply refers to mean, variance and covariance invariance (over t) (Lütkepohl, Saikkonen, and Trenkler 2004). Considering h =*0* we can see that (2) reduces to : $\mathbb{E}[(y_t - \mu_y)^2] = \gamma_0$ which is time-independent by definition.

As an example; within financial time series we often find what we call unit-root non-stationarity. An example for such a unit-root process is a the "classical" random-walk:

$$y_t = y_{t-1} + e_t \tag{1}$$

Where $e_t \sim N(0,1)$ is white noise . Summing over T periods yields the following;

$$y_t = y_0 + \sum_{t=0}^{T} e_t \tag{2}$$

From which we can derive the mean and variance of y_t as $E[y_t] = \mathbb{E}[y_0] + \mathbb{E}[\sum_{t=0}^{T} e_t] = y_0 + 0$ and $var(y_t) = t\sigma_{y_t}$. Notice the variance of y_t is a function of t, and will increase as t gets larger. As the variance of the unit-root process of y_t is dependent on time,t by definition it is non-stationary.

What might be noteworthy is, some processes will not appear stationary in some finite sample - indicating a start-up period (Lütkepohl, Saikkonen, and Trenkler 2004) - and hence these processes might only be stationary asymptotically. However, we will not be distinguishing between asymptotic stationarity and stationarity. Stationarity is critical for inference, given a process defined as in equation 2, which was characterised by $e_t \sim N(0,1)$ the sum of the errors will add to one, and thus imply a persistent effects with non-convergence even if t increases indefinitely. Hence, we will not be able to derive any meaningful inference from such estimator (Sjö 2011).

A common and often useful transformation imposed on non-stationary time series is taking the difference aligning with the order of integration. Or rather Integration, I(d), refers to the amount of d-times differencing that is necessary in order for the series to become stationary. E.g. a series that necessitates two times differencing is said to be integrated of order d=2, or *I(2)*.

6.2 Testing for Stationarity and Non-Stationarity

Having introduced what we refer to as stationary or non-stationary the next section will depict two methods of testing for stationarity or non-stationariy in the uni-variate case. The two test in questions are: (1) Augmented Dickey Fuller (ADF) , and (2) Kwiatkowski–Phillips–Schmidt–Shin (KPSS). It is important and necessary to not that, that although that both test investigate the same concept, *ADF is defined in testing for non-stationarity, whereas KPSS tests for stationarity.*

6.2.1 Augmented-Dickey-Fuller Test

As mentioned briefly before, the Augmented-Dickey-Fuller test is a commonly used procedure testing for a unit-root with a null hypothesis of non-stationarity (Said and Dickey 1984).par In order to test the null against alternative of a stationary time series we subtract y_{t-1} on both sides of a AR(p) series and obtain;

$$\Delta y_t = \phi y_{t-1} + \sum_{j=1}^{p-1} \psi_j \Delta y_{t-j} + e_t \tag{3}$$

Accordingly, the ADF test, tests the hypothesis H_0 against the alternative H_1.

$$H_0 : \phi = 0$$
$$H_1 : \phi < 0$$

Equation 3 represents the augmented-DF test that allows for the inclusion of higher order lags. Instead of simply including all corresponding auto-regressive terms by adding them to the least-squares equation, we are able to simplify by incorporating the lagged differences in y, y_{t-j}. Doing so, allows us to take into account high-order autoregressive processes, and thus dynamics.

The model is estimated us ordinary least squares (OLS). However, not that the test-statistic on ϕ does not follow a t-Distribution hence a standardized t-test is not applicable. The critical values of the test must be obtained using simulation.

Although we have omitted the deterministic terms in 3, depending on the deterministic terms included in our base-model (3), e.g. constant or constant and linear trend ($\tau_\mu; \tau_\tau$), different critical values must be used.

6.2.2 KPSS test

Other than ADF test explained above, the KPSS test test for a time-series integration properties under the null of stationarity. The Augmented-Dickey-Fuller test as mentioned tests H_0 of non-stationary. Generally within statistics, tests are designed in order to reject the null-hypothesis. With that in mind, the ADF-test is less ideal, as we do-not want to reject the null hypothesis. We would rather conclude on a test where we reject the null of stationarity of a series to conclude non-stationarity. The KPSS test does precicly such. Following Lütkepohl (2006) closely, he describes the KPSS test as follows:

Consider a series y_t, which we split into a stationary *I(0)* , and a potentially non-stationary part.

$$y_t = x_t + z_t \tag{4}$$

Where z_t is a stationary process *I(0)* and;

$$x_t = x_{t-1} + e_t, \quad e_t \sim iid(0, \sigma_e^2) \tag{5}$$

Provided by equation 5, we are interested in testing:

$$H_0 : \sigma_e^2 = 0$$
$$H_1 : \sigma_e^2 > 0$$

If H_0 holds then the series y_t is composed of a stationary process z_t and a constant (as the variance of x_t is zero), therefore y_t is stationary. The KPSS test statistic is derived as follows;

$$KPSS = \frac{1}{T^2} \sum_{t=1}^{T} \frac{S_t^2}{\sigma_\infty^2} \tag{6}$$

Where $S_t = \sum_{j=1}^{t} \hat{w}_j$ and $\hat{w}_t = y_t - \bar{y}$. *Note:* $\hat{w}_j$ simply refers to the residals of a regression of y_t on a constant and time trend.

Similar to the ADF test, the inclusion of deterministic terms such as a trend change the critical values of the test. Therefore, it is important to determine such terms depending on the underlying series - although quite subjective this can often be decided on by visually inspecting a time-series plot. Provided a deterministic trend exists in the time series, the equation 5 changes into;

$$y_t = \mu_1 t + x_t + z_t \tag{7}$$

with $\hat{w}_t$ becomes stemming from;

$$y_t = \mu_0 + \mu_1 t + w_t \tag{8}$$

However, the process at deriving the test statistic still corresponds to equation 6.

ADF- and KPSS tests are often used simultaneously in order to conclude on stationarity a given time series. Ideally, we would like to find similar result for a series with either ADF- or KPSS- test. Hence, in an ideal case of non-stationarity we reject its $H_0^{ADF} : \phi = 0$ and fail to reject $H_0^{KPSS} : \sigma_e^2 = 0$.

6.3 Model Specification and Residual Diagnostics

Order of lags included in our estimations is of great importance. We compare the information criterion to find optimal amount of lags and check the diagnostics of the model residuals to assess whether the specification is correct.

6.3.1 Information Criteria

In order to assess the Goodness-of-Fit of our model specification we employ several information criteria, Akaike Information, and Bayesian Information Criteria. Generally, the lower the value of the respective information criteria the better the fit of the model specification.

$$AIC_p = ln|\Omega_p| + \frac{2 * p * k^2}{N} \tag{9}$$

$$BIC_p = ln|\Omega_p| + \frac{p * k^2 ln(t)}{N} \tag{10}$$

Where N=T= sample size, p the number of lags in the VAR(P) model, and K the number of endogenous variables included in the system.

It can be seen that the two information criteria differ with regards to their respective second term. Having a closer look, we notice that:

$$\frac{AIC}{\partial k} < \frac{BIC}{\partial k} \tag{11}$$

Meaning that AIC penalizes less with respect to number of regressors in the system. Hence, BIC will generally select a more parsimonious model specification.

6.3.2 Autocorrelation Function

In order to visually assess serial-correlation and unity root in our individual time-series' we employ what is generally referred to as autocorrelation functions. According to Box, Jenkins, et al. (2015) (2016) the autocorrelation function of a random variable Y_T at lag p is defined as:

$$\rho_p = \frac{\mathbb{E}[(y_t - \mu)(y_{t+p} - \mu)]}{\sqrt{\mathbb{E}[(y_y - \mu)^2]\,\mathbb{E}[(y_{t+p} - \mu)^2]}} \approx \frac{\gamma_k}{\gamma_0} \tag{12}$$

which approximately corresponds to the fraction of autocovariance (γ_k) at lag k over the autocovariance at k=0.

6.3.3 Tests on Model Residuals

Normality-Test

Given a well specified VAR/VECM process we expect to see a white-noise process in our model residuals. More generally, within economics we often make the implicit assumption of multivariate normality (Hendry and Juselius 2000).

Hence, we test our model residuals with respect to skewness, kurtosis and normality. Although we move within the multivariate setting the following section will refer to the univariate case in order to establish intution.

The test-statistisc are χ^2

$$Skewness_{\chi^2,1} : \lambda_1 = \frac{Ts^2}{6} \tag{13}$$

$$Kurtosis_{\chi^2,1} : \lambda_2 = \frac{T(k-3)^2}{24} \tag{14}$$

$$J - B\ Normality_{\chi^2,2} : \lambda_3 = \lambda_1 + \lambda_2 \tag{15}$$

Autoregressive Conditional Heteroskedasticity (ARCH)

In order to assess whether there are ARCH effects present in VAR/VECM models we use a Lagrange-Multiplier (LM) test. Enders (2008) presents a two-step procedure, involving the squared residuals in the auxiliary regression ($2^{nd} Step$):

$$\varepsilon_t^2 = \lambda_0 + \lambda_1 \varepsilon_{t-1}^2 + ... + \lambda_p \varepsilon_{t-p}^2 \tag{16}$$

where the ε_t simiply represents the residuals from the 1^{st} step, that is the VAR/VECM estimation.

The corresponding null hypothesis H_0, of no ARCH effects;

$$H_0 : \lambda_1 + ... + \lambda_{t-p} = 0 \tag{17}$$

Consequently, failing to reject H_0 we conclude with no significant ARCH effects.

Portmanteau Test for Serial Correlation

Testing for remaining serial correlation in econometric models is an important process. If our estimated models' residuals still depict serial correlation it suggests that the models are not well specified. In order to have a well specified model we test for serial correlation for different number of lags included in our VAR models using the Box-Pierce test statistic (Box and Pierce 1970). The Portmanteau test statistic can be formulated as follows;

$$Q_h = T \sum_{j=1}^{h} tr(\hat{C_j}'\hat{C_0}^{-1}\hat{C_j}\hat{C_0}^{-1}) \tag{18}$$

Where $\hat{C_i} = \frac{1}{T}\sum_{t=i+1}^{T} \hat{u}_t \hat{u}_t'$. The test statistic is testing for no-serial correlation up to additional lag order h. The null hypothesis for the test is no-serial correlation therefore failing to reject the null indicates not serially correlated residuals. The test statistic is approximately distributed as $\chi^2(K^2(h-p))$.

6.4 Cointegration

Within economics or financial time series, we often are confronted with multiple variables that are non-stationary. Non-stationary as described in the preceding section. Working with non-stationary time series we have the opportunity to either look at their "stable" relationships, that generally depict lower variability than the original series or their cumulative disturbances, which in fact are the part the inherently causes the non-stationarity (Soren Johansen 1995).

The proper statistical term of modeling the cumulative disturbances between two non-stationary variables is referred to as cointegration. Within the following section we purposefully introduce the concept of cointegration within a VAR, setting in order to provide context while providing a rigorous definition of the concept in question. However we will first start of with a simplified two-dimensional setting to establish intuition:

Consider a two-dimensional process Y_t, $t = 1, ..., T$

$$Y_{1t} = \sum_{i=1}^{t} \epsilon_{1i} + \epsilon_{2t} \tag{19}$$

$$Y_{2t} = \theta \sum_{i=1}^{t} \epsilon_{1i} + \epsilon_{3t} \tag{20}$$

It is easy to see that Y_t contain both *I(1)* processes $\sum_{i=1}^{t} \epsilon_{1i}, and\theta \sum_{i=1}^{t} \epsilon_{1i}$ but that can be made stationary given a cointegration vector $\beta' = [\theta, -1]$ such that $\beta' Y_t \sim I(0)$.

$$\beta' Y_t = \theta Y_{1t} - X_{2t} = \theta \epsilon_{2t} - \epsilon_{2t} \sim I(0) \tag{21}$$

Hence, Johansen defines cointegration of a system Y_t cointegrated, if there exists a cointegration vector $\beta \neq 0$ that allows the product $\beta' Y_t \sim I(0)$ to be made stationarty for a suitable choice of distribution.

Now let us consider the following VAR specification (a more detailed elaboration on VAR and VECM systems can be found in the preceding section);

$$y_t = \rho + A_1 y_{t-1} + ... + A_p y_{t-p} + \varepsilon_t \tag{22}$$

Where y_t is a vector of variables with length K. Transforming the system by subtracting y_{t-1} from both sides, and adding and subtracting $(A_1 + A_2 + ...A_i)y_{t-i}$ for i=1,...p-1, we obtain the following;

$$\Delta y_t = \rho + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \Pi y_{t-1} + \varepsilon_t \tag{23}$$

Where $\Gamma_i = -(A_{i+1} + ... + A_p)$ for i=1,...p-1, and

$\Pi = -(I_K - A_1 - ... - A_p)$ where I_K is a K x K identity matrix.

Let $\Pi := \alpha\beta'$, where α is is labeled the adjustment matrix and β' the cointegration vector consisting of the individual cointegration vectors. With α of dimensions [K x r], and β' being [r x K]. r being the number of cointegration vectors and K the number of endogenous variables in the system.

The cointegration-rank, equals the number of independent linear relationships in the system or in other words the number of eigenvalues that are different from zero of Π in the cointegrated VAR system in 23. Hence, given a cointegration relationship matrix Π is of reduced rank.

6.4.1 Determination of Cointegration Rank

Søren Johansen (1988) discusses a sequential procedure in determining the rank of the cointegrating vectors. We refer to the procedure as sequential as the test hypothesis are defined ass follows:

$$H_0 : Rank(\Pi) = r$$
$$H_1 : Rank(\Pi) = r + 1$$

We have introduced prior the concept of reduced rank under cointegration. It is precicely this reduced rank relationship that Soren Johansen (1995) makes use of when testing for the number of independent linear relationships in Π.

Consequently;

- If $Rank(\Pi)$=0, then all variables in the system of Y_t and thus Π are I(1) but not cointegrated.
- If $Rank(\Pi)$=K, it means that Π full rank then the variables in y_t are stationary, as all variables are independent.
- If $Rank(\Pi) = 0 < r < K$, Π is of reduced rank and there are r cointegration-relations in the system.

6.4.2 Deterministic Terms in β'

So far we have neglected any deterministic terms in our system; neither 21 nor 23 have previously included such. Nevertheless, determining the rank of Π as laid out previously, or more precisely the test statistic is affected by the deterministic terms included in the system.

S. r. Johansen (1994) defines five cases within his framework of sequential cointegration rank testing; Recall equation 23 of a vector-error-correction system specification without deterministic terms; which we can simply adapt to include that latter:

$$\Delta y_t = \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \alpha\beta' y_{t-1} + v + \delta t + \varepsilon_t \tag{24}$$

Where $v = \alpha\mu + \gamma$ and $\delta t = \alpha\rho t + \tau t$

We can then rewrite our model as;

$$\Delta y_t = \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \alpha(\beta' y_{t-1} + \mu + \rho t) + \gamma + \tau t + \varepsilon_t \tag{25}$$

Such that the identification problem becomes much clearer, any tests on β' in 23, now depend on the assumptions on the deterministic terms in 25, as we can only identify the rank of $\Pi = \alpha\beta'$, where $\beta = (\beta' y_{t-1} + \mu + \rho t)$

Consequently, Johansen provides the following 5 cases:

Case 1 : $v = 0$ and $\delta = 0$: No deterministic component.

Case 2 : $\tau = \rho = \gamma = 0$: Mean of cointegration vectors is μ, no trends in levels or first differences.

Case 3 : $\tau = \rho = 0$: Unrestricted constant, no quadratic trend in levels, linear trend in first differences and variables are stationary around a constant mean.

Case 4 : $\tau = 0$: No quadratic trends in levels, variables are trend stationary.

Case 5 : No restrictions on deterministic components.

Hence, we need to make an assumption on our system and choose the appropriate case when determining the cointegration vector. In practice, Cases 4-5 are less relevant, as empirically assuming no restrictions on deterministic components is not of relevance, and a quadratic trend in levels highly unlikely for most financial and economic time-series.

6.5 Restrictions on β

Before discussing over-identifying restrictions on the long-run structure β' let us first rewrite our conventional VECM process, into a more concise and interpretable form.

Recall that given a non-stationary process that there are r cointegration relationships with $p > r > 0$;

$$\Pi = \alpha\beta' \tag{26}$$

With $\alpha, \beta = [\ p \times r\ ]$ To put it in other words, if $p > r > 0$ then there are r linear combinations of the system that make our non-stationary series, stationary.

Also, recall equation 23, *Note: We are omitting exogenous variables, e.g. dummies for simplicity*:

$$\Delta y_t = \rho + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \Pi y_{t-1} + \varepsilon_t$$

Assuming: $\Lambda_{0t} = \Delta y_t; \Lambda_{1t} = y_{t-1}\ \Lambda_{2t} = [\Delta y'_{t-1}, ..., \Delta y'_{t-k+1}]$

We can rewrite 23 as:

$$\Lambda_{0t} = \Pi\Lambda_{1t} + \Psi\Lambda_{2t} + \epsilon \tag{27}$$

where: $\Psi = [\Gamma_1, ...\Gamma_{k-1}]$ The idea next is to take out the transtory effects, that is Λ_{2t}. The idea is to perform a step OLS regression, regressing (1) Λ_{2t} on Λ_{0t}, and (2) Λ_{2t} on Λ_{1t}, which can easily be extended to a VAR(k) process (Juselius 2006). She concludes on the concentrated "R"-model:

$$R_{0t} = \alpha\beta' R_{1t} + e \tag{28}$$

Which represents the "clean" equilibrium model, without transitory effects Λ_{2t}.

As we are using a maximum likelihood estimation, hence estimating the model by conditional on the short-run dynamics simply enables use to a more computational efficient estimation.

6.5.1 Hypothesis on β

When testing restrictions on the long-run vector β it is convenient to present these in the direct parametrization $H = R_{\perp}$

$$\beta = H\varphi, \tag{29}$$

where H $[ptimess], \varphi$ $[s \times r]$.

such that:

$$sp(\beta) \subset sp(H) \tag{30}$$

Which simply means that our restrictions on Π lead to ta restricted estimation of an r (coin. rank) dimensional subspace in R^P. Given 30 we know that any restrictions on H and thus β hold for all vectors in the vector subspace of R^p as provided by 29 (Soren Johansen 1995). Thus, we can simply estimate the restricted Φ without knowing the cointegrating relations in the system.

6.5.2 Formulating Hypothesis on β: $H = R_{\perp}$

Then we can formulate our hypothesis:

$$\mathcal{H}_0 : \beta^c = \mathbf{H}\varphi \tag{31}$$

Given a K = 4, dimensional VECM, with r = cointegrating relationships as defined in 44, the following two hypothesis are equivalent given the direct/indirect parametrization:

$$R = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}, R_{\perp} = H = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix} \tag{32}$$

We define the constrained long-run structure as:

$$\beta^c = (\mathbf{H}_1\varphi_1, ...\mathbf{H}_r\varphi_r) \tag{33}$$

where $\varphi_i \; [s_i \times 1]; \; \mathbf{H}_i \; [p1 \times s_i] \; with p1 = dim(x_{t-1}), \; and \; i = 1, ..., r$

6.6 Restrictions on α - Weak Exogeneity

6.6.1 Hypothesis on α

Similar to testing restrictions on the long-run structure β we can test over-identifying restrictions on our adjustment coefficients α (Soren Johansen 1995). Which once again hinges on the direct parametrization $R = H_{\perp}$

$$\mathcal{H}^c_{\alpha} : \alpha = \mathbf{A}\alpha_1 \tag{34}$$

where α $[p \times r]$, $\mathbf{A}$ $[p \times s]$, α_1 $[s \times r]$ with $s \leq r$

Which is equivalent to saying:

$$\mathcal{H}^c_{\alpha}(r) : \; \mathbf{R}\alpha' = 0 \tag{35}$$

where once again:

$$sp(\alpha) \subset sp(A) \tag{36}$$

6.6.2 Formulating Hypothesis on α: $H = R_{\perp}$

Such that the null hypothesis, can be formulated as:

$$\mathcal{H}_o : A\alpha_1 = \begin{pmatrix} \alpha_1 \\ 0 \end{pmatrix} \tag{37}$$

$$A = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}, R = H_{\perp} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix} \tag{38}$$

6.7 VAR and Cointegrated VAR (VECM)

We have previously briefly introduced a vector auto-regressive process (VAR) and the cointegrated VAR process also referred to as Vector-Error-Correction Model (VECM). As discussed in the empirical strategy, we use a VECM process in order to model our system endogenously in the short and long-run.

The section is structured, we will first consider a simple VAR process, and will subsequently reparametrize such into a VECM.

6.7.1 VAR

In line with Juselius (2006) and Soren Johansen (1995) we construct a VAR(p) - system on the variable space Y_t containing K variables, such that $Y_t = [y_{1t}, ..., y_{Kt}]$, over time $t = 1, 2, ..., T$.

Consequently,

$$y_t = A_1 y_{t-1} + ... + A_p y_{p-t+1} + u_K t \tag{39}$$

where,

$$u_T = [u_{1t}, ..., u_{Kt}]_{[1\times K]} \sim (0, \Sigma_u),\ \mathbf{A}_i\ is\ [K \times K]$$

Closely linked to $\mathbb{E}[u_t u_t\ T] = \Sigma_u$, that is a time-invariant positive-definite covariance matrix is the characteristic of a stable VAR(P)-process. Meaning, our VAR(p) process generate stationary time-series, with time-invariant moments. The stability condition for a VAR(P) process is defined as the following:

$$det(I_K - A_1 z - .. - A_p z^p) \neq 0\ for\ |z| \leq 1 \tag{40}$$

If —z— = 1, then the process is said to have a (unit) root. Meaning, some (or all) K endogenous variables are integrated of order one $\sim I(1)$. If this is the case, we can either estimate a VAR(p) in first-differences, or investigate the possibility of cointegration in the non-stationary system of variables using a Vector-Error-Correction Model (VECM).

Empirically we investigate stability by looking at the eigenvalues of A of a VAR(P) process in companion form. Consider a VAR(1):

$$\xi_t = A\xi_{t-1} + \vartheta_t \tag{41}$$

then;

$$\xi_t = \begin{bmatrix} y_t \\ \vdots \\ y_{t-p+1} \end{bmatrix}, A = \begin{bmatrix} A_1 & A_2 & \dots & A_{p-1} & A_p \\ I & 0 & \dots & 0 & 0 \\ 0 & I & \dots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \dots & I & 0 \end{bmatrix}, \vartheta_t = \begin{bmatrix} u_t \\ 0 \\ \vdots \\ 0 \end{bmatrix} \tag{42}$$

where, $\xi_t\ [KP \times 1]; \vartheta_t\ [KP \times 1], A\ [KP \times KP]$

Given that the eigenvalues of our companion matrix A are within the unit circle, that is < 1 our process is considered stable.

Equation 39 might represent a convenient form in terms of forecasting, as all variables are fully endogenous and no restrictions are made on matrix A. However, it is difficult to determine any relationships between the various regressors K in the system of 39.

More concisely, all instantaneous effects of Y_t in 39 are only captured in the residual-covariance-variance matrix Σ_ϵ. More so, the covariance-matrix is full rank - making it impossible to pinpoint any relationships within the system.

6.7.2 VECM

Given that Equation 40 does not hold, and our variables are nonstationary, $\neq I(0)$, and co-integrated we can investigate what is generally referred to VECM.

We have mentioned earlier that as an alternative to estimation a VECM given some cointegration vector β' we can also estimate a VAR in first differences: Reconsider equation 39, but with y_t now Δy_t. Then;

$$\Delta y_t = A_1 \Delta y_{t-1} + \cdots + A_p \Delta y_{p-t+1} + e_t \tag{43}$$

Which produces a stable VAR process, assuming all variables were non-stationary $\sim I(1)$.

Nevertheless, as can easily be seen we accomplish this by deleting any long-run movements in the levels as we simply consider the difference variables. If however, our system is cointegrated, the there exists a possibility to include the long-run movements in our VAR(p) system:

The general form of a VECM is given by:

$$\Delta y_t = \Pi y_{t-1} + \Gamma y_{t-1} + ... + \Gamma_{p-1}\Delta y_{t-p+1} + CD_t + u_t \tag{44}$$

where $y_t = (y_{1t}, ..., y_{Kt})'$ is a $(Kx1)$ vector of endogenous variables, z_t is a vector of exogenous variables; D_t containing deterministic trends, u_t being (K x 1)

the white noise $\sim (0, \Sigma_u)$ term, and lastly, $\Pi = \alpha\beta', \Gamma_j \ (j = 1, ..., p-1), C$

representing all structural form parameter matrices. **A** is (K x K) invertible, allowing instantaneous relations among vector y_t.

Comparing, equations 44, and 43 it is easy to see that the long-run movements of the levels-data enters the VECM as: $\Pi y_{t-1} = \alpha\beta' y_{t-1}$. That is, the α representing the speed of adjustment coefficients (also loading matrix), and β' the cointegration vector introduced in a previous section.

In case of cointegration, Π is of reduced rank, and $\alpha, \beta \ is \ [K \times r]$. Where once again, r refers to the cointegration rank - that is, the number of independent linear relationships in the endogenous variable system. Aka, the number of long-term relationships.

6.8 Impulse Response Functions (IRF)

When aiming to identify any structural shocks within a VAR setting, we are faced with what is often referred to as the *Identification Problem.* Generally, given K(K+1)/2 independent equations in the residual covariance matrix $\Sigma_u \neq K^2$ unknown parameters in B_0^{-1} we need to impose K(K-1)/2 restrictions (Lütkepohl and Poskitt 1991; Juselius 2006). We distinguish between two structural approaches in identifying any underlying shocks: (1) recursively Identified Models and (2) Non-recursively Identified Models.

6.8.1 Identification Problem

Within this research setting, we focus on what is referred to as *Recursively Identified Models.* Recursively is characterised as *Just-Identification* by imposing the K(K-1)/2 necessary restrictions as zero restrictions on $A_0, \ and \, \Sigma$. In doing so we impose orthogonal errors in our residual covariance structure. Nevertheless, the fact that do achieve *Just-Identification*, we need to impose a causal-chain through the order of our variables in the system - to avoid an additional over-identifying restriction.

We achieve orthogonality in our errors by imposing a *Cholesky Decomposition* on our system.

6.8.2 Reduced-form IRF

The impulse response of a reduced form VAR, given the corresponding MA-representation:

$$y_t = \mu + \sum_{i=0}^{\infty} \Phi_i u_{t-i} \tag{45}$$

Considering the response to a shock:

$$\frac{\partial y_{t+i}}{\partial u_t'} = \Phi_i \tag{46}$$

such that;

$$\frac{\partial y_{i,t+i}}{\partial u_{jt}} = \phi_{ij} \tag{47}$$

However, $\mathbb{E}[u_{it}, u_{jt}] \neq 0$, thus isolating the underlying shocks is not possible. Consequently, we need to impose orthogonality in our residual covariance-variance matrix, by assuming: $\vartheta_t = \hat{\Omega}^{1/2} u_t$, where $\hat{\Omega}^{1/2}$ is the lower-triangular matrix of the Cholesky decomposition.

6.8.3 Orthogonal IRF

In order to derive the Impulse-Responses we consider the MA representation of the respective VAR, of our VECM. Given that 40 holds, the now stable VAR process defined in 39 has a corresponding Wold Moving - Average representation (MA). The Wold-MA representation will play an essential part in deriving the impulse-responses in the following section.

$$y_t = \mu + \sum_{i=0}^{\infty} \Phi_i u_{t-i} \tag{48}$$

$$= \mu + \sum_{i=0}^{\infty} \Phi_i \mathbf{P}\mathbf{P}^{-1} u_{t-i} \tag{49}$$

$$= \mu + \sum_{i=0}^{\infty} \Theta \mathbf{P}^{-1} u_{t-i} \tag{50}$$

$$= \mu + \sum_{i=0}^{\infty} \Theta w_{t-i} \tag{51}$$

Where we once again, used Cholesky Decomposition as in 55 to find a matrix P, such that (Lütkepohl and Poskitt 1991):

$$\Sigma = \mathbf{P}\mathbf{P}' \; and \tag{52}$$

$$I_K = \mathbf{P}^{-1}\Sigma\mathbf{P}'^{-1} \tag{53}$$

Again, by decomposing our covariance-variance matrix into two lower triangular matrices, we impose a causal chain. Given that our covariance-variance matrix contains the contemporaneous correlations of our system, a lower-triangular decomposition imposes a causal chain on these contemporaneous correlations. More specifically, a variable that occurs before another variable in the system, is by definition contemporaneously uncorrelated with all subsequent variables, and so forth.

$$\Sigma_{K=4} = PP' = \begin{bmatrix} \Omega_{11} & 0 & 0 & 0 \\ \Omega_{21} & \Omega_{22} & 0 & 0 \\ \Omega_{31} & \Omega_{32} & \Omega_{33} & 0 \\ \Omega_{41} & \Omega_{42} & \Omega_{43} & \Omega_{44} \end{bmatrix} \begin{bmatrix} \Omega_{11} & 0 & 0 & 0 \\ \Omega_{21} & \Omega_{22} & 0 & 0 \\ \Omega_{31} & \Omega_{32} & \Omega_{33} & 0 \\ \Omega_{41} & \Omega_{42} & \Omega_{43} & \Omega_{44} \end{bmatrix}' \tag{54}$$

Structural Approach

In the section above, we simply decompose the covariance variance matrix into a lower triangular matrix and made use of this property to construct orthogonal impulse responses. However, we can also look at this identification issue by taking it into the estimation procedure and estimating a structural VECM with lower triangular covariance-variance matrix. Recall equation, 44 which depicts our general VECM setting that we started off. However, it is unlikely that the residual covariance-variance matrix is uncorrelated. In order to achieve uncorrelated errors we can simply multiply our system by the inverse of what is referred to as the Cholesky decomposition (Juselius 2006).

Cholesky - Decomposition

Cholesky decomposition says that:

$$\hat{\Omega} = \hat{\Omega}^{1/2}(\hat{\Omega}^{1/2})' \tag{55}$$

In other words, Cholesky Decomposition of a matrix $\hat{\Omega}$ splits the matrix into two upper-triangular matrices.

Given such we can rewrite equation 44 as:

$$\underbrace{\hat{\Omega}^{1/2}}_{A_0}\Delta y_t = \underbrace{\hat{\Omega}^{1/2}\alpha}_{\text{a}} y_{t-1} + \underbrace{\hat{\Omega}^{1/2}\Gamma y_{t-1}}_{A_1} + ... + \underbrace{\hat{\Omega}^{1/2}\Gamma_{p-1}}_{A_p}\Delta y_{t-p+1} + \underbrace{\hat{\Omega}^{1/2}C}_{C^*} D_t + \underbrace{\hat{\Omega}^{1/2}u_t}_{\vartheta_t} \tag{56}$$

Where it is easy to see;

$$\mathbb{E}[\vartheta_t\vartheta_t'] = \hat{\Omega}^{1/2}Cov(u_t u_t')\hat{\Omega}'^{1/2} = \hat{\Omega}^{1/2}\hat{\Omega}'^{1/2} = I \tag{57}$$

In order to reach stability, all variables in the VAR system must be stationary otherwise deviations from the equilibrium will not converge to unconditional mean. However, we have previously introduced the concept of cointegration where we also set-up the cointegration problem within a VECM system. given that two non-stationary variables in our system are cointegrated, we can exploit precisely this cointegration relationship in our VECM model. More intuitively, if we were not interested in any long-run effects, aka cumulative disturbances that introduce non-stationarity - we could simply estimate a VAR in first differences. However, if we are interested in the long-run effects in our system a VECM allows us to precisely do so.

6.9 Deterministic Components in D_t

In order to capture any seasonal fluctuations in our model we impose monthly dummies. In line with Soren Johansen (1995) we adopt centered dummies $D_t^M = [D_t^1, ..., D_t^M],\ for\ M \in (1, ..., 12)$.

Given the Granger's Representation Theorem, we can similarly decompose our deterministic components into a common trend and a stochastic component.

$$C\Phi \sum_{i=1}^{t} D_i + \sum_{i=0}^{\infty} C_i \Phi D_{t-i} \tag{58}$$

Looking at an intervention dummy-variable;

$$D_t = \begin{cases} 0, & t \leq t_o \\ 1, & \text{otherwise} \end{cases} \tag{59}$$

Such that the deterministic component sums to:

$$\sum_{i=1}^{t} D_i = \begin{cases} 0, & t \leq t_o \\ 1, & \text{otherwise} \end{cases} \tag{60}$$

With infinite sum,

$$\sum_{i=0}^{\infty} C_i \Phi D_{t-i} = \begin{cases} 0, & t \leq t_o \\ \sum_{i=0}^{t-t_0} C_i \Phi, & \text{otherwise} \end{cases} \tag{61}$$

Given that we employ a seasonal dummy (monthly) it is easy to see that, D_t in 60 grows linearly with $\frac{1}{M} \Rightarrow \frac{1}{12}$. On the other hand, the infinite sum in 61 will introduce a varying mean with its respective seasonality.

In order to combat the introduction of a linear trend in 60 we orthogonalize our dummies, by centering such around their respective (constant) mean. This will remove the linear trend in the sum 60 and leaves us with a seasonally varying mean only.

7 Data

The dataset in use stems from various sources. Most generally, spans the time frame 31^{st} of December 2009 up to 28^{th} of December 2017. The Frequency is weekly, thus 418 observations. Nevertheless, estimations are performed on more specific sub-samples. The main variables of interest in our analysis are *Carbon Allowance Prices*, *Fossil-Fuel Prices*, *Energy Prices* and the *Fuel Share in Electricity Generation*. We will briefly discuss each variable separately, including any transformations and changes applicable. More so, we will elaborate on our sub-sampling choices.

7.1 Data Sources

We construct the dataset in use in the analyses by using variables from different sources. The majority of our variables was retrieved using Reuters Datastream, EUA spot prices, coal spot prices, as well as natural gas prices, and the FX exxchange rate. More specifically, EUA, German Electricity Prices, and natural gas prices of Gaspool are traded on the European Energy Exchange (EEX). The corresponding coal prices are obtained from the Intercontinental Exchange (ICE) and are consequently denoted in USD. Next to using datastream, we obtain the electricity generation input fuel decomposition manually from Frauenhofer ISE, which summarizes data provided by EEX. The data was triangulated to check for potential input errors arising from the manual input.

Prior to the analyses, variables explained above underwent few transformations. Firstly, all price variables are converted into Euro from the daily exchange rate obtained again from Datastream. More so we detect and correct for outliers using the method proposed in **??**, which present an automated outlier detection using level shift, additive and seasonal shift outliers.

7.2 Variables

Carbon Prices

EUA spot prices are used to depict carbon emission prices within our research setting. As the commodity is already denoted in EUR no adaptions are required.

Fuel Share

we construct a variable depicting ratio of gas and coal used in electricity generation in Germany with the following simple formula: $\frac{Gas^{INPUT}}{HardCoal^{INPUT}}$. Doing so we attempt to capture how electricity generating firms are actually switching their production from using fuels with different levels of carbon emissions.

Switch

Furthermore, regarding the fossil fuel prices, following many researches within the topic e.g; Alberola, Chevallier, and Chèze (2008), Creti, Jouvet, and Mignon (2012), Koch (2014), instead of using the natural gas and coal variables separately we use the fuel switch price variable which is depicting the price at which marginal costs of gas and coal fired power plants are equal. Following Alberola et al.

switch price is calculated using following:

$$0.36 \times switch + 50\% \times P_{Gas} = 0.86 \times SWITCH + 36\% \times P_{Coal} \tag{62}$$

There are few reasons to use switch price instead of natural gas and coal separately; First, the aforementioned papers finds that switch price is a significant driver for carbon allowance prices, used as a proxy for abatement cost. Second, including more variables in a complex multivariate statistical analysis can cause problems for serially correlated data Tsay (2005). Having two separate variables may increase serial correlation in our system therefore a single variable that depicts the co-movements of natural gas and coal is preferred to be used in the analyses.

Electricity Prices

Electricity Prices are originally obtained as prices per hour per day. Consequently, we are able to aggregate electricity prices according to demand - that is Average, Peak and Off-Peak. Consequently, we average electricity prices depict simply the average of that day - aggregated for the week. Peak Electricity prices depict the average electricity price for hours 8AM to 21PM. Similarly the off-peak electricity variable, averages the hours of off-peak electricity usage which corresponds to hours between 22 pm. to 7 am. All the price variables mentioned are obtained from the Thomson Reuters Datastream database.

As mentioned before, we obtain electricity generation by input fuel from EEX. The measurement unit is Terrawatt-hour (TWh). Next to coal and gas production, we also obtain data on brown coal, uranium, solar, wind, hydro etc. power generation. This, will later allow us to account for any changes arising form the merit order in electricity production, as well as trends policies affecting other input fuels.

7.3 Frequency

Eventhough price variables are available in Datastream database on a daily frequency, the data is on weekly basis. There are a several reasons for doing so. Firstly, the fuel mix of German electricity generation is on weekly basis only. Although certainly available on a daily basis, within the scope of this research we were unable to obtain this format ourselves. Second, our price variables become severely serially correlated on a daily frequency, requiring high order of lags to model sufficiently. More so, daily frequency also introduces additional noise to our data such as day regarding to external events.

7.4 Sub-samples

The full sample spans from 31/12/2009 to 28/12/2017 for total of 418 observations. The estimations are done separately on two different phases for comparison reasons explained in the estimation strategy section. We split into two for Phase II and III, observation numbers of phases become 157 and 209 respectively. Phase II spans from 31/12/2009 to 31/12/2012 and Phase III spans from 31/12/2013 to 28/12/2017. We exclude the first year of Phase III in the sub-sample in order to account for transition between phases, as well as the excessive amount of over-allocation carried over to phase III from phase II. Additionally, year one is found behave very differently from all subsequent year and depicts significant serial correlation when included in the models. In similar fashion we excluded years past 2018 as around that time, the Market Stability Reserve kicks in and distorts the overall cap setting.

7.5 Exogenous Variables

The variables that will be used in the estimations are carbon price, switch price, electricity price and fuel mix. Aside from the variables in our estimation systems we want to account for other possible variables exogenously. From Mansanet-Bataller, Pardo, and Valor (2007) we know that weather has an effect on EUA and possibly other variables in our system. Furthermore, Knittel and Roberts (2005), investigates electricity prices and finds strong seasonality within. While we are not particularly interested in the magnitude of this effect we want to account for it. Considering effects of weather can mostly be captured with effects of months we include monthly centered dummy variables exogenously in our models. Following Chevallier (2009) we also know stock market movements influence EUA prices. In order to account for movements in the economy, we include returns of STOXX 50 index exogenously as well. We obtain STOXX 50 index from Datastream database in weekly frequency. Lastly, explained in the introduction section, there are constitutional changes for Germany's electricity production within our sample. Based on the merit order in electricity production, German electricity producers might be switching their fuel usage in production in the short run. In order to account for it we regress fuel mix variable on solar, wind, brown coal (lignite) and uranium usage in electricity production and use the respective residuals in our further analysis.

The time series plots for the full-sample is presented in Figures 2 and 3. Descriptive statistics of the variables are presented in Table 1.

Table 1: Descriptive statistics for Phase 2 and 3

	Phase 2					
	EUA	**Switch**	**Avg. Elec.**	**Peak Elec.**	**Off-Peak Elec.**	**Fuel Share**
Mean	11,55	66,96	48,74	54,99	39,98	0,57
Median	12,71	67,36	48,39	54,25	40,25	0,57
Minumum	6,27	53,53	31,30	34,49	16,44	0,26
Maximum	16,69	79,55	71,03	84,68	55,94	0,94
Std. Dev.	3,51	6,37	7,67	8,70	7,35	0,13
Skewness	-0,17	0,16	0,22	0,56	-0,49	0,14
Kurtosis	1,41	1,98	2,97	3,73	3,32	2,95
Observations	157	157	157	157	157	157
	Phase 3					
	EUA	**Switch**	**Avg. Elec.**	**Peak Elec**	**Off-Peak Elec.**	**Fuel Share**
Mean	6,22	75,75	34,27	38,32	28,47	0,41
Median	6,05	80,62	33,43	37,28	28,88	0,39
Minumum	4,07	54,43	20,2	17,14	8,67	0,14
Maximum	8,65	86,28	62,88	77,15	42,91	0,84
Std. Dev.	1,19	9,14	7,00	8,95	5,78	0,17
Skewness	0,28	-0,73	0,90	1,08	-0,79	0,37
Kurtosis	1,96	1,93	4,72	5,59	4,92	2,33
Observations	209	209	209	209	209	209

Figure 2: Time series plots for level and first differenced series (1/2)

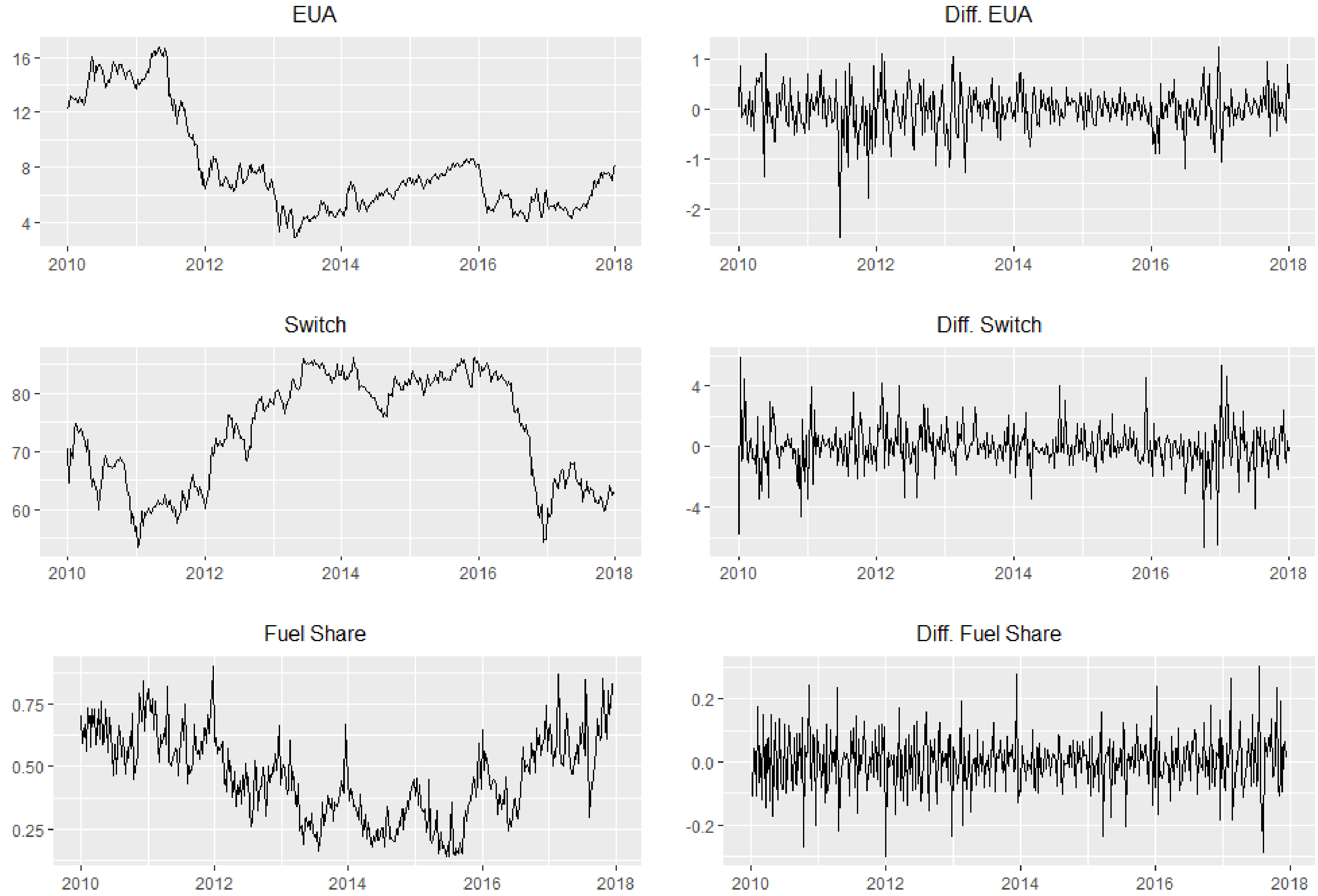
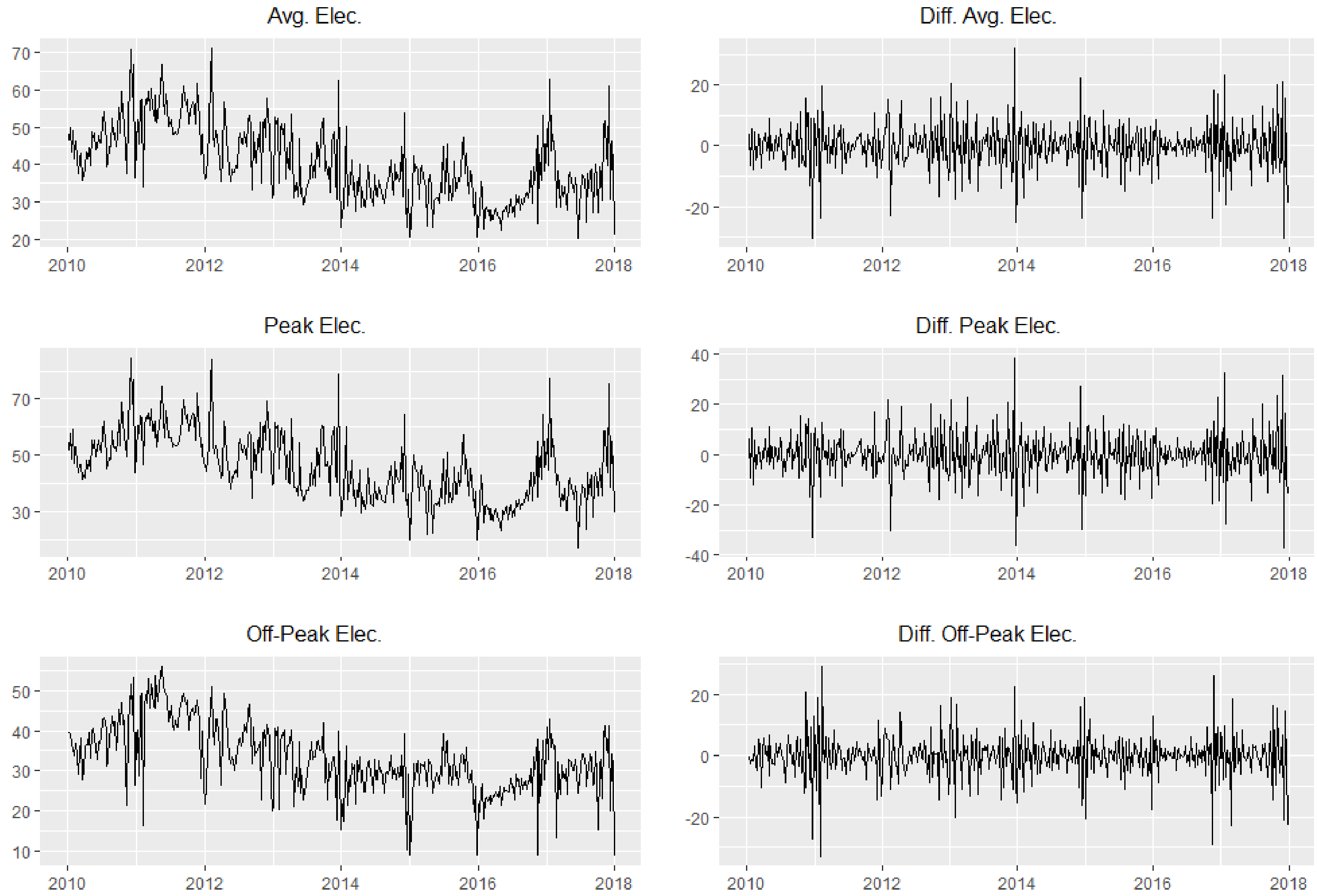


Figure 3: Time series plots for level and first differenced series (2/2)



8 Data Analyses

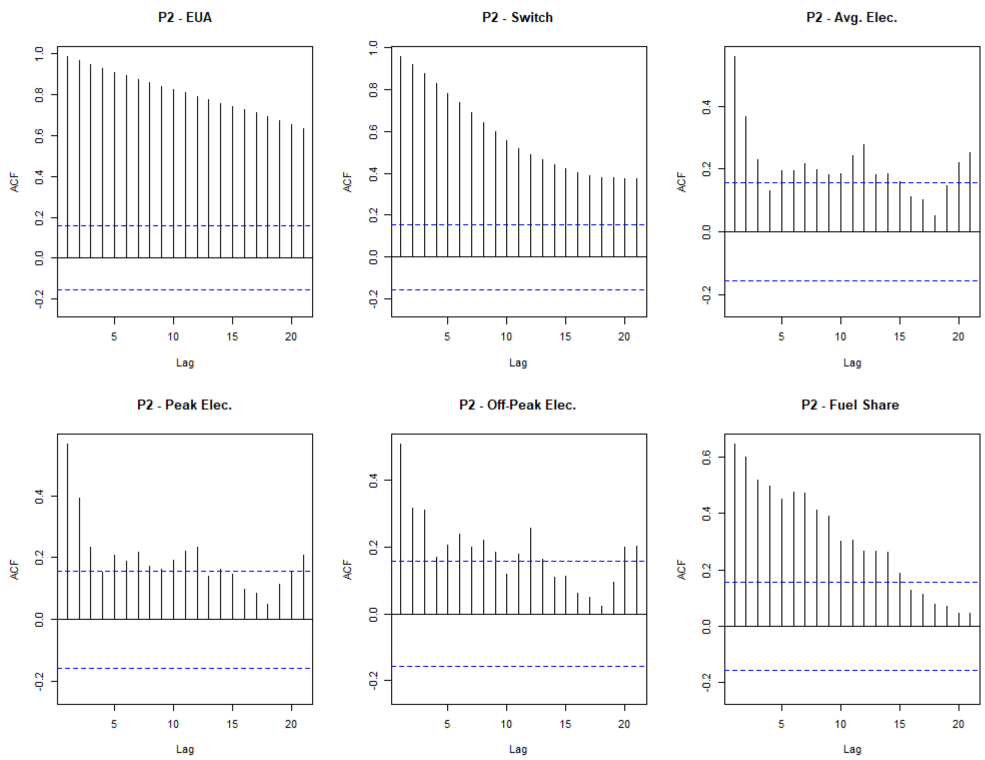
The following section presents the data analyses including stationarity testing, model specification and cointegration analyses. Additionally we present our estimation results and impulse response analyses.

8.1 Autocorrelation Functions

The following section will briefly analyse the univariate series behaviour with respect to each variable in our system, sub-sampled for both phases.

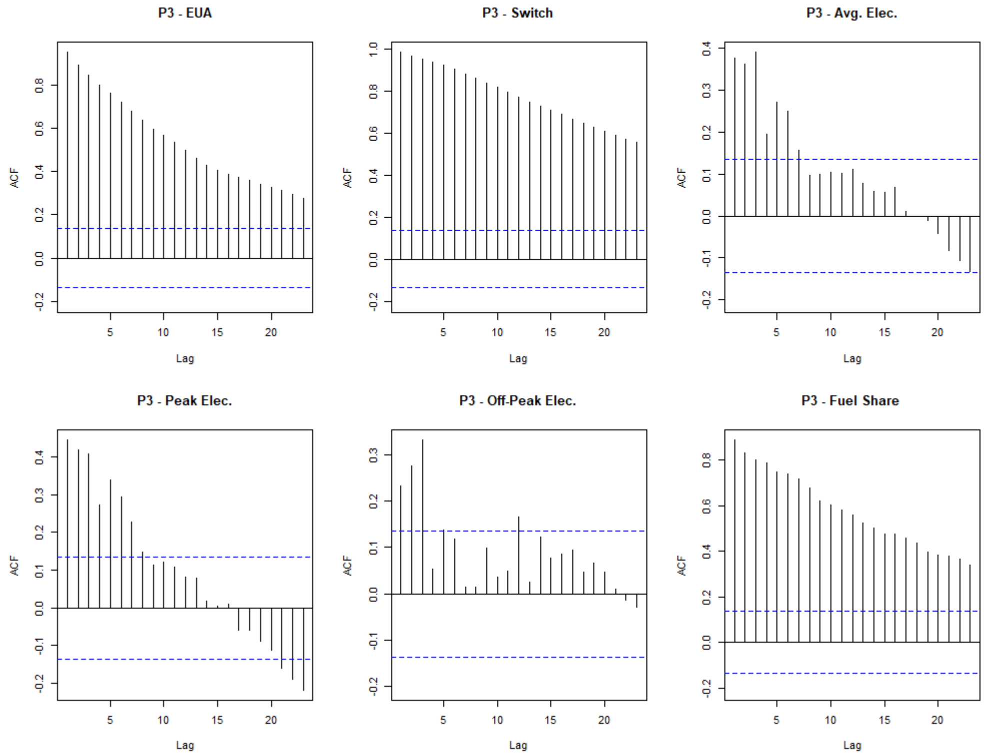
Phase 2

Figure 4: ACF plots for Phase 2(Levels)



Phase 3

Figure 5: ACF plots for Phase 3 (Levels)

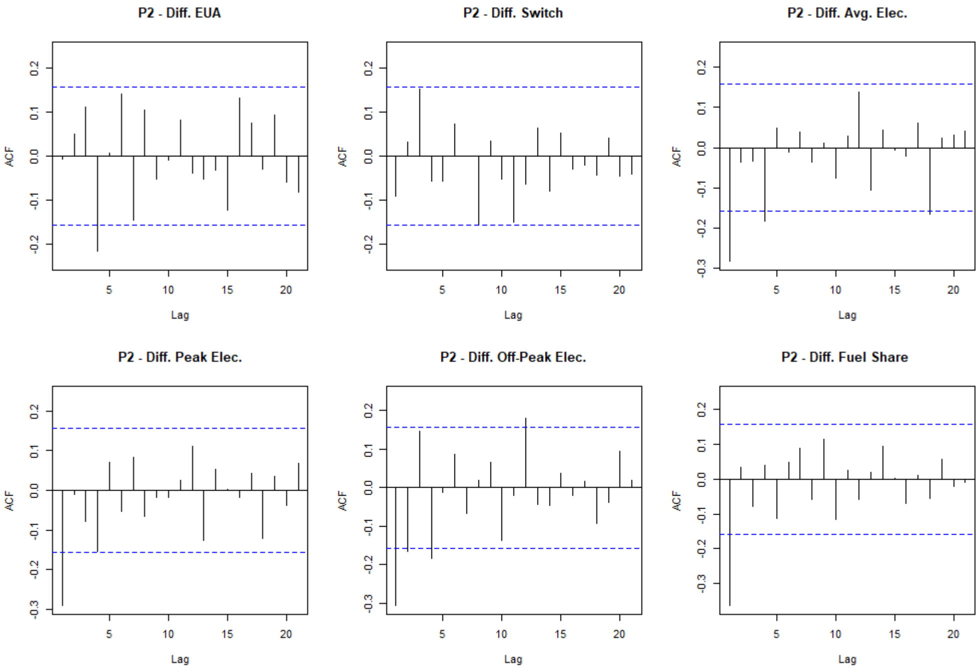


ACF plots for *EUA* and *Switch* prices as well as the *Fuel Share* show slowly decreasing spikes that are significant until very high orders of lag-lengths in both phases. This indicates towards non-stationarity of the series. All 3 types of electricity price in both phases also have significant spikes until high orders. For Phase III the electricity price series are depicting a wave-like pattern. Off-Peak electricity price series in Phase III is not showing as much persistence having first three spikes significant and one more in higher lags. Different electricity variables showing different patterns indicates different levels of serial correlation between them. In Phase III, the electricity variables are showing persistence in their ACFs, however, the first lag of their ACF is actually not close to 1 but around 0.4 level. When the ACF plots of first differenced series are observed, we see that there is not much persistence in the differences series. The differenced electricity prices have significant lags for the first three and other variables have few significant lags for later lags.

While most variables are showing some form of persistence in their time series in levels, testing for unit root can be useful to conclude whether our variables are stationary or not. Please refer to the following section unit root and stationarity testing.

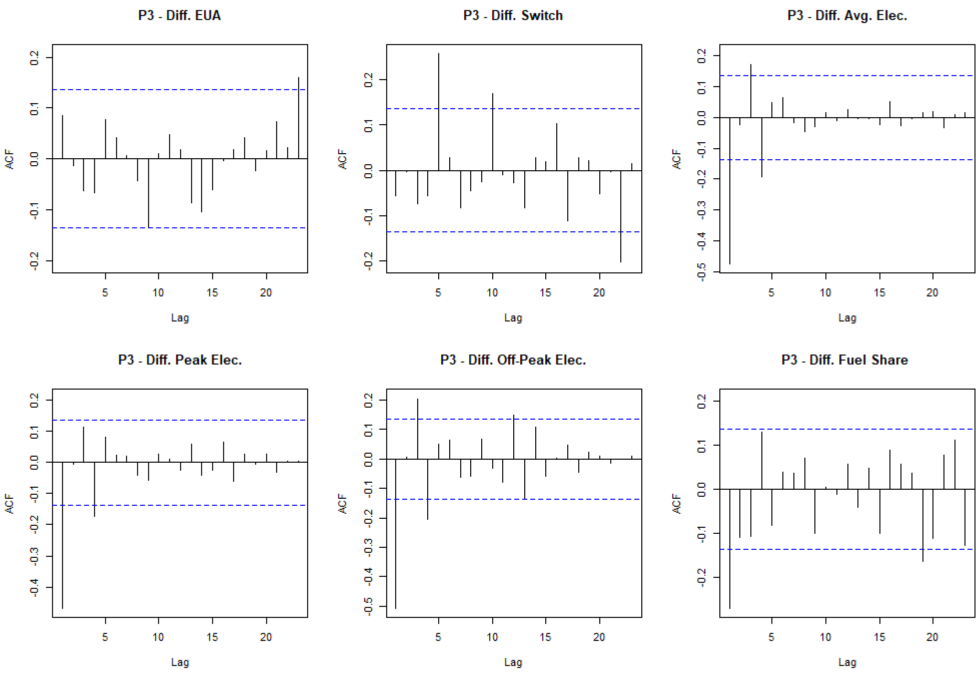
Phase 2

Figure 6: ACF plots for Phase 2 (First differenced)



Phase3

Figure 7: ACF plots for Phase 3 (First differenced)



8.2 Unit Root and Stationarity Tests

As introduced in the methodology section, we will make use of ADF, and KPSS tests in order to statistically conlclude on the stationarity of our series at hand. The test results are presented in Table 2 (ADF) and Table 3 (KPSS).We impose the test on both phases individually, as well as for the full combined sample period. For ADF test, test statistics and the critical values are provided at %10, %5, %1 significance level whereas for KPSS test results approximate p-values are given.

Once again, the specification of deterministic terms included in the tests is of great importance. As we are imposing a deterministic terms on the tests that is not suitable for the time series in question, the test results might be misleading. Elder and Kennedy (2001) explain concisely and simple that if y_t is growing, then existence of a unit-root should be tested with at least a drift term. Investigating the time series plots for our data presented in Figures 2 and 3 while variables used depicts local trends, based only on the plots a long term trend is hard to conclude. Accordingly, we employ the ADF test by including a drift term. For the KPSS we employ the most general specification with both trend and constant.

Table 2: Augmented Dickey-Fuller Test Statistics for Level Data

ADF Test	
Phase 2 and 3	
	test statistic
EUA	-1,76
Switch	-1,24
Avg. Elec	-1,71
Peak Elec.	-2,07
Off-Peak Elec.	-1,65
Fuel Ratio	-2,07
Phase 2	
	test statistic
EUA	-0,39
Switch	-0,70
Avg. Elec.	-1,91
Peak Elec.	-2,18
Off-Peak Elec.	-1,65
Fuel Ratio	-2,47
Phase 3	
	test statistic
EUA	-1,51
Switch	-0,78
Avg. Elec.	-2,38
Peak Elec.	-2,70$\hat{+}$
Off-Peak Elec.	-2,28
Fuel Ratio	-0,73

* Critical values for ADF test are; -2.57 for 10%, -2.87 for 5%, -3.44 for 1%.
** 12 lags are included in ADF tests.
*** Significance codes are 1% $**$, 5%$*$, 10%$^+$.

Table 3: KPSS Test for Level Data

KPSS Test	
Phase 2 and 3	
	p-values
EUA	< 0.01
Switch	< 0.01
Avg. Elec.	< 0.01
Peak Elec.	< 0.01
Off-Peak Elec.	< 0.01
Fuel Ratio	< 0.01
Phase 2	
	p-values
EUA	< 0.01
Switch	< 0.01
Avg. Elec.	< 0.01
Peak Elec.	< 0.01
Off-Peak Elec.	< 0.01
Fuel Ratio	0.031
Phase 3	
	p-values
EUA	< 0.01
Switch	< 0.01
Avg. Elec.	0.016
Peak Elec.	0.023
Off-Peak Elec.	0.024
Fuel Ratio	< 0.01

*The KPSS test results are obtained with the short lag version. However test results with long lag version hints towards identical results.

As explained in the methodology section, the null hypothesis of the ADF test is non-stationarity. Looking at table 2, we cannot reject the null hypothesis for any variables and samples apart for Peak Electricity for Phase III sub-sample. More so, only at a %10 level. Based on Table 3 the null of stationarity is significantly rejected for all variables in all samples at %5 level. While the power of these tests are not very high applied individually, when they hint towards the same result we can safely conclude on a robust result regarding the stationarity of the series Schlitzer (1995). Considering ADF test can only reject non-stationarity at %10 level for Peak Electricity in Phase III and KPSS test rejecting stationarity, we conclude that our variables are non-stationary.

In order to further investigate the order of integration of our variables, we utilize the same procedure of tests on first differenced data. Both tests agree on the stationarity of the differenced variables. Test results for differenced data can be found in Tables 18 and 19 in the appendix section.

8.3 Model Specification and Lag Selection

In the previous section, we conclude the non-stationarity of our variables' time series. In this section we will be specifying the models that will be used in the further analyses. Before testing for optimal lag lengths to be specified in the models we formally present the general formulation of our models. Following Tsay (2005)'s notation, we have the VAR(p) model formulated as follows;

$$y_t = \phi_0 + \Phi \sum_{i=1}^{p} y_{t-i} + \phi_1 exog. + a_t$$

Where y_t is our dependent variable system and *exog.* are the exogenous variables in the VAR system. Elaborated in the estimation strategy section, one of our interest in the analyses is the dynamics of price of electricity for different hours of the day. Hence we split between peak and off-peak hour prices which is explained in the data section and estimate using three different systems. Therefore, for different systems, y_t vector becomes the following;

$$y_t = \begin{bmatrix} EUA \\ Switch \\ Avg.Elec. \\ FuelShare \end{bmatrix}, \begin{bmatrix} EUA \\ Switch \\ PeakElec. \\ FuelShare \end{bmatrix}, \begin{bmatrix} EUA \\ Switch \\ OffPeakElec. \\ FuelShare \end{bmatrix}$$

Furthermore, we explain in the data section that in order to account for monthly seasonality, and possible effects of weather as well as the movements in the whole economy we put monthly dummy variables and weekly returns from EURO STOXX 50 index as exogenous variables in the model. Vector *exog.* becomes as follows;

$$exog. = \begin{bmatrix} EUSTOXX50 \\ Months \end{bmatrix}$$

Where *Months* vector consists of eleven columns of centered dummy variables. Values in these columns are taking the value of (0.9167) if the date corresponds to the month of the column and value of (0.0833) if otherwise. We continue with the lag selection process of the models we specify.

Determination of the order of lags to be included in our models are crucial for cointegration analyses as well as the estimated model. In order to determine of the optimal lag length specified in the model, first we compare information criterion of the different models. AIC and BIC of VAR(p) models until p=6 is presented below. Table 4 presents information criterion for Phase II models and Table 5 presents information criterion for Phase III models.

Table 4: Information criterion for Phase 2

	With Avg. Elec.		**With Peak Elec.**		**With Off-Peak Elec.**	
	AIC	**BIC**	**AIC**	**BIC**	**AIC**	**BIC**
VAR(1)	-2.073	**-1.756**	-1.815	**-1.499**	-2.163	**-1.846**
VAR(2)	**-2.100**	-1.464	**-1.837**	-1.200	**-2.203**	-1.566
VAR(3)	-1.962	-1.003	-1.716	-0.757	-2.061	-1.102
VAR(4)	-1.923	-0.638	-1.683	-0.398	-1.995	-0.711
VAR(5)	-2.006	-0.393	-1.748	-0.135	-2.065	-0.452
VAR(6)	-1.983	-0.039	-1.710	0.233	-2.041	-0.096

*Column 1, refers to the VAR(p) specification in use, where p = the lag length included

Table 5: Information criterion for Phase 3

	With Avg. Elec.		**With Peak Elec.**		**With Off-Peak Elec.**	
	AIC	**BIC**	**AIC**	**BIC**	**AIC**	**BIC**
VAR(1)	-3.578	**-3.320**	-3.178	**-2.920**	-3.842	**-3.585**
VAR(2)	-3.564	-3.047	-3.157	-2.640	-3.839	-3.322
VAR(3)	-3.558	-2.780	-3.152	-2.374	-3.827	-3.094
VAR(4)	-3.594	-2.553	-3.188	-2.145	-3.863	-2.822
VAR(5)	-3.582	-2.276	-3.182	-1.876	-3.830	-2.524
VAR(6)	**-3.645**	-2.072	**-3.238**	-1.666	**-3.887**	-2.314

*Column 1, refers to the VAR(p) specification in use, where p = the lag length included

The lowest information criteria are highlighted in the tables. Based on them, information criteria suggests different lag lengths in models on Phase II sub-sample. AIC is consistently selecting a VAR(2) model while BIC is consistently selecting a VAR(1) model. This result is somewhat expected as the main difference between the two information criteria is that BIC penalizes more for additional parameters in the model, selecting a less order of lag. Results for models with Phase III data is more conflicting. While AIC is selecting the maximum lag length we check for, VAR(6), BIC is selecting a VAR(1) specification.

Even though, the analyses is suggesting a VAR(6) model for one of our sub-samples, the extensive literature on financial prices, more specifically commodity prices usually selects lag length of one or two. Awokuse and J. Yang (2002) finds optimal lag of two when trying to model macroeconomic variables with commodity prices, or in a similar framework Fell (2010), uses two lags while using similar variables to ours. Additionally, Juselius (2006) mentions that a well specified VAR model with financial prices will use at most two lags.

Albeit existing literature is mostly consistent on VAR(2) model specification for commodity prices, our system of variables also include *Fuel Share* variable, which is not a price variable. Considering it might not be possible for electricity producing companies to switch between different sources quickly, such variable may be better modeled with higher order of lags. It is important to check for serial correlation structure for different lag lengths while selecting the optimal lag. Selecting the lag length only based on the information criteria but having correlated residuals in the model will cause problems in further analyses as the estimated model won't be well specified.

P-values from portmanteau test for serial correlation results are presented in Tables 6 and 7 for Phase II and III respectively. The test is done by including additional twelve lags to the initial VAR(p) lag specification. The test is done on twelve lags as we have weekly data and twelve weeks corresponds to one quarter of the year.

Table 6: Serial correlation test results for Phase 2

	With Avg. Elec.	**With Peak Elec.**	**With Off-Peak Elec.**
VAR(1)	0.038	0.046	0.082
VAR(2)	0.112	0.154	0.136
VAR(3)	0.173	0.181	0.283
VAR(4)	0.162	0.160	0.257
VAR(5)	0.125	0.121	0.117
VAR(6)	0.243	0.214	0.121

*12 lags are included in Portmanteau serial correlation test.

*Column 1, refers to the VAR(p) specification in use, where p = the lag length included

Table 7: Serial correlation test results for Phase 3

	With Avg. Elec.	**With Peak Elec.**	**With Off-Peak Elec.**
VAR(1)	0.010	0.010	0.002
VAR(2)	0.070	0.057	0.045
VAR(3)	0.257	0.218	0.116
VAR(4)	0.116	0.133	0.073
VAR(5)	0.051	0.069	0.034
VAR(6)	0.698	0.622	0.748

*12 lags are included in Portmanteau serial correlation test.

*Column 1, refers to the VAR(p) specification in use, where p = the lag length included

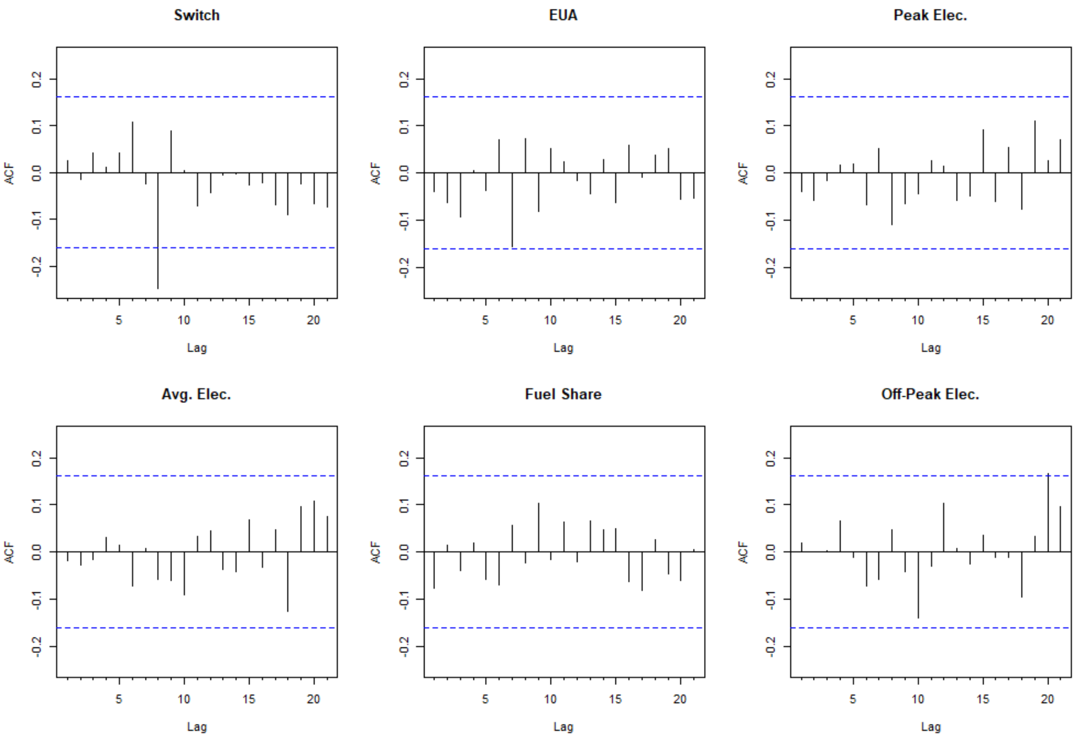
In order to conclude no serial correlation we want to not reject the test statistics. Based on tables the first lag length that we fail to reject no serial correlation for Phase II sub-sample is the second lag, which is consistent for all three of the models that uses a different electricity price variable at %10 level.

For serial correlation in Phase III, the test results suggest serial correlation at %10 level for models with *Average Electricity* and *Peak Electricity* and at %5 level for model with *Off-Peak Electricity* variables at second lag. We can only conclude no serial correlation for Phase III confidently at third lag. No serial correlation is satisfied with two lags for Phase II models and three lags for Phase III models. However as our goal is to compare the two sub-samples ideally we want them to have as similar specification as possible. If we were to estimate Phase III model with two lags we will have flawed specification due to serial correlation therefore we decided to use VAR(3) specifications for both sub-samples in the further analyses.

We check the residuals of the selected specifications by investigating the ACFs of them. ACF plots of the residuals from variables are presented in figures 8 and 9. Note that residuals of EUA, Switch, Avg. Elec. are obtained from the model with Avg. Elec. while residuals of Peak Elec. and Off-Peak Elec. are obtained from their respective models.

Phase 2

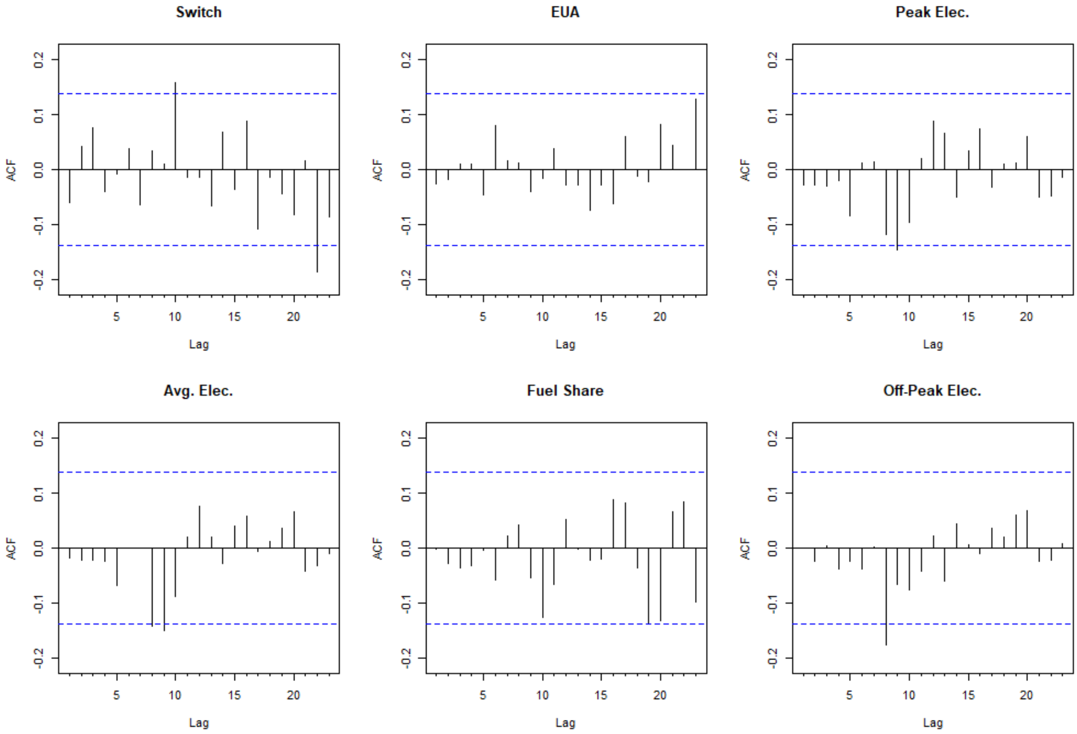
Figure 8: ACF plots of VAR(3) model residuals for Phase 2



**Switch-*, *EUA-*, *Average Electricity-* residuals are obtained from the Average Electricity model specification. ACF plots for Peak and Off-Peak Electricity are based on residuals from their respective model specification. Their corresponding *EUA, and SWITCH* ACF plots are found in the appendix figures 14 and 15.

Phase 3

Figure 9: ACF plots of VAR(3) model residuals for Phase 3



**Switch-, EUA-, Average Electricity-* residuals are obtained from the Average Electricity model specification. ACF plots for Peak and Off-Peak Electricity are based on residuals from their respective model specification. Their corresponding *EUA, and SWITCH* ACF plots are found in the appendix figures 16, 17.

Based on the ACF plots of Phase II model residuals, most of them depict white-noise residuals with barely any significant spike. Switch variable has one significant spike at 8th lag. For Phase III the residuals also mostly behave like white noise with some borderline significant spikes at the higher order lags.

Table 8: VAR(3) diagnostic tests

	Phase 2		
	With Avg. Elec.	**With Peak Elec.**	**With Off-Peak Elec.**
Normality	104,78 (0,00)	83,49 (0,00)	205,61 (0,00)
Kurtosis	75,36 (0,00)	63,85 (0,00)	139,99 (0,00)
Skewness	29,42 (0,00)	19,63 (0,00)	65,62 (0,00)
No ARCH	507,08 (0,40)	511,22 (0,35)	487,98 (0,64)
	Phase 3		
	With Avg. Elec.	**With Peak Elec.**	**With Off-Peak Elec.**
Normality	161,16 (0,00)	193,34 (0,00)	324,90 (0,00)
Kurtosis	146,54 (0,00)	171,36 (0,00)	262,61 (0,00)
Skewness	14,62 (0,00)	21,98 (0,00)	62,29 (0,00)
No ARCH	501,34 (0,47)	477,79 (0,75)	541,33 (0,09)

*The values indicate χ^2 values for the test and values in parentheses indicate corresponding p-values.

No ARCH effect is concluded for Phase II sub-sample as we cannot reject based on our test statistics. In Phase III we cannot reject for systems with average and peak electricity and its only borderline for off-peak electricity. We conclude that there is no apparent ARCH effect in our models.

However, Jarque-Bera test for normality is rejecting significantly H_0: of normality of the models' residuals. Non-normality is not due to kurtosis or skewness specifically, as both measures of no kurtosis and no skewness are rejected. While its not ideal, in applied work VEC models seem to often have non-normal distribution for their residuals which can be seen in the works of Johansen and Juselius (1990) and Juselius and MacDonald (2004). Furthermore, Gonzalo (1994), shows that properties of optimal inferences in maximum likelihood estimators hold even in finite samples, even when residual distribution is non-normal.

Considering non-normality is not a major problem and the models are not depicting serial correlation, we conclude that we have valid model specifications and which yield valid results.

8.4 Cointegration Analyses

Concluding existence of unit root in the variables in our system, we proceed by investigating whether a long-run relationship exists between them. We have prior introduced the concept of cointegration, paired with the appropriate test: Thus, the cointegration analyses using the sequential Johansen cointegration test results are presented in table below.

The test is performed on 3 different samples; these are Phase II, Phase III and the sample that includes the both. Additionally, we test with three variable systems: *Average*, *Peak* and *Off-Peak* electricity prices as the electricity price variables.

As mentioned in the methodology section the assumption on the deterministic terms included in the cointegration test matters greatly. Lütkepohl (2005), suggests including the trend term in the process if linear trend in levels is a possibility. However, we also argue that this decision also result in loss of explanatory power. Given the low power of the test, we decide against the inclusion of a trend in levels and proceed with the case 2.

$$Case\ 2 : \tau = \rho = \gamma = 0$$

: Mean of cointegration vectors is μ, no trends in levels or first differences.

For the determination of specification in cointegration tests, visual inspection of the series can be useful. Lütkepohl gives the example of an interest rate series, as such series is unlikely to have a long term trend therefore just including a mean term in cointegration specification is likely sufficient. Consequently, looking at the time series plots presented in the data section, while there might be some local trending behaviour in the series, it is hard to conclude on a long term trend. For this reason we conclude that only having a mean term in the specification is sufficient. The lag lengths specified in the test is based on the optimal lag length decided in the model specification section for Phase II and III, and we use K=2 lags for the full-sample.

Table 9: Johansen Cointegration test results

Phase 2 and 3						
	Test Statistic			**Critical Values**		
H_0	**with Avg.**	**with Peak**	**with Off-Peak**	**%10**	**%5**	**%1**
r≤3	1.74	1.73	1.70	7.52	9.24	12.97
r≤2	5.43	5.41	5.44	17.85	19.96	24.60
r≤1	50.80	50.59	44.61	32.00	34.91	41.07
r=0	120.25	114.18	144.01	49.65	53.12	60.16
Phase 2						
	test statistic					
H_0	**with Avg.**	**with Peak**	**with Off-Peak**	**%10**	**%5**	**%1**
r≤3	1.41	1.34	1.46	7.52	9.24	12.97
r≤2	8.20	7.99	8.42	17.85	19.96	24.60
r≤1	28.53	27.97	27.28	32.00	34.91	41.07
r=0	70.67	65.83	81.15	49.65	53.12	60.16
Phase 3						
	test statistic					
H_0	**with Avg.**	**with Peak**	**with Off-Peak**	**%10**	**%5**	**%1**
r≤3	1.08	1.10	1.01	7.52	9.24	12.97
r≤2	10.24	10.42	9.89	17.85	19.96	24.60
r≤1	25.91	27.18	23.93	32.00	34.91	41.07
r=0	62.84	62.16	63.23	49.65	53.12	60.16

*Trace-Test represents a sequential test; we first test *r=0* and sequentially move up until we cannot reject our Null any longer.

Results from Johansen trace test are presented in Table 9 above. The test result for the full-sample which contains both phases is showing there are two cointegrating relationships for all systems with different electricity price as the test statistics for r≤1 is larger than 1% significance level. However when divided into sub-samples as Phase II and Phase III, number of cointegrating relationships is dropping to one, as the test fails to reject less than two cointegrating relationships. Different ranks of cointegration between full-sample and sub-samples may suggest that the long-run relationship apparent in the full-sample becomes insignificant when the sample is divided. Furthermore, Hakkio and Rush (1991), argues that length of time period included in the cointegration analyses is crucial. Considering when divided into two sub-samples the time span of our data is only around 3 years for Phase II and around 4 years for Phase III, testing cointegration in the full-sample might be yielding a more robust long-run relationsip between our variables. Additionally, the rank of cointegration doesn't change when we test for it with Case 3 specification, the trace test results with Case 3 can be found in Table 20 in the appendix section.

Nevertheless, we find that there exists a long run relationship between the variables in all three of the systems tested. We proceed with modeling the vector error correction models with one cointegrating relationship in both sub-samples of Phase II and III.

9 Estimation Results

9.1 Vector Error Correction Models

Long Run Estimations on System with Average Electricity

We have so far determined the optimal number of lags and the rank of cointegration of our respective model specifications. In this section we present and analyze the vector error correction estimation (VECM) results. As mentioned in the model specification section even though, we have determined optimal lag length of p=2 for all Phase II VAR models based on serial-correlation and information criteria we present the VECM results for lag length of p=3 instead of two for easier comparsion between two phases. We are aware that within econometric modelling we often strive for the most parsimonious model, however we decided in this instance that enforcing the same lag-structure yield more benefits. Given that the optimal lag length p was determined within a VAR setting, the corresponding VEC models will have $p^* = p - 1$ lags. This, simply stems from the combination of variables in levels and first differences included in a VECM. We present all models with different electricity prices in order to assess whether electricity producing firms changing prices for certain times of the day.
Following Freitas and Silva (2013), we normalize our cointegration vector, β on the electricity price variables. By normalizing on the electricity price, we can more easily see the long run effects of the *EUA, Switch and Fuel Share* on the electricity prices. This makes sense in our case, as electricity prices depict a measurable output of firm behaviour, and as such the relationship is in our main interest.

The long run equations for the system using Average Electricity estimations are obtained as follows;

$$\textbf{Phase II:} \quad \textit{Average Electricity} = -0.918\ \textit{Switch} - 84.620\ \textit{Fuel Share} + 1.237 EUA \tag{63}$$

$$\textbf{Phase III:} \quad \textit{Average Electricity} = -0.660\ \textit{Switch} - 26.123\ \textit{Fuel Share} + 1.058 EUA \tag{64}$$

The estimated cointegrating relationships in equations 63 & 64 show that electricity prices are affected by *Switch* and *Fuel Share* negatively and positively by the EUA - aka carbon prices. It can also be inferred that such relationship is consistent in both phases. The expectation for the EUA coefficient is to be positive. It suggest that an increase in carbon prices is reflected in higher electricity prices. This hints towards permanent cost pass-through effects to electricity prices. Therefore, the estimated long-run relationship between electricity prices and carbon prices are sensible. The long-run coefficient for the EUA variable is slightly smaller in Phase III. This is indicative of a lower cost passing through in Phase III. The cointegrating relationships are similar to those that are found by Fell (2010) and Freitas and Silva (2013).

With regards to *Switch, & Fuel Share* the coefficients are negative. An increase in Switch depicts an increased opportunity of switching, as input costs of gas decrease relative to coal. This, means that firms can lower their electricity prices, as marginal production costs are lower.

Similarly, the coefficient of *Fuel Share* is negative. Once more, Fuel Share is defined as the ratio of gas over coal used in production. Consequently, an increase in *Fuel Share* depicts a relative increase of gas in the production mix. One can easily think of three scenarios as to why firms switch to gas production: (1) A significant increase in carbon prices, (2) A significant increase in coal prices, (3) A significant increase in electricity demand beyond base load. The first two represent opportunities for reducing cost as opposed to using coal, and thus could potentially lead to a decrease in electricity prices. The (3) option would likely lead to an increase, as firms simply produce as a response to demand, and not as a response to their respective input prices.

Short Run Estimations on System with Average Electricity

Short run estimations for the models with *Average Electricity* model specification are presented in tables 10 and 11 for Phase II and III respectively.

In Phase II, the error correction term (ECT) coefficients are significant for *Average Electricity* and *Fuel Share*. Within the *Switch* and *EUA* equations' the ECT coefficients are not very significant both being slightly above 10% significance level. The insignificant ECT coefficient may be indicating towards the two variable being driven by other factors outside our variable system. The ECT coefficient within the *average electricity* price equation depicts a negative and significant coefficient (p =0.000). The negative sign implies that electricity price is converging back to the long run equilibrium. The coefficient of -*0.428* implies electricity price corrects about 43% every time period, within our system this corresponds to one week. *Switch* equation's ECT is also negative but smaller in magnitude and insignificant (p=0.114). Again, this suggest that *Switch* is correcting to the long run relationship although much smaller. However, statistically there is not enough evidence to conclude on the correction-behaviour. *EUA and Fuel Share* equations' ECT coefficients are negative as well and small in absolute values, indicating that these two variables are converging to the long run equilibrium very slowly. Nonetheless, *Fuel Share*'s ECT term is significant at a 5% significance level (p=0.000). The EUA ECT term is insignificant even at 10% (p=0.130).

Looking at the short-run coefficients, *average electricity* prices are affected by *Fuel Share* and *Switch*, positively by *Fuel Share* and negatively by *Switch*. Additionally, the *EUA* coefficients are positive for *Average Electricity* equation, and significant at a 10% significance level (p =0.055).

Switch is not affected by any other variable in the system significantly. *Fuel Share* is only affected by *average electricity* prices, meaning electricity producers use more natural gas fired plants when electricity gets more expensive, thus driving short run dynamics. *EUA* prices are only affected by changes in *fuel share* variable at borderline significance (p=0.100). For Phase III, the ECT coefficient of our *Average Electricity* equation is almost identical to the one present in Phase II. Yet, in Phase III *Average Electricity*'s speed of correction is higher considering ECT coefficient is considerably larger in absolute values compared to Phase II, being -0.697 in Phase III. It is significant at a 1% significance level (p=0.000). The *Switch* variable's ECT coefficient is still insignificant (p=0.470), as well as, *Fuel Share*'s (p=0.446). The ECT^{EUA} coefficient is significant in Phase III (p=0.029) but now its positive, albeit very small (0.015). Given the negative sign for *EUA* in the cointegration vector β, it is correcting towards the long-run path, although only very gradually.

Average Electricity prices seem to depicts more short run determinants in Phase III considering there are more significant coefficients in the *Average Electricity* equation. *Average Electricity* is significantly negatively affected by its own lags ($EUA_{t-1} : -0,256,\ EUA_{t-2} : -0.151$)) at 5% significance. Similarly, *EUA* prices depict negative adjustment within the short dynamics at 5% significance. *Switch* in Phase III affects *electricity price* positively (0.713) in the short run (p=0.018). Based on the *Switch* equation, Switch is negatively impacted by its own lag at a 10% level and positively by carbon prices (p =0.027) in the short run. The latter is in-line with the intuition, as higher carbon prices would lead lower demand for coal compared to natural gas, consequently raising the switch price. Fuel Share is only affected by its own lags at high significance ($FuelShare_{t-1} : p = 0.000,\ FuelShare_{t-2} : p = 0.003$).

Finally, short run dynamics in carbon prices are only affected by changes in *Switch* and only at a borderline significance (p=0.091). This result for carbon prices is surprising. Previous literature extensively tested for possible short run determinants. As such prior research has found, *electricity or Switch* prices to significantly affect the short-run dynamics. However we were only able to find few borderline significant short-run drivers for carbon price which is not consistent between phases.

Table 10: Phase II VECM results (with Average Electricity)

	Average Electricity			Switch			Fuel Share			EUA		
	Estimate	**Std. Error**	**Pr(>|t|)**	**Estimate**	**Std. Error**	**Pr(>|t|)**	**Estimate**	**Std. Error**	**Pr(>|t|)**	**Estimate**	**Std. Error**	**Pr(>|t|)**
ECT	−0.428**	0.105	0.000	−0.039	0.025	0.114	−0.007**	0.002	0.000	−0.014	0.009	0.130
Intercept	69.116**	18.997	0.000	5.328	4.483	0.237	1.343**	0.273	0.000	1.906	1.615	0.240
Average Electricity-1	−0.159	0.101	0.118	0.026	0.024	0.278	0.005**	0.001	0.002	0.006	0.009	0.514
Switch-1	0.325	0.363	0.373	−0.048	0.086	0.575	0.003	0.005	0.540	−0.012	0.031	0.707
Fuel Share-1	26.224**	8.018	0.001	0.894	1.892	0.637	-0.172	0.115	0.139	1.128^{+}	0.682	0.100
EUA-1	1.602	1.020	0.119	−0.144	0.241	0.550	−0.018	0.015	0.216	−0.088	0.087	0.309
Average Electricity-2	−0.054	0.086	0.529	0.030	0.020	0.141	0.001	0.001	0.507	0.000	0.007	0.965
Switch-2	−0.838**	0.349	0.018	−0.067	0.082	0.415	0.006	0.005	0.225	0.003	0.030	0.926
Fuel Share-2	9.178	6.711	0.174	−0.411	1.584	0.796	0.017	0.096	0.858	0.393	0.571	0.493
EUA-2	2.012^{+}	1.039	0.055	−0.160	0.245	0.515	−0.012	0.015	0.410	0.020	0.088	0.821

*Significance codes are 1% $**$, 5%$*$, 10%$^{+}$

Table 11: Phase III VECM results (with Average Electricity)

	Average Electricity			Switch			Fuel Share			EUA		
	Estimate	**Std. Error**	**Pr(>|t|)**	**Estimate**	**Std. Error**	**Pr(>|t|)**	**Estimate**	**Std. Error**	**Pr(>|t|)**	**Estimate**	**Std. Error**	**Pr(>|t|)**
ECT	−0.697**	0.115	0.000	0.021	0.029	0.470	-0.001	0.001	0.446	0.015*	0.007	0.029
Intercept	60.608**	11.515	0.000	−1.668	2.898	0.566	0.155	0.147	0.294	−1.330^{+}	0.703	0.060
Average Electricity-1	−0.256*	0.103	0.014	−0.026	0.026	0.319	−0.001	0.001	0.567	−0.007	0.006	0.296
Switch-1	0.368	0.299	0.220	−0.133^{+}	0.075	0.080	−0.004	0.004	0.314	−0.031^{+}	0.018	0.091
Fuel Share-1	9.802	6.023	0.105	−2.282	1.516	0.134	−0.347**	0.077	0.000	−0.001	0.368	0.997
EUA-1	0.853	1.222	0.486	−0.104	0.308	0.736	−0.023	0.016	0.139	0.037	0.075	0.620
Average Electricity-2	−0.151*	0.074	0.041	−0.022	0.018	0.237	−0.000	0.001	0.978	−0.002	0.004	0.654
Switch-2	0.713*	0.299	0.018	-0.055	0.075	0.468	0.005	0.004	0.161	-0.014	0.018	0.458
Fuel Share-2	0.740	5.802	0.899	-0.357	1.460	0.807	−0.222**	0.074	0.003	-0.106	0.354	0.766
EUA-2	−2.518*	1.185	0.035	0.664*	0.298	0.027	0.015	0.015	0.331	−0.027	0.072	0.714

*Significance codes are 1% $**$, 5%$*$, 10%$^{+}$

Long Run Estimations on Systems with Peak and Off-Peak Electricity

Having extensively discussed the result for average electricity prices we will now move towards splitting the effects into peak and off-peak electricity hours. Generally, it is argued that peak hours respond more in line with market dynamics as peak prices are more reliant on short-run electricity demand dynamics.

Again, the estimated long run relationship are normalized for electricity prices. We present the cointegration relationship for the systems with *Peak Electricity* and *Off-Peak Electricity* below;

$$\textbf{Phase II:} \quad Peak.Elec. = -0.953Switch - 84.454FuelShare + 1.260EUA \tag{65}$$

$$\textbf{Phase III:} \quad Peak.Elec. = -0.804Switch - 33.472FuelShare + 1.035EUA \tag{66}$$

$$\textbf{Phase II:} \quad Off-Peak.Elec. = -0.881Switch - 79.248FuelShare + 1.111EUA \tag{67}$$

$$\textbf{Phase III:} \quad Off-Peak.Elec. = -0.463Switch - 15.713FuelShare + 1.026EUA \tag{68}$$

Based on the long-run equations presented above, we see that relationships for systems with *Peak* and *Off-Peak Electricity* variables are identical to the system with *Average Electricity* variable in terms of signs. We expected that coefficients would not change signs but that they will have different magnitudes for different systems. Coefficients for carbon price variable in Phase II are all identical between three different systems, all being between the range of 1.1 to 1.3. Nevertheless, *Off-Peak* coefficients are generally lower in magnitude than its *Peak* counterparts. For Phase III equations, this coefficient decreases for all three systems consistently to around 1, with less magnitude difference between *Peak and Off-Peak*. This indicates that electricity prices depend less on carbon prices in long-run. The expectation based on previous literature was that peak electricity prices would be affected more by changes in carbon prices however, it is hard to conclude that by looking at our estimated long-run coefficients.

The ECT coefficients are also similar between different variable systems. For Phase II all ECT coefficients are negative with Peak Electricity and Fuel Share equations having significant error correction terms for all three systems ($ECT^{PEAK} : p = 0.000, ECT^{OFF\ PEAK} : p = 0.000$). Nonetheless, for the model specification employing *Off-Peak*, the ECT^{EUA} coefficient is only at borderline significance at (p=0.099). In Phase III $ECT^{SWITCH}, ECT^{FUEL\ SHARE}$ coefficients for Switch and Fuel Share becomes insignificant irrespectively of the model specification. However, ECT^{EUA} is now significantly positive for both model specifications, depite being low in magnitude ($ECT^{EUA}_{PEAK} = 0.012, ECT^{EUA}_{OFFPEAK} = 0.017$).

Short Run Estimations on Systems with Peak and Off-Peak Electricity

Comparing the short-run coefficients of two different variable systems; the electricity price equations are virtually identical in Phase II. The only notable difference is that *Off-Peak* electricity prices are more dependent on their own lags compared to *Average* and *Peak* prices ($OFFPEAK_{t-1} : p = 0.044, OFFPEAK_{t-2} : p = 0.021$).

During Phase III, all electricity prices definitions are negatively affected by changes in carbon prices at lag 2 (p=0.051, and p0.057). *Switch* is not affected by any other variables in the system in the short-run whereas *Fuel Share* is generally affected by it own lags only. Which seems consistent between the two different model specifications. Finally, once again we fail to find any significant short-run determinants for carbon prices in Phase III. We can only find borderline significance for *Switch* at a 10% level.

Table 12: Phase II VECM results (with Peak. Elec.)

	Peak Electricity			**Switch**			**Fuel Share**			**EUA**		
	Estimate	**Std. Error**	**Pr(>|t|)**	**Estimate**	**Std. Error**	**Pr(>|t|)**	**Estimate**	**Std. Error**	**Pr(>|t|)**	**Estimate**	**Std. Error**	**Pr(>|t|)**
ECT	-0.476**	0.111	0.000	-0.038	0.023	0.110	-0.006**	0.001	0.000	-0.012	0.008	0.161
Intercept	83.236**	21.803	0.000	5.541	4.561	0.227	1.281**	0.282	0.000	1.767	1.647	0.285
Peak Electricity-1	-0.113	0.105	0.284	0.028	0.022	0.204	0.004**	0.001	0.001	0.003	0.008	0.707
Switch-1	0.497	0.407	0.225	-0.048	0.085	0.572	0.003	0.005	0.556	-0.013	0.031	0.672
Fuel Share-1	28.879**	8.689	0.001	0.667	1.818	0.714	-0.223*	0.112	0.049	1.021	0.656	0.122
EUA-1	2.007	1.147	0.083	-0.143	0.240	0.553	-0.019	0.015	0.205	-0.085	0.087	0.329
Peak Electricity-2	-0.014	0.087	0.874	0.033$^+$	0.018	0.074	0.001	0.001	0.278	-0.000	0.007	0.961
Switch-2	-0.838*	0.393	0.035	-0.064	0.082	0.435	0.005	0.005	0.298	0.002	0.030	0.957
Fuel Share-2	13.614$^+$	7.389	0.068	−0.497	1.546	0.748	−0.016	0.095	0.869	0.317	0.558	0.570
EUA-2	2.169$^+$	1.172	0.066	-0.178	0.245	0.468	-0.014	0.015	0.357	0.027	0.089	0.759

*Significance codes are 1% ∗∗, 5%∗, 10%$^+$

Table 13: Phase III VECM results (with Peak. Elec.)

	Peak Electricity			**Switch**			**Fuel Share**			**EUA**		
	Estimate	**Std. Error**	**Pr(>|t|)**	**Estimate**	**Std. Error**	**Pr(>|t|)**	**Estimate**	**Std. Error**	**Pr(>|t|)**	**Estimate**	**Std. Error**	**Pr(>|t|)**
ECT	-0.733**	0.114	0.000	0.018	0.023	0.435	-0.001	0.001	0.365	0.012*	0.006	0.034
Intercept	80.460**	14.416	0.000	-1.873	2.965	0.528	0.176	0.150	0.240	−1.331$^+$	0.721	0.067
Peak Electricity-1	-0.205*	0.103	0.047	-0.021	0.021	0.311	-0.001	0.001	0.456	-0.006	0.005	0.270
Switch-1	0.429	0.365	0.241	−0.133$^+$	0.075	0.078	-0.004	0.004	0.282	−0.030$^+$	0.018	0.099
Fuel Share-1	17.710*	7.376	0.017	-2.343	1.517	0.124	-0.343**	0.077	0.000	-0.007	0.369	0.984
EUA-1	0.520	1.494	0.728	-0.103	0.307	0.739	-0.023	0.016	0.133	0.033	0.075	0.661
Peak Electricity-2	-0.097*	0.074	0.193	-0.019	0.015	0.205	-0.000	0.001	0.824	-0.003	0.004	0.488
Switch-2	1.122$^+$	0.365	0.002	-0.056	0.075	0.460	0.005	0.004	0.171	-0.013	0.018	0.495
Fuel Share-2	6.397	7.074	0.367	-0.317	1.455	0.828	-0.215**	0.073	0.004	-0.102	0.354	0.774
EUA-2	−2.845$^+$	1.451	0.051	0.648*	0.298	0.031	0.014	0.015	0.365	-0.027	0.073	0.709

*Significance codes are 1% ∗∗, 5%∗, 10%$^+$

Table 14: Phase II VECM results (with Off-Peak. Elec.)

	Off-Peak Electricity			**Switch**			**Fuel Share**			**EUA**		
	Estimate	**Std. Error**	**Pr(>|t|)**	**Estimate**	**Std. Error**	**Pr(>|t|)**	**Estimate**	**Std. Error**	**Pr(>|t|)**	**Estimate**	**Std. Error**	**Pr(>|t|)**
ECT	-0.477**	0.108	0.000	-0.040	0.027	0.139	-0.008**	0.002	0.000	-0.016^{+}	0.010	0.099
Intercept	69.437**	17.059	0.000	4.555	4.219	0.282	1.272**	0.255	0.000	1.944	1.512	0.201
Off-Peak Electricity-1	-0.203*	0.099	0.044	0.022	0.025	0.382	0.004**	0.001	0.004	0.011	0.009	0.226
Switch-1	0.172	0.353	0.627	-0.045	0.087	0.609	0.004	0.005	0.439	-0.011	0.031	0.717
Fuel Share-1	26.761**	7.858	0.001	0.958	1.943	0.623	-0.157	0.117	0.183	1.209^{+}	0.696	0.085
EUA-1	1.040	0.976	0.289	-0.131	0.241	0.588	-0.015	0.015	0.309	-0.094	0.086	0.277
Off-Peak Electricity-2	-0.193*	0.083	0.021	0.019	0.020	0.361	0.000	0.001	0.687	0.003	0.007	0.689
Switch-2	-0.719*	0.338	0.035	-0.064	0.083	0.441	0.008	0.005	0.120	0.006	0.030	0.846
Fuel Share-2	6.134	6.555	0.351	-0.395	1.621	0.808	0.038	0.098	0.696	0.453	0.581	0.437
EUA-2	2.080^{+}	0.981	0.036	-0.127	0.242	0.601	-0.012	0.015	0.420	0.007	0.087	0.939

*Significance codes are 1% $**$, 5%$*$, 10%$^{+}$

Table 15: Phase III VECM results (with Off-Peak. Elec.)

	Off-Peak Electricity			**Switch**			**Fuel Share**			**EUA**		
	Estimate	**Std. Error**	**Pr(>|t|)**	**Estimate**	**Std. Error**	**Pr(>|t|)**	**Estimate**	**Std. Error**	**Pr(>|t|)**	**Estimate**	**Std. Error**	**Pr(>|t|)**
ECT	-0.676**	0.121	0.000	0.022	0.035	0.527	-0.000	0.002	0.782	0.017*	0.008	0.042
Intercept	36.823**	7.830	0.000	-1.004	2.257	0.657	0.082	0.115	0.478	-0.879	0.547	0.110
Off-Peak Electricity-1	-0.332**	0.106	0.002	-0.029	0.031	0.344	0.000	0.002	0.958	-0.007	0.007	0.374
Switch-1	0.302	0.262	0.251	-0.130^{+}	0.076	0.086	-0.003	0.004	0.368	-0.032^{+}	0.018	0.081
Fuel Share-1	-2.313	5.168	0.655	-2.087	1.490	0.163	-0.357**	0.076	0.000	0.040	0.361	0.912
EUA-1	1.276	1.070	0.234	-0.098	0.308	0.750	-0.021	0.016	0.189	0.045	0.075	0.545
Off-Peak Electricity-2	-0.199**	0.073	0.007	-0.016	0.021	0.449	0.001	0.001	0.477	-0.001	0.005	0.867
Switch-2	0.181	0.263	0.492	-0.051	0.076	0.502	0.005	0.004	0.176	-0.016	0.018	0.389
Fuel Share-2	-8.881^{+}	5.110	0.084	-0.421	1.473	0.775	-0.232**	0.075	0.002	-0.056	0.357	0.875
EUA-2	-1.988^{+}	1.037	0.057	0.701*	0.299	0.020	0.014	0.015	0.348	-0.029	0.072	0.686

*Significance codes are 1% $**$, 5%$*$, 10%$^{+}$

9.2 Restrictions on α and β Matrices

Up to this point we have estimated and analyzed the VEC models without imposing any restrictions on either α or β. We can however impose restrictions on the loading matrix (α) and cointegration vector (β). Consider the following VECM specification;

$$\Delta x_t = \alpha\beta' x_{t-1} + \phi\Delta x_{t-1} + \varepsilon_t$$

From the VECM estimation results in Vector Error Correction Models subsection we saw that the error correction terms for certain equations are insignificant. More precicely, *Switch* is insignificant for both phases and whereas our *Fuel Share* variable is for Phase III only. This hints towards that these variables are not moving with the estimated long-run equation. In order to formally test for weak exogeneity of the variables in our system, we can impose zero restriction on the α matrix and test the H_0 whether zero restrictions are sensible or not. In a four variable system the α matrix is a 4×1 matrix.

$$\alpha = \begin{bmatrix} \alpha_{11} \\ \alpha_{21} \\ \alpha_{31} \\ \alpha_{41} \end{bmatrix}$$

By imposing zeros to the corresponding rows of α matrix we can test whether there are weakly exogenous variables with a LR test. Testing each variable in our system individually we can impose the α matrices in the following format and test the restrictions;

$$\alpha = \begin{bmatrix} 0 \\ \alpha_{21} \\ \alpha_{31} \\ \alpha_{41} \end{bmatrix}, \begin{bmatrix} \alpha_{11} \\ 0 \\ \alpha_{31} \\ \alpha_{41} \end{bmatrix}, \begin{bmatrix} \alpha_{11} \\ \alpha_{21} \\ 0 \\ \alpha_{41} \end{bmatrix}, \begin{bmatrix} \alpha_{11} \\ \alpha_{21} \\ \alpha_{31} \\ 0 \end{bmatrix}$$

The χ^2 test-statistics and p-values of test results are presented in table 16. The results differ between two phases. We are rejecting H_0 for electricity price variables, as well as, *Fuel Share*, while we cannot reject for *Switch* and *EUA* variables in Phase II. The results for Phase II implies that *Switch* and *EUA* are weakly exogenous and are not correcting towards the long-run equilibrium within the system. *Switch* and *EUA* are the most global variables in the system which might be the reason for their long-run driving force, but lack of short-run dynamics. In Phase III Switch is still weakly exogenous as we cannot reject the H_0 for it, but this time we reject the null of weak-exogeneity for *EUA*. Different than Phase II, in this period *Fuel Share* variable is weakly exogenous based on the test. *Switch* being the long-run driver in the system for Phase III is still economically sensible. With regards to *Fuel Share*, the lack of correcting behaviour in the variable might have several reasons. (i) Either fuel mix is too sticky in practice, and thus is more rigid than anticipated, or (ii) fuel mix moves with forward markets rather than spot prices. It is sensible to assume that firms forecast their electricity demand, and buy their input fuels and carbon allowances on forward rather than spot markets. Thus, creating a mismatch between commodity spot prices, and changes in production fuel share. Hence, making the *Fuel Share* weakly exogenous in our system for Phase III.

Table 16: Testing weak exogeneity on α

	Phase 2					
	With Avg. Elec.		**With Peak Elec.**		**With Off-Peak Elec.**	
	χ^2	**p-value**	χ^2	**p-value**	χ^2	**p-value**
Switch	2.36	0.12	2.81	0.09	1.63	0.20
EUA	2.31	0.13	2.62	0.11	2.07	0.15
Avg. Elec.	6.81	0.01	-	-	-	-
Peak Elec.	-	-	7.99	0.00	-	-
Off-Peak Elec.	-	-	-	-	8.82	0.00
Fuel Share	6.45	0.01	4.37	0.04	10.38	0.00
	Phase 3					
	With Avg. Elec.		**With Peak Elec.**		**With Off-Peak Elec.**	
	χ^2	**p-value**	χ^2	**p-value**	χ^2	**p-value**
Switch	1.41	0.23	1.57	0.21	1.04	0.31
EUA	4.93	0.03	4.74	0.03	4.34	0.04
Avg. Elec.	26.01	0.00	-	-	-	-
Peak Elec.	-	-	30.51	0.00	-	-
Off-Peak Elec.	-	-	-	-	18.14	0.00
Fuel Share	0.01	0.99	0.02	0.90	0.17	0.68

As *Switch* is consistently weakly exogenous in both sub-samples we can estimate the long run relationship by restricting the corresponding α element for *Switch* variable and see whether β changes significantly or not. The long-run relationships with α restrictions on *Switch* becomes;

$$\textbf{Phase II:} \quad Avg.Elec. = -0.988Switch - 223.382FuelShare + 3.814EUA \tag{69}$$

$$\textbf{Phase III:} \quad Avg.Elec. = -2.144Switch - 129.525FuelShare + 0.821EUA \tag{70}$$

$$\textbf{Phase II:} \quad PeakElec. = -1.010Switch - 245.009FuelShare + 4.260EUA \tag{71}$$

$$\textbf{Phase III:} \quad PeakElec. = -2.593Switch - 157.638FuelShare + 0.824EUA \tag{72}$$

$$\textbf{Phase II:} \quad Off - PeakElec. = -0.984Switch - 206.403FuelShare + 3.413EUA \tag{73}$$

$$\textbf{Phase III:} \quad Off - PeakElec. = -2.166Switch - 132.960FuelShare + 1.112EUA \tag{74}$$

The long-run relationships we obtain by imposing weak-exogeneity to *Switch* can be compared to the unrestricted models' long-run relationships presented in the vector error correction estimation subsection. The direction of the relationship is still the same with *Switch* and *Fuel Share* being negative and *EUA* being positive. For Phase II relationships coefficient for *EUA* are larger than the unrestricted models'. Consequently for Phase III, *Switch* variable's coefficient is considerably larger compared to the unrestricted models. While magnitudes of the variables in the long-run relationships differ, the direction of them are same, hence we continue our analyses with the unrestricted model.

Similar to the imposing α restrictions, we can impose zero or sign restriction on the β matrix and estimate the restricted VECM. β is a $[K \times r]$, where K is equal to the number of variables including the constant and r being the rank of cointegration. We have 4 variables in our system and we include the intercept making [K=5]. Then the β matrix can be written as;

$$\beta = \begin{bmatrix} \beta_{11} \\ \beta_{21} \\ \beta_{31} \\ \beta_{41} \\ \beta_{51} \end{bmatrix}$$

Similar to the weak exogeneity test, we can test whether certain variables are significant or not for the long-run cointegrating relationship. To do so, we can restrict the estimated elements in β to zero and simply perform an LR test. Note that the cointegration relationship is normalized for the electricity price variables, meaning that β_{11} element in the matrix is 1 by definition. Once again we test the individual variable's long run coefficient by imposing following β matrices to the estimation;

$$\beta = \begin{bmatrix} 1 \\ 0 \\ \beta_{31} \\ \beta_{41} \\ \beta_{51} \end{bmatrix}, \begin{bmatrix} 1 \\ \beta_{21} \\ 0 \\ \beta_{41} \\ \beta_{51} \end{bmatrix}, \begin{bmatrix} 1 \\ \beta_{21} \\ \beta_{31} \\ 0 \\ \beta_{51} \end{bmatrix}, \begin{bmatrix} 1 \\ \beta_{21} \\ \beta_{31} \\ \beta_{41} \\ 0 \end{bmatrix}$$

The test results are χ^2 -distributed, where the corresponding test-statistics and p-values are presented in table 17.

Table 17: Testing cointegrating relationship on β

	Phase 2					
	With Avg. Elec.		**With Peak Elec.**		**With Off-Peak Elec.**	
	χ^2	**p-value**	χ^2	**p-value**	χ^2	**p-value**
Electricity	39.45	0.00	39.96	0.00	41.76	0.00
Switch	29.03	0.00	28.66	0.00	46.89	0.00
EUA	15.99	0.00	15.84	0.00	19.25	0.00
Fuel Share	38.89	0.00	42.15	0.00	55.26	0.00
	Phase 3					
	With Avg. Elec.		**With Peak Elec.**		**With Off-Peak Elec.**	
	χ^2	**p-value**	χ^2	**p-value**	χ^2	**p-value**
Electricity	35.91	0.00	33.96	0.00	38.26	0.00
Switch	43.48	0.00	47.49	0.00	35.66	0.00
EUA	33.71	0.00	1.65	0.80	23.33	0.00
Fuel Share	45.77	0.00	32.71	0.00	37.40	0.00

*We normalize the long-run relationship to electricity price variable for other variables and we normalize for Switch to test the β element of electricity price variables.

The results above show that estimated cointegrating relationships are mostly significant. Even though, *EUA* is significant for the systems with *Average Electricity* and *Off-Peak Electricity* it is insignificant for *Peak Electricity* prices in Phase III with (p=0.80) eventhough it is signifcant in Phase II.

Besides zero restrictions we can similarly set sign restrictions or impose an entirely different cointegrating relationship on β matrix and estimate VECM with self-imposed restrictions. Unlike Johansen and Juselius (1990) in their paper on Danish and Finnish macroeconomic data we do not possess a robust economic theory with regards to the long-run relationships between our variables, as such we do not attempt to impose our own cointegration relationship. Our estimated unrestricted cointegration vectors in the vector error correction models section make economic sense. Additionally, we are not particularly interested in testing certain long-run relationships between our variables. We are simply comparing these statistical relationships between sub-samples and specifications. Another reason for why we don't impose any restrictions on α or β matrices is because, Sims (1980) already argues that user-imposed restrictions on complex systems of equations in VAR models like ours are not desirable. Therefore, we continue our analyses by using the estimated cointegration relationship.

9.3 Parameter Stability

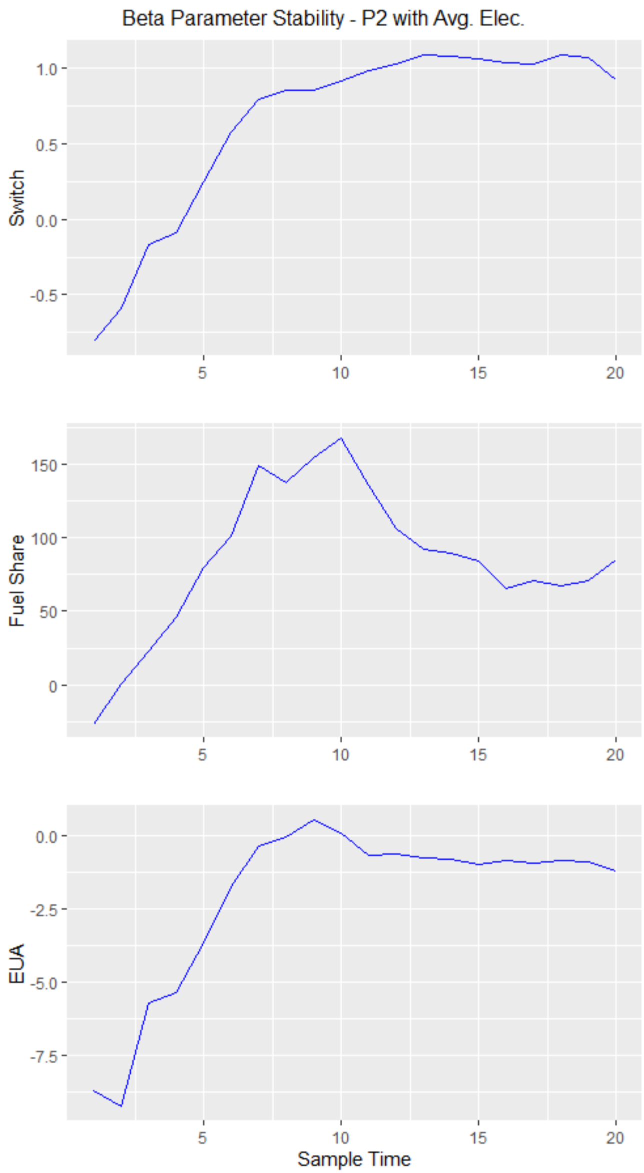
In order to see whether the cointegrating relationship between our variables is changing or not through our sample, we recursively estimate the β from the VECM specification. We start our estimation with 54 observations for Phase II and 52 observations for Phase III and increase the sample size by 5 at each step before estimating and saving the β coefficient. Plots for the β coefficients are presented below in figures 10 and 11. The cointegrating relationship is normalized by the electricity prices which means they take the value of 1 in each estimation. Note that we are plotting the values from β coefficient, the long-run coefficients presented in the Vector Error Correction Models section are these values but multiplied by -1.

The plots for Phase II with different electricity prices are identical to each other. β elements for *Switch* starts off by having a negative value but about a quarter way into the Phase II sample it becomes positive and stays around 1 for the second half of the sample. *Fuel Share* β element is quickly picking up to around 170 level in the middle of the sample but then decreases down to 70 levels. *EUA* variable's β element is negative at around -8 level but then increases, shortly becoming positive around mid-sample and then stays around at -1 level for the second half of the Phase II sample. All β elements are depicting convergence to their full-sample estimations without large jumps.

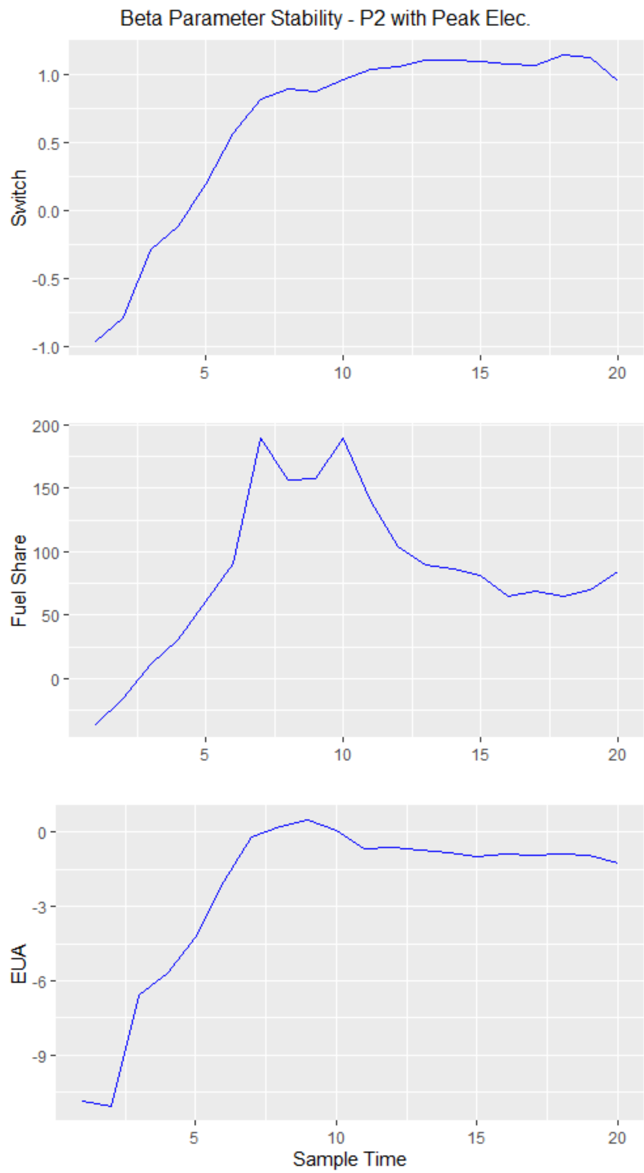
The plots for Phase III shows much more movement in the first parts of the sample. For the systems with average and off-peak electricity prices there are very large jumps in β values for all three variables.

These large movements however, are not persistence as the values are dying down and going back to a stable level quickly through the sample. We might be seeing such movements due to estimation of a strong long run coefficient in a short span of time. EUA variable's β values shows large movements around 0 before dying down to around -1 level around mid-sample. As these are happening in the early stage of recursive estimation with a relatively small sample size, a strong relationship in a short amount of time can affect the estimation results and depict large movements in the plots. Nevertheless, these strong movements die off before mid-sample, which indicates somewhat consistent long run relationship between our variables in most of the sample.

Figure 10: Parameter Stability for Phase II



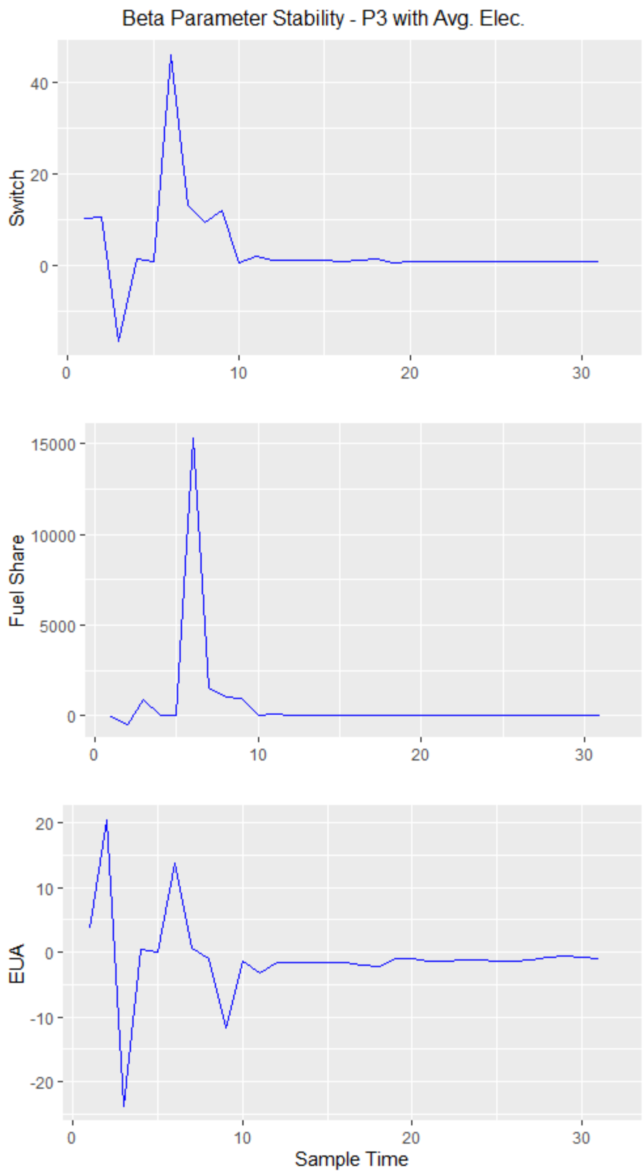
(a) P2: Beta Parameters over time for system with Average Electricity



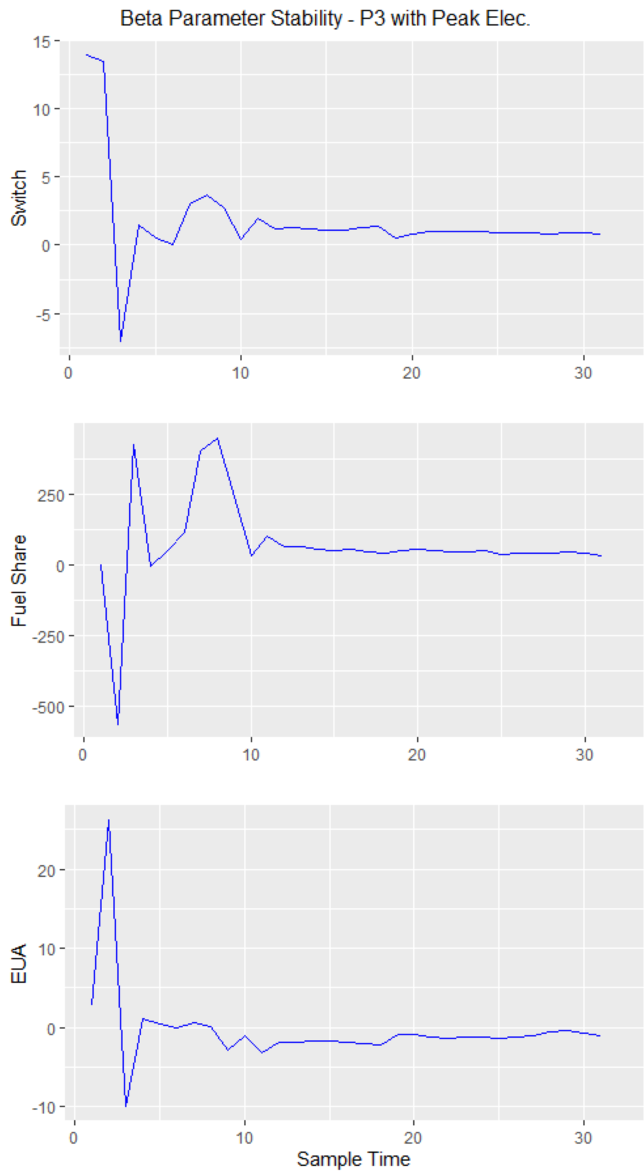
(b) P2: Beta Parameters over time for system with Peak Electricity

(c) P2: Beta Parameters over time for system with Off-Peak Electricity

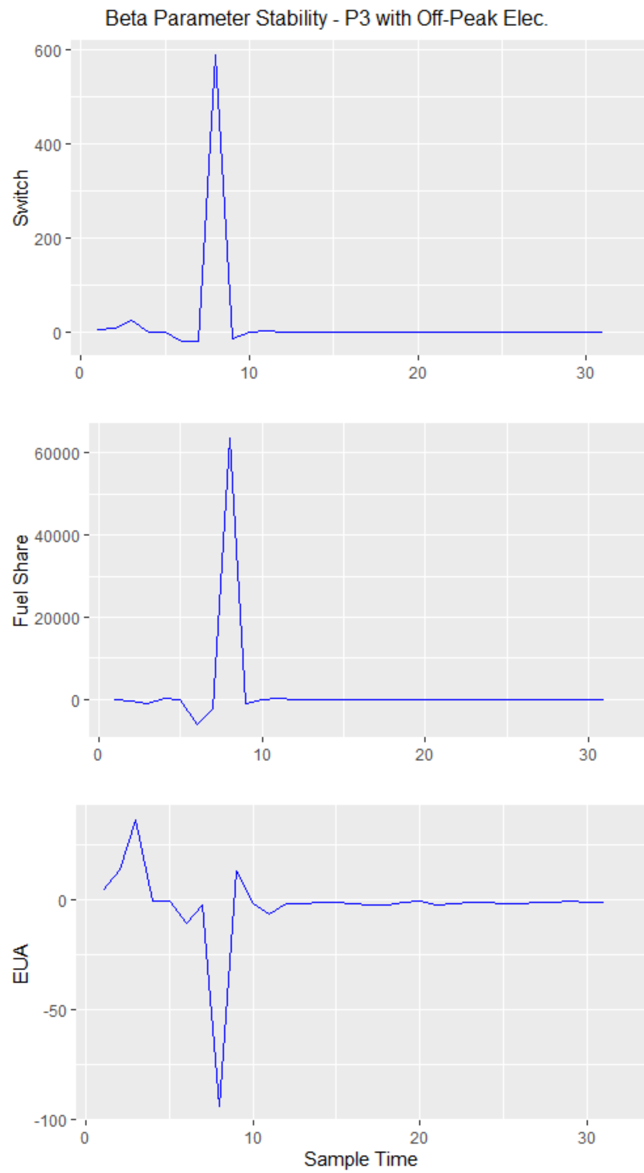
Figure 11: Parameter Stability for Phase III



(a) P3: Beta Parameters over time for system with Average Electricity



(b) P3: Beta Parameters over time for system with Peak Electricity



(c) P3: Beta Parameters over time for system with Off-Peak Electricity

9.4 Impulse Response Functions (IRF)

In the broadest sense, this research has hypothesized a shift in dynamics between the variables included in our systems. Within our problem statement we have thus narrowed our broad research question of whether resource allocation matters within a cap and trade system for market dynamics, to the more context and testable hypothesis regarding a switch in electricity generating firm behaviour. Within the context of this research, we aim to investigate the change in firm behaviour using impulse response functions. As mentioned in our methodology, impulse response functions plot a variable's response to a shock to another variable in the system over time. Thus, impulse response functions present a fitting tool to assess whether electricity and power generation firm's behaviour to shocks in carbon prices has changed due to a regime switch in resource allocation.

More so, we employ orthogonal impulse responses. Doing so, implies that the order of our variable matter - as we introduce a recusive, causal chain. Preceeding this analysis, we have tested exclusion restricitons on our α coefficients to test on weak exogeneity. We concluded with weakly-exogeonous *SWITCH FUEL SHARE*. Practically, this means that either variable is a driver in our long-run equation - yet not influences by any other variable. Again, the order of the variable in our recursive system matters - as the preceding variable in not contemporaneously affected by following variables. Hence, in other words - it is weakly exogenous to the following variables. With that in mind, we set the order of our system as follows:

$$y_t = \begin{bmatrix} SWITCH \\ FUEL\ SHARE \\ EUA \\ Electricity\ Prices \end{bmatrix} \tag{75}$$

The choice between the order of *SWITCH and FUEL SHARE* was further motivated by the market share with regards to the world. Whereas *SWITCH* represents global prices, *FUEL SHARE* is a Germany specific variable.

In line with the preceding analysis we have divided our analysis into three model specifications, that is *(i) Average Electricity Price, (ii) Peak Hour Electricity Price, and (iii) Off-Peak Hour Electricity Price.* More so, we will once more present the analysis first within phases, and thus between different definitions of electricity prices, before making a cross-comparison between the two sample phases. We will chronologically start with Phase II, before moving forward in time. More so, as our interest lies on the sector level response, we will here focus on electricity prices, and fuel-mix. The full-set of impulse response functions can be found in the appendix.

Phase II

Figure (a)-(c) on page 95 depict the impulse response functions for a shock in carbon price - as measured by EUA Spot prices, on switch, electricity prices, and energy fuel mix.

Starting with the system with *Average Electricity* we see a delayed negative response of Fuel Share to a (positive) shock in carbon prices. Although insignificant at first, the response seems permanent at the very least with respect to h=10 steps ahead, considering the 95% confidence intervals are below zero consistently. Regardless to whether one argues a transitory or permanent effect, it seems puzzling as to why an increase in spot carbon prices increases the relative share of the carbon intensive fuel input. This is especially puzzling as the system does account for changes in electricity production using alternative fuels, or generation methods. If anything, prior research would hint towards fuel adjustments to the more carbon neutral good. Nevertheless, the relative preference of one good to the other is not only dependent on their externality costs but also their respective input prices. The respective input prices, namely hard coal and natural gas prices are determined on the world stage and thus unlikely being affected by national, and EU level shocks.

With regards to average electricity price; as hypothesized throughout our research - as well as shown in previous literature, electricity providers pass-through higher carbon price opportunity costs to consumers. Thus, even though firms receive excessive amounts of carbon emission permits (EUA) for free within Phase 2, firms still seem to pass-through a price-increase in the EUA spot price. The price increase initially overshoots the long-run effect, yet either way is positive. One might also want to note, that by construction the average electricity price is some linear combination of peak and off-peak electricity prices - and hence, it is wise to look at the dynamics with regards to the latter two.

The second model specification employing *"Peak Electricity"* is depicted in figure (b) on page 95, peak electricity prices respond once more delayed, and negative to a shock in EUA permit prices. Although, the negative movements still seems puzzling, research generally agrees on higher responds rates during peak hours **Source missing**. Such relationship can be seen from comparatively tighter confidence intervals as well. Higher pass-through rates generally stem from the usage of flexible, but higher marginal-cost plants during high demand hours.

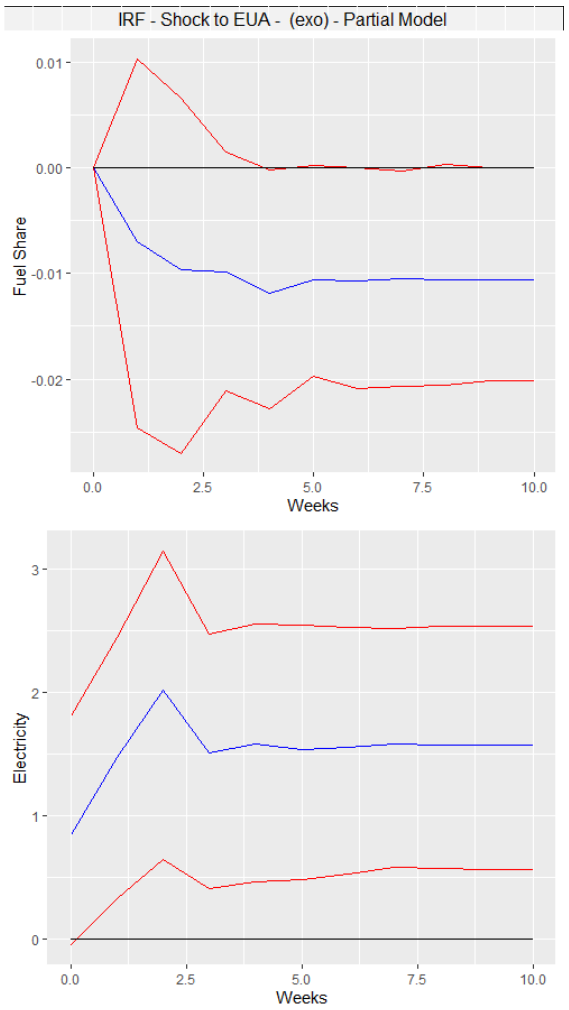
The combination of peak-hour electricity demand increase and subsequent movement up the marginal cost merit order of electricity production generally allows firms to charge higher electricity prices during such times. It is thus, not surprising to see a positive opportunity-cost pass-through within peak prices. However, it is interesting to see that the average electricity price response is more significant than the peak electricity price for the very short-term response (t+1). Nonetheless, the response is rather similar to the average electricity price.

And lastly, *"Off-Peak"* electricity prices. Figure (c) on page 95 depicts our last model specification within Phase II. Continuing with fuel mix, we see a less-significant response of fuel share in off-peak hours. Such result is not surprising, and was one of the motivations behind splitting prices between peak and off peak hours. Off-peak hour energy production consists of low marginal cost generation plants, that is nuclear power plants, and coal. Off-Peak hour energy volume represents a low demand phase, and thus the production volume during such hours of the day corresponds to the base load energy production. The base load energy demand is rather stable, and not much influenced by prices in general, as the base load market mostly moves within the forward electricity market.
Nevertheless, firms seem consistent in their cost-pass through and exploit movements in carbon prices even during off-peak hours. Although the pass through is somewhat lower, it is consistently positive over the sample length in the impulse response function.

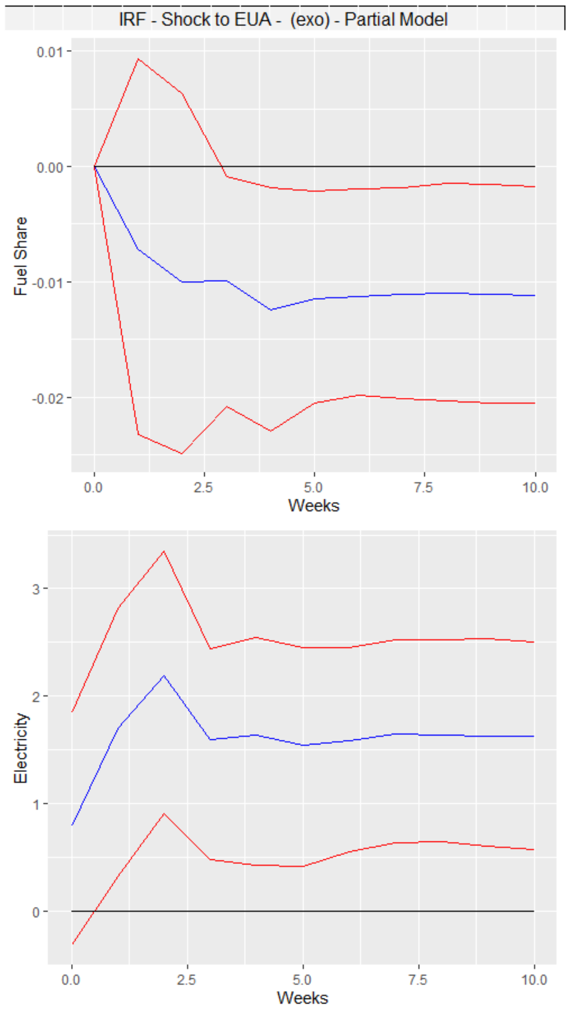
Phase III

Having talked about the response to a shock in carbon prices on electricity prices and fuel-mix, we will now present the equivalent analysis on Phase III.

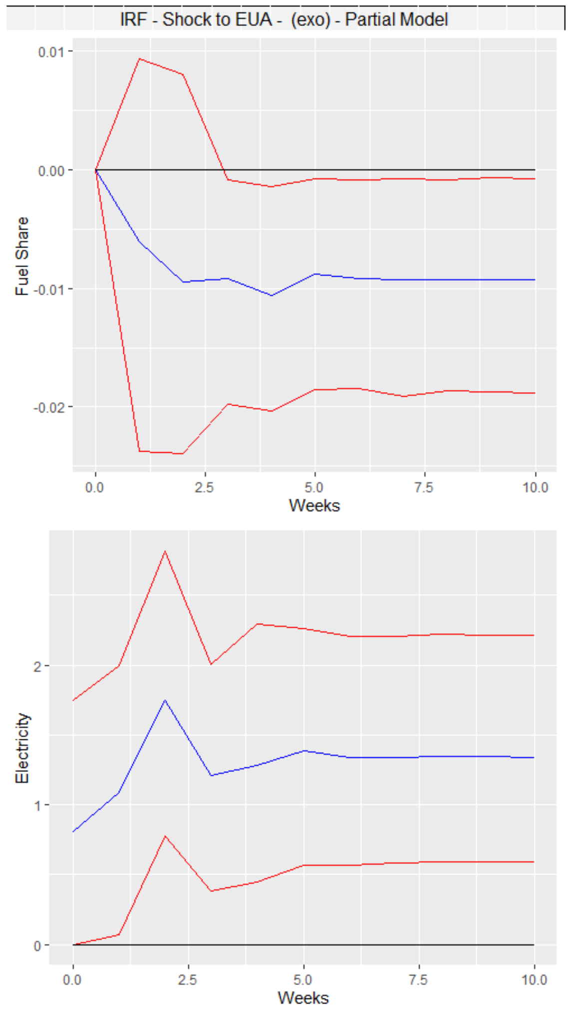
We had initially hypothesized higher sensitivity of energy production fuel input mix to shock in carbon prices. The fundamental idea is that given that electricity firms incur initial carbon costs through auctioning, firms marginal production costs will now include the carbon costs. Hence, given a significant increase in carbon prices, or a significant increase in coal prices - firms will have an incentive to switch to coal. However, within the sample period of Phase III this effect is not present in the impulse response functions employing average electricity prices. The impulse responses of the fuel ratio variable are insignificant at all steps ahead, and on top of that do not respond at all for h=10 steps ahead. There might be multiple reasons as to why we are unable to find a significant response of fuel mix to shocks in carbon prices. Germany as a nation, currently employs heavy energy sector reforms that leave the sub-market of fossil-fuel combustion energy production with a tremendous amount of



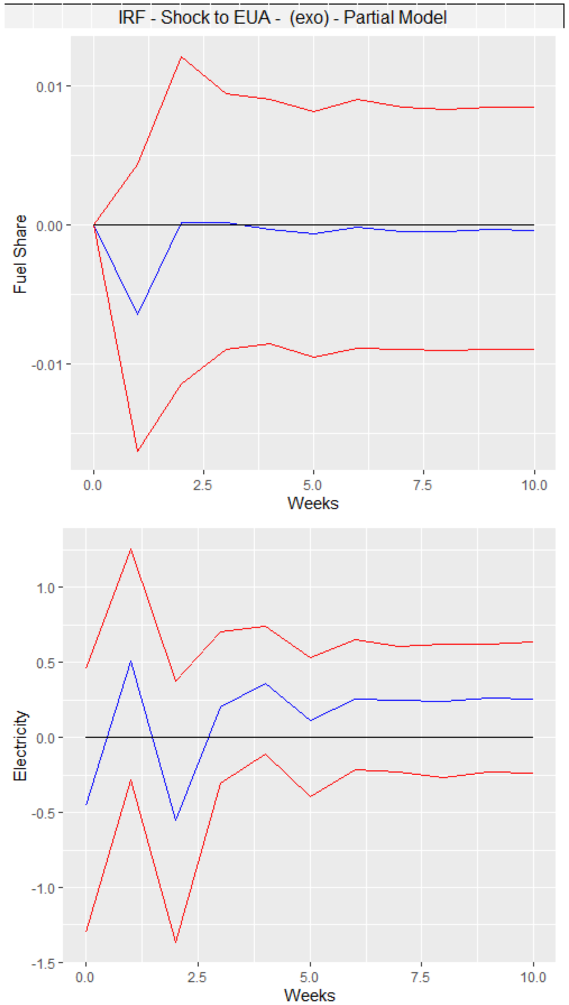
(a) P2: EUA on Average Electricity Price, and Fuel Mix



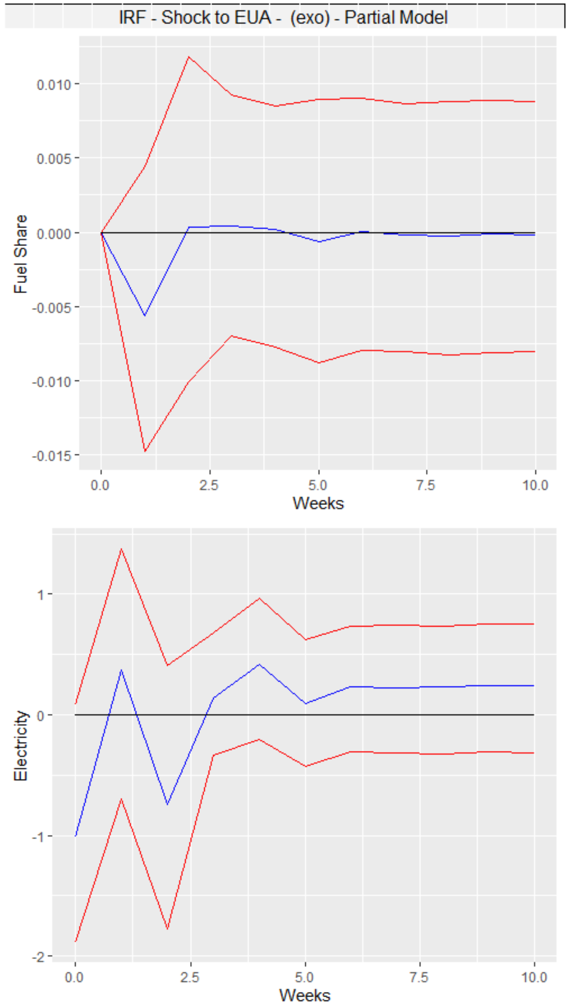
(b) P2: EUA on Peak Electricity Price, and Fuel Mix



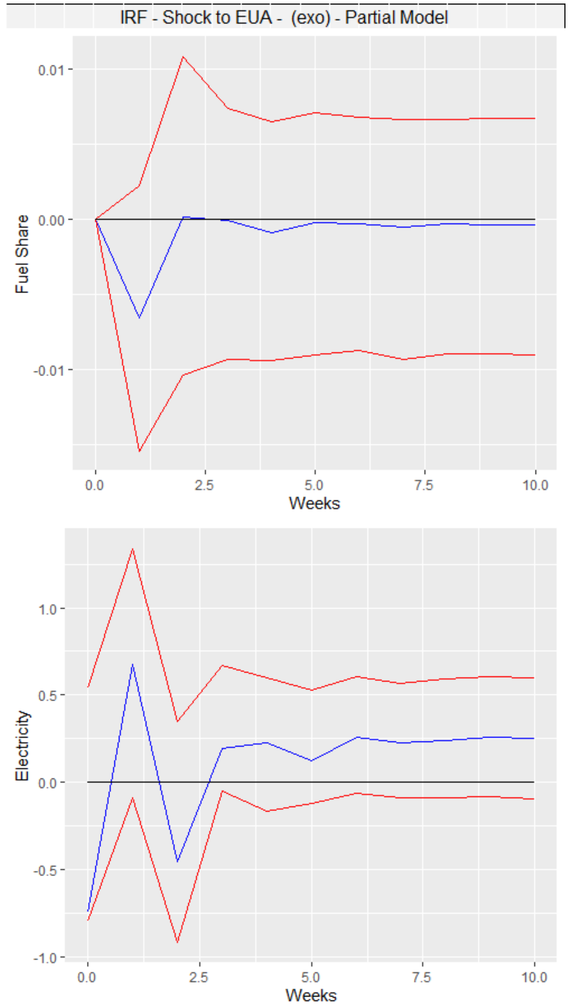
(c) P2: EUA on Off-Peak Electricity Price, and Fuel Mix



(a) P3: EUA on Average Electricity Price, and Fuel Mix



(b) P3: EUA on Peak Electricity Price, and Fuel Mix



(c) P3: EUA on Off-Peak Electricity Price, and Fuel Mix uncertainty. Within the current research setting, we attempt to incorporate the policy effects on energy production by deducting the effects of energy production from other sources on our fuel-mix variable. Another reason as to why we are unable to find a response might be related to the fact that we are looking at shocks to spot prices. It is reasonable to believe that firms are not able to capture the benefits of a fuel-switch in the short run, or simply because switching incurs cost itself. Which in turn, might introduce a threshold abatement price.

Similarly to model employing *Average Electricity Price*, neither*Peak-* nor *Off-Peak Price* specifications lead to a different conclusion. None of the variables presented on page 96 depicts a significant response to a shock in carbon prices. We had briefly introduced the notion of a threshold price, and a non-feasibility of an input switch in the short-run to changes in spot carbon prices.
With regards to cost-pass through, although Phase III represents a time-period where firms at first are faced with a marginal-cost increase in production firms do not seem to pass on such cost-increase based on insignificant impulse responses. There might be several reasons for such, which we will further extend within the discussion section. Nonetheless, we know that firms have already increased prices within Phase II, and thus generated windfall profits. We also saw, that these effects seemed permanent from the impulse responses in Phase II on page 95. Hence, the question within Phase III is not whether firms pass-through the carbon cost - but rather whether firms pass-through the cost of carbon emissions a second time. Additionally Fell (2010), mentions that *RWE*, one of the largest electricity producing firm in Germany has been issued a warning by German Federal Cartel Office for excessively passing through carbon costs. Such might also be a reason why we are not seeing additional pass through in Phase III. Germany's electricity prices already rank 2nd highest within the European Union, and hence electricity demand might simply not support a much higher electricity price.

Concluding briefly, with the beginning of the paper we claimed that resource allocation should matter within a cap and trade system, as it influences firm behaviour. We attempt to answer this question by comparing the dynamics between carbon prices and the electricity sector in Germany by imposing a one time positive shock to carbon prices and investigating responses.

10 Discussion

Along the problem statement in section 4 we have laid out our research questions and corresponding hypotheses. We found our hypotheses on previous literature regarding carbon pricing, as well as background information regarding the EU ETS, and electricity market dynamics. Our research questions are concerned with effects of auctioning as an allocation method for carbon allowances on electricity market dynamics.

We hypothesize that this change in the institutional design impacts the market in the following; Considering the switch to auctioning from an initial grandfathering mechanism, there are no more opportunity costs present for firms subject in the market to pass through. Given that such pass-through was permanent and phase III prices already incorportate CO2 costs, we argue that there will not be any further pass-through of carbon-costs to electricity prices. We also argue that the electricity sector, subject to auctioning in Phase III, has the opportunity to switch their *Fuel Share* in electricity production as a response to changes in carbon prices. Consequently, firms will switch towards more carbon friendly technologies in their electricity generation. As demonstrated in the estimation strategy, by comparing the two phases with two different allocation methods we are able to assess the differences between difference eras. In this section we will further discuss our findings, what each suggests and how they relate to our initial hypotheses

As mentioned in the results section, we find a positive cost-pass through in Phase II, as well as, no significant pass-through in Phase III. And hence, we do not reject our H1[4]. On top of that, our IRF's suggest negative *Fuel Share* adjustments in Phase II, and no significant adjustments of *Fuel Share* in Phase III. More specifically, in Phase III firms are not significantly reacting to a shock to carbon prices in terms of their generation *Fuel Share*. Whereas, the electricity behaviour is very much in-line with previous research, and our own hypothesis - the negative *Fuel Share* adjustments seem puzzling at first. Based on our hypothesis about the changes to fuel mix, we expected a significantly positive response of *Fuel Share* to a carbon price shock[5].

Our impulse responses show a negative response of *Fuel Share* variable to an *EUA* shock in Phase II. Therefore, our findings from impulse response analyses reject our hypothesis H2.

One might argue that fuel mix of electricity generating firms shows "stickiness" in their time series and is the reason why we are not seeing a positive response. Rogge and Hoffmann (2010), mentions that implementing new plants and new technologies takes long time due to the long lifetimes of existing ones. Based on this, our models may not be capturing a very long-run dynamics of fuel mix in electricity generation hence the insignificant response of the *Fuel Share* variable to *EUA* shocks in

[4]

[5] $Fuel\ Share = \frac{GAS\ USAGe}{COAL\ USAGE}$

Phase III. However such argument falls short for explaining why we are seeing a significant negative response of the *Fuel Share* in Phase II as the observed response means firms use relatively more coal, a more carbon emitting fuel, when carbon allowance prices increase.

In his interviews conducted, Hoffmann (2007) finds that historically increasing gas prices are causing coal fueled plants to be preferred over gas fueled ones. Additionally, he finds that if it wasn't for nuclear power phase-out in Germany, elaborated in background section, old coal plants would have been pushed out of the market, reducing coal usage and cutting down emissions.

For the latter argument however, we are accounting for the nuclear power usage in electricity generation by regressing *Fuel Share* on changes in uranium usage in electricity generation and use the residuals as the final *Fuel Share* variable. As we are accounting for such, our estimation results should not depict any movements related to nuclear power phase-out in Germany. Regarding the first argument,Hoffmann (2007) argues the relationship can be logically formulated as follows; an increase in carbon prices leads to an increase in natural gas prices as its a less carbon emitting fuel. In turn this then leads to more coal usage because coal is less costly compared to natural gas following a cyclical relationship. In fact, we can test this relationship within our estimation result as well, considering we have switch price in our variable system, depicting the ratio of coal and natural gas prices. From full IRF plots presented in the Appendix section we observe that in Phase II, a shock to carbon prices has no significant impact on the switch price, indicating that relative cost-effectiveness of natural gas and coal stays stable when *EUA* changes. Based on what we observe in impulse responses such relationship of high carbon prices increasing natural gas prices, and subsequently increasing coal usage is unlikely.

Another finding by Rogge and Hoffmann is that, EU ETS contributed to an increase in retrofit activities for older coal plants, increasing their efficiency (Rogge, Schneider, and Hoffmann 2011). Hoffmann also argues that due to the cost pass-through behaviour, some plants that were not profitable before are once again profitable (Hoffmann 2007). Windfall profits obtained from passing through costs might be leading towards introduction of new coal plants through retrofit activities by making them more profitable. In our impulse response analyses, we do observe cost pass-through during the period where we are also observing increased coal usage in electricity production. Such relationship might be the reason behind why we see increasing carbon prices leading to more coal usage in generation. It can also explain why the negative response of *Fuel Share* to *EUA* shocks is not observed in Phase III as there is no further pass-through in the phase. Furthermore, Rogge, Schneider, and Hoffmann (2011), emphasize increasing research on carbon capture and storage system technologies' within EU

ETS. It is also likely that electricity generating firms are focusing more towards technologies that would decrease their carbon emissions from existing plants rather than switching towards less carbon intensive fuels.

Another possible reason for why we are observing a negative response for *Fuel Share* variable could be explained by switching behaviours in fuel mix for electricity generation, more specifically cross-border energy switching. (E. D. Delarue and D'haeseleer 2007) E. D. Delarue and D'haeseleer (2007), argue that for switching to occur, two conditions must be met:

1. Profitable Economics Incentive: Carbon emission permit prices must be sufficiently large, and natural gas prices sufficiently low for gas-fired plants to allow for profitable switching.
2. Physical Switch Potential:
   (a) **In-System Switch/System Capacity:** Given a sufficiently diverse power system, a country can switch electricity production by input internally. In our case, the assumption was that the system must have enough gas-fire plants to handle electricity load in order to accommodate switching (E. Delarue, Voorspools, and D'haeseleer 2008).
   (b) **Cross-Border Electricity Switch:** Given that (a) does not hole, a country/firm is equally able to change production by outsourcing electricity production. As opposed to switching its own production input, a firm can given an electricity, input, and EUA price simply decide to source electricity in a neighbouring country (E. Delarue, Voorspools, and D'haeseleer 2008).

Within our research setting, we had implicitly assumed in-system switch, meaning that Germany's electricity producers have sufficient capacity to switch from coal to gas. Nevertheless, this might simply not be the case. More so, Germany does not have any natural gas endowments, and as such is fully reliant on natural gas import - exposing it to uncertainties revolving world natural gas price.
On the other hand, The Netherlands depict a natural gas reliant electricity generation. And as such, given a sufficiently high carbon price, paired with a no-excess gas electricity generation capacity, Germany's electricity producers would have an incentive to buy electricity from The Netherlands. This arguments also hold with other sources of energy as long as these are less carbon intensive as coal and lignite electricity generation. Another example is France's nuclear power reliant electricity generation. Country's with lower carbon intensive energy generation - have lower exposure to carbon trades, and thus their respective electricity marginal production has lower dependency on carbon

prices.

Based on this argument, Germany might simply reduce their natural gas share, if foreign electricity prices are lower than domestic gas electricity marginal cost of production.

Given that we measure *Fuel Share* as a ratio of natural gas electricity production over coal electricity production, a decrease in this ratio can either be caused by an increase of coal in electricity generation, all else equal. Or by a reduction of gas in electricity generation, ceteris paribus.

To conclude our hypothesis regarding the fuel mix for energy generation in Germany we have argued why we might be observing a negative response to carbon shocks in Phase II and no response in Phase III. No significant response in Phase III can be explained by too low carbon prices to switch production technology to natural gas or cost and time required for switching generation technology, essentially making the generation technology "sticky". In order to argue for why we might be seeing negative response in Phase II, we used previous literature to find possible explanations. We emphasize on two possible reasons why we might be seeing more coal usage when carbon prices increase. First one being, higher windfall profits might be leading more retrofit activities, making coal plants profitable that weren't before. Second possible reason we emphasize is the cross-country fuel switching behaviour.

Regarding our hypothesis about electricity price dynamics to changes in EU ETS system; we find in impulse response analyses that there have been cost pass-through during Phase II based on positive shocks to EUA significantly increasing electricity prices. In Phase III, this cost pass-through behaviour is not apparent as the response of electricity prices are not significantly positive or negative. Such findings confirm our hypothesis regarding electricity price dynamics. Previous literature such as Fell (2010), Freitas and P. P. d. Silva (2015), Thoenes (2014) and Bunn and Fezzi (2008) finds positive cost pass-through for different electricity markets within EU in Phase II. Therefore, our findings for Phase II is consistent with existing research. Additionally we hypothesized that with introduction of auctioning as the method of allocation in EU ETS firms will not pass through carbon costs a second time to the electricity prices. Carbon allowances are no opportunity costs for the firms anymore such that we cannot see a pass-through to electricity prices with the new allocation method. Additionally, we know from Fell (2010), that German Federal Cartel Office issued a warning to RWE for excessively passing through these carbon costs. Based on this, another reason why the pass-through is not observed in Phase III might be that electricity generating firms are hesitant towards similar warnings or more serious sanctions.

11 Conclusion

The switch to auctioning from grandfathering as the EU ETS moves from Phase II to Phase III is arguably the most substantial institutional change in the system's history. This paper analyzes and compares the two phases in order to find whether significant differences in dynamics mainly between carbon allowance prices and electricity market exist. Our hypotheses were:

1. There is not any further cost pass-through to electricity prices with the introduction of auctioning system in Phase III.
2. Electricity producing companies switch their fuel mix in generation towards less carbon emitting fuels.

In order to test these hypotheses we set up a system of equations with four variables; carbon allowance prices, electricity prices in Germany, switch price between natural gas and coal and ratio of natural gas and coal usage in Germany's electricity production. By specifying models that pass most of the diagnostic checks we test the long run relationship between these variables. Test for cointegration finds that there is a long run relationship between our variables within our sub-samples of two phases. We proceed by estimating a VEC model and compare both long-run and short-run coefficients for the systems. Furthermore we test the weak-exogeneity of our variables. The *Switch* variable found to be one of the driving force of the system in both phases. While *EUA* is weakly-exogenous in Phase II this changes in Phase III where *Fuel Share* variable becomes weakly-exogenous. We lastly analyze and compare the impulse responses of our Electricity price variables and the *Fuel Share* variable for a shock to carbon prices. Supporting our first hypothesis, we find no pass-through in Phase III as opposed to Phase II. The response of *Fuel Share* to an *EUA* shock is negative in Phase II and not significant in Phase III. We discuss that several potential reasons on why higher carbon prices might be leading to more coal usage.

Policy Implications

Within section 2 we had argued the distributional effects of allocation methods on rent collection. The main argument was regarding windfall-profits accumulated in the electricity sector. By raising prices and passing through opportunity-costs arising from grandfathering, that is the free allocation of a market asset, electricity firms were able to generate significant profits in phase I and II. Although the pass-through of opportunity-costs is a valid argument that has been acknowledged within economics ever since, political concerns arise from the redistribution of costs from poor to rich.

The EU ETS only compensates sectors with direct emission outputs under grandfathering, i.e. the electricity and power sector. However, it could be possible that effects on these sectors will eventually trickle-down to other sectors. The problem in this scenario persists in that subsequent "indirect" sectors are not compensated by the EU ETS for their indirect carbon emissions.

We will illustrate this by looking at the aluminium sector, a power intensive industry. An aluminium processing firm depicts significant energy consumption, thus energy prices generally affect aluminium production. Under grandfathering, electricity prices have increased, leaving aluminium prices with higher electricity input costs. Consequently, aluminium producers face lower margins, or increase prices. The problem intensifies as aluminium is an internationally traded good, and thus subject to international market prices. Where German aluminium production can no longer support world prices, its demand will decline - and thus employment. Which can hypothetically affect the economy through unemployment rates.

Although within auctioning, electricity prices do not decline, the rent is collected in form of an auction revenue by governments. And hence, the rent collected from firms can be "recycled" in order to combat negative interaction effects of higher electricity prices. From a political and social welfare perspective such is more desirable.

Within our research we show that allocation method has a significant effect on pass-through behaviour in that firms do not pass-through the auction price a second time. This implies, that rents are now collected in form of auction revenue and firms do no longer collect windfall profits.

From a policy perspective this is important as it implies that market structure can correct rent distribution among market participants.

Limitations and Future Research

Within the analyses present we made effort in isolating the effects of the EU ETS market on Germany's electricity sector.

We made a conscious decision in taking a certain sub-sample of our available time-series, to exclude any transition periods, or other EU ETS policy interventions i.e. the introduction of the *Market Stability Reserve*. Furthermore, account for Germany specific energy policies that potentially influence the fuel mix, as well as effect on the merit order from other input fuels (solar, wind, hydro, nuclear, lignite).

Nevertheless, throughout our analyses we treat Germany under autarky. Germany as a nation, as well as energy producer is very much intertwined on a European level. As such, we fully exclude effects of cross-border energy trade. As mentioned in the discussion, cross-border energy exchange might be a potential reason for our negative fuel share adjustments in phase II. Given that carbon prices increase sufficiently, German energy producers might find it more profitable to import energy from other countries. However, as Germany's base load is dependent on coal - imported energy might be mainly during peak times. The point here is that we encourage looking at Germany as part of the EU energy network by accounting for cross-border electricity trades. The same reasoning applies to studying any effects of EU on electricity firms in other countries. Treating Germany as an isolate economy with respect to energy production and consumption might not fully represent the full picture.

More so, our analysis employs a recursive estimation procedure in order to detangle the effects of a shock to EUA prices. Nevertheless, by doing so we introduce a causal chain. Although we believe that our order represent the mechanism at hand in the EU ETS, a more structural model detangling transitory and permanent effects might present beneficial in assessing the effects of carbon prices on firm behaviour.

12 Bibliography

References

Aatola, Piia, Markku Ollikainen, and Anne Toppinen (2013). "Price determination in the EU ETS market: Theory and econometric analysis with market fundamentals". In: *Energy Economics* 36, pp. 380–395.

Abrell, Jan and Hannes Weigt (2008). "The interaction of emissions trading and renewable energy promotion". In: *Dresden University of Technology Working Paper no. WP-EGW-05.*

Alberola, Emilie, Julien Chevallier, and Benoıˆt Chèze (2008). "Price drivers and structural breaks in European carbon prices 2005–2007". In: *Energy policy* 36.2, pp. 787–797.

Anderson, Barry and Corrado Di Maria (2011). "Abatement and Allocation in the Pilot Phase of the EU ETS". In: *Environmental and Resource Economics* 48.1, pp. 83–103.

Awokuse, Titus and Jian Yang (2002). "Asset Storability and Hedging Effectiveness in Commodity Futures Markets". In:

Benz, Eva, Andreas Löschel, and Bodo Sturm (2010). "Auctioning of CO2 emission allowances in Phase 3 of the EU Emissions Trading Scheme". In: *Climate Policy* 10.6, pp. 705–718.

Betz, Regina and Misato Sato (2006). *Emissions trading: lessons learnt from the 1st phase of the EU ETS and prospects for the 2nd phase.*

Bohm, Peter (1999). *International Greenhouse Gas Emission Trading: With Special Reference to the Kyoto Protocol.* Nordic Council of Ministers.

Box, George EP, Gwilym M Jenkins, et al. (2015). *Time series analysis: forecasting and control.* John Wiley & Sons.

Box, George EP and David A Pierce (1970). "Distribution of residual autocorrelations in autoregressive-integrated moving average time series models". In: *Journal of the American statistical Association* 65.332, pp. 1509–1526.

Braun, Marcel (2009). "The evolution of emissions trading in the European Union–The role of policy networks, knowledge and policy entrepreneurs". In: *Accounting, Organizations and Society* 34.3-4, pp. 469–487.

Bunn, Derek W and Carlo Fezzi (2008). "A vector error correction model of the interactions among gas, electricity and carbon prices: an application to the cases of Germany and the United Kingdom". In: *Markets for carbon and power pricing in Europe: Theoretical issues and empirical analyses*, pp. 145–159.

Castagneto-Gissey, Giorgio (2014). “How competitive are EU electricity markets? An assessment of ETS Phase II”. In: *Energy Policy* 73, pp. 278–297.

Chaton, Corinne, Anna Creti, and Benoıt Peluchon (2015). “Banking and back-loading emission permits”. In: *Energy policy* 82, pp. 332–341.

Chevallier, Julien (2009). “Carbon futures and macroeconomic risk factors: A view from the EU ETS”. In: *Energy Economics* 31.4, pp. 614–625.

– (2010). “Carbon prices during the EU ETS phase II: Dynamics and volume analysis”. In:

– (2011). “Macroeconomics, finance, commodities: Interactions with carbon markets in a data-rich model”. In: *Economic Modelling* 28.1-2, pp. 557–567.

Christiansen, Atle C et al. (2005). “Price determinants in the EU emissions trading scheme”. In: *Climate Policy* 5.1, pp. 15–30.

Considine, Timothy J (2000). “The impacts of weather variations on energy demand and carbon emissions”. In: *Resource and Energy Economics* 22.4, pp. 295–314.

Convery, Frank J (2009). “Origins and development of the EU ETS”. In: *Environmental and Resource Economics* 43.3, pp. 391–412.

Creti, Anna, Pierre-André Jouvet, and Valérie Mignon (2012). “Carbon price drivers: Phase I versus Phase II equilibrium?” In: *Energy Economics* 34.1, pp. 327–334.

Delarue, Erik D and William D D’haeseleer (2007). “Price determination of ETS allowances through the switching level of coal and gas in the power sector”. In: *International Journal of Energy Research* 31.11, pp. 1001–1015.

Delarue, Erik, Kris Voorspools, and William D’haeseleer (2008). “Fuel switching in the electricity sector under the EU ETS: review and prospective”. In: *Journal of Energy Engineering* 134.2, pp. 40–46.

Deloitte, C. (2015). *European Energy Market Reform: Countryprofile: Germany.* Deloitte Conseil.

Demailly, Damien and Philippe Quirion (2006). “CO2 abatement, competitiveness and leakage in the European cement industry under the EU ETS: grandfathering versus output-based allocation”. In: *Climate Policy* 6.1, pp. 93–113.

Dyer, Jeffrey H, Harbir Singh, and Prashant Kale (2008). “Splitting the pie: rent distribution in alliances and networks”. In: *Managerial and Decision Economics* 29.2-3, pp. 137–148.

EC.Europa, EC (2020). *EU Emission Trading System (2005-2012) EC EUROPA*. URL: `https://ec.europa.eu/clima/policies/ets/pre2013_en` (visited on 09/12/2020).

Economics, Frontier (2006). “CO2 trading and its influence on electricity markets”. In: *Final report to DTe, Frontier Economics Ltd, London.*

Egenhofer, Christian (2007a). “EU ETS Options for Cap Setting, Allocation and Distribution of Allowances after 2012”. In: *Background Paper. CEPS Task Force on Completing the Review of the EU ETS*.

– (2007b). “The Making of the EU Emissions Trading Scheme:: Status, Prospects and Implications for Business”. In: *European Management Journal* 25.6, pp. 453–463.

Eikeland, Per Ove and Jon Birger Skjærseth (2019). “Oil and power industries’ responses to EU emissions trading: laggards or low-carbon leaders?” In: *Environmental Politics* 28.1, pp. 104–124.

Elder, John and Peter E Kennedy (2001). “Testing for unit roots: what should students be taught?” In: *The Journal of Economic Education* 32.2, pp. 137–146.

Ellerman, A Denny and Barbara K Buchner (2008). “Over-allocation or abatement? A preliminary analysis of the EU ETS based on the 2005–06 emissions data”. In: *Environmental and Resource Economics* 41.2, pp. 267–287.

– (2007). “The European Union emissions trading scheme: origins, allocation, and early results”. In: *Review of environmental economics and policy* 1.1, pp. 66–87.

Ellerman, A Denny, Claudio Marcantonini, and Aleksandar Zaklan (2014). “The EU ETS: Eight years and counting”. In: *Robert Schuman Centre for Advanced Studies Research Paper* 2014/04.

– (2016). “The European Union emissions trading system: ten years and counting”. In: *Review of Environmental Economics and Policy* 10.1, pp. 89–107.

Enders, Walter (2008). *Applied econometric time series*. John Wiley & Sons.

European Energy Exchange (2020). *Emission Auctions*. URL: `https://www.eex.com/en/markets/environmental-markets/emissions-auctions` (visited on 09/12/2020).

Fabra, Natalia and Mar Reguant (2014). “Pass-through of emissions costs in electricity markets”. In: *American Economic Review* 104.9, pp. 2872–99.

Fell, Harrison (2010). “EU-ETS and Nordic electricity: a CVAR analysis”. In: *The Energy Journal* 31.2.

Fitch-Roy, Oscar, Jenny Fairbrass, and David Benson (n.d.). “Ideas, coalitions and compromise: reinterpreting EU-ETS lobbying through discursive institutionalism”. In: *Journal of European Public Policy* 27 ().

Freitas, Carlos J Pereira and Patrıcia Pereira da Silva (2015). “European Union emissions trading scheme impact on the Spanish electricity price during phase II and phase III implementation”. In: *Utilities Policy* 33, pp. 54–62.

Gaines, Sanford E (1991). “The Polluter-Pays Principle: From Economic Equity to Environmental Ethos, 26 Tex”. In: *Int’l LJ* 463, pp. 463–96.

González, Pablo del Rıo (2006). “Harmonization versus decentralization in the EU ETS: an economic analysis”. In: *Climate Policy* 6.4, pp. 457–475.

Gonzalo, Jesus (1994). “Five alternative methods of estimating long-run equilibrium relationships”. In:

Goulder, Lawrence H, Marc AC Hafstead, and Michael Dworsky (2010). “Impacts of alternative emissions allowance allocation methods under a federal cap-and-trade program”. In: *Journal of Environmental Economics and management* 60.3, pp. 161–181.

Grubb, Michael, Christian Azar, and U Martin Persson (2005). “Allowance allocation in the European emissions trading system: a commentary”. In: *Climate Policy* 5.1, pp. 127–136.

Grubb, Michael and Karsten Neuhoff (2006). “Allocation and competitiveness in the EU emissions trading scheme: policy overview”. In: *Climate Policy* 6.1, pp. 7–30.

Hahn, Robert W (1984). “Market power and transferable property rights”. In: *The Quarterly Journal of Economics* 99.4, pp. 753–765.

Hahn, Robert W and Robert N Stavins (2011). “The effect of allowance allocations on cap-and-trade system performance”. In: *The Journal of Law and Economics* 54.S4, S267–S294.

Hakkio, Craig S and Mark Rush (1991). “Cointegration: how short is the long run?” In: *Journal of international Money and Finance* 10.4, pp. 571–581.

Hammoudeh, Shawkat, Duc Khuong Nguyen, and Ricardo M Sousa (2014). “What explain the short-term dynamics of the prices of CO2 emissions?” In: *Energy Economics* 46, pp. 122–135.

Hendry, David F and Katarina Juselius (2000). “Explaining cointegration analysis: Part 1”. In: *The Energy Journal* 21.1.

Hepburn, Cameron et al. (2006). “Auctioning of EU ETS phase II allowances: how and why?” In: *Climate Policy* 6.1, pp. 137–160.

Hintermann, Beat (2010). “Allowance price drivers in the first phase of the EU ETS”. In: *Journal of Environmental Economics and Management* 59.1, pp. 43–56.

– (2011). “Market power, permit allocation and efficiency in emission permit markets”. In: *Environmental and Resource Economics* 49.3, pp. 327–349.

Hoffmann, Volker H (2007). “Eu ets and investment decisions:: The case of the german electricity industry”. In: *European Management Journal* 25.6, pp. 464–474.

Ji, Jingna, Zhiyong Zhang, and Lei Yang (2017). “Comparisons of initial carbon allowance allocation rules in an O2O retail supply chain with the cap-and-trade regulation”. In: *International Journal of Production Economics* 187, pp. 68–84.

Ji, Qiang, Dayong Zhang, and Jiang-bo Geng (2018). “Information linkage, dynamic spillovers in prices and volatility between the carbon and energy markets”. In: *Journal of Cleaner Production* 198, pp. 972–978.

Johansen, S and Katarina Juselius (1990). “Maximum likelihood estimation and inference on cointegration—with appucations to the demand for money”. In: *Oxford Bulletin of Economics and statistics* 52.2, pp. 169–210.

Johansen, S ren (1994). “The role of the constant and linear terms in cointegration analysis of nonstationary variables”. In: *Econometric reviews* 13.2, pp. 205–229.

Johansen, Soren (1995). “Likelihood-Based Inference in Cointegrated Vector Autoregressive Models Oxford University Press”. In: *New York*.

Johansen, Søren (1988). “Statistical analysis of cointegration vectors”. In: *Journal of economic dynamics and control* 12.2-3, pp. 231–254.

Jouvet, Pierre-André and Boris Solier (2013). “An overview of CO2 cost pass-through to electricity prices in Europe”. In: *Energy Policy* 61, pp. 1370–1376.

Juselius, Katarina (2006). *The cointegrated VAR model: methodology and applications.* Oxford university press.

Juselius, Katarina and Ronald MacDonald (2004). “International parity relationships between the USA and Japan”. In: *Japan and the World economy* 16.1, pp. 17–34.

Knittel, Christopher R and Michael R Roberts (2005). “An empirical examination of restructured electricity prices”. In: *Energy Economics* 27.5, pp. 791–817.

Koch, Nicolas (2014). “Dynamic linkages among carbon, energy and financial markets: a smooth transition approach”. In: *Applied Economics* 46.7, pp. 715–729.

Koujianou Goldberg, Pinelopi and Rebecca Hellerstein (2013). “A structural approach to identifying the sources of local currency price stability”. In: *Review of Economic Studies* 80.1, pp. 175–210.

Le Comte, Douglas M and Henry E Warren (1981). “Modeling the impact of summer temperatures on national electricity consumption”. In: *Journal of Applied Meteorology* 20.12, pp. 1415–1419.

Lütkepohl, Helmut (2005). *New introduction to multiple time series analysis.* Springer Science & Business Media.

Lütkepohl, Helmut and Don S Poskitt (1991). "Estimating orthogonal impulse responses via vector autoregressive models". In: *Econometric Theory*, pp. 487–496.

Lütkepohl, Helmut, Pentti Saikkonen, and Carsten Trenkler (2004). "Testing for the cointegrating rank of a VAR process with level shift at unknown time". In: *Econometrica* 72.2, pp. 647–662.

Mansanet-Bataller, Maria, Angel Pardo, and Enric Valor (2007). "CO2 prices, energy and weather". In: *The Energy Journal* 28.3.

Martinez, Kim Keats and Karsten Neuhoff (2005). "Allocation of carbon emission certificates in the power sector: how generators profit from grandfathered rights". In: *Climate Policy* 5.1, pp. 61–78.

Matthes, Felix C and Karsten Neuhoff (2007). "Auctioning in the European Union Emissions Trading Scheme". In: *Öko-Institut & University of Cambridge. A report to WWF.*

Montgomery, W David (1972). "Markets in licenses and efficient pollution control programs". In: *Journal of economic theory* 5.3, pp. 395–418.

Moutinho, Victor, Mara Madaleno, and Pedro Miguel Silva (2016). "Which factors drive CO 2 emissions in EU-15? Decomposition and innovative accounting". In: *Energy Efficiency* 9.5, pp. 1087–1113.

Nakamura, Emi and Dawit Zerom (2010). "Accounting for incomplete pass-through". In: *The Review of Economic Studies* 77.3, pp. 1192–1230.

Neuhoff, Karsten, Kim Keats Martinez, and Misato Sato (2006). "Allocation, incentives and distortions: the impact of EU ETS emissions allowance allocations to the electricity sector". In: *Climate Policy* 6.1, pp. 73–91.

Oberndorfer, Ulrich (2009). "EU emission allowances and the stock market: evidence from the electricity industry". In: *Ecological Economics* 68.4, pp. 1116–1126.

Olivier, Jos GI, Jeroen AHW Peters, and Greet Janssens-Maenhout (2012). "Trends in global CO2 emissions 2012 report". In:

Parker, Larry (2008). *Climate change and the EU Emissions trading Scheme (ETS): Kyoto and Beyond.* Congressional Research Service.

Perino, Grischa and Maximilian Willner (2016). "Procrastinating reform: The impact of the market stability reserve on the EU ETS". In: *Journal of Environmental Economics and Management* 80, pp. 37–52.

Rickels, Wilfried et al. (2007). *The determinants of allowance prices in the European emissions trading scheme: Can we expect an efficient allowance market 2008?* Tech. rep. Kiel Working Paper.

Rogge, Karoline S and Volker H Hoffmann (2010). "The impact of the EU ETS on the sectoral innovation system for power generation technologies–Findings for Germany". In: *Energy Policy* 38.12, pp. 7639–7652.

Rogge, Karoline S, Malte Schneider, and Volker H Hoffmann (2011). "The innovation impact of the EU Emission Trading System—Findings of company case studies in the German power sector". In: *Ecological Economics* 70.3, pp. 513–523.

Said, Said E and David A Dickey (1984). "Testing for unit roots in autoregressive-moving average models of unknown order". In: *Biometrika* 71.3, pp. 599–607.

Sartor, Oliver, Clement Pallière, and Stephen Lecourt (2014). "Benchmark-based allocations in EU ETS Phase 3: an early assessment". In: *Climate Policy* 14.4, pp. 507–524.

Schlitzer, Giuseppe (1995). "Testing the stationarity of economic time series: further Monte Carlo evidence". In: *Ricerche Economiche* 49.2, pp. 125–144.

Sijm, Jos (2005). "The interaction between the EU emissions trading scheme and national energy policies". In: *Climate Policy* 5.1, pp. 79–96.

Sijm, Jos, Yihsu Chen, and Benjamin F Hobbs (2012). "The impact of power market structure on CO2 cost pass-through to electricity prices under quantity competition–A theoretical approach". In: *Energy Economics* 34.4, pp. 1143–1152.

Sijm, Jos, Karsten Neuhoff, and Yihsu Chen (2006). "CO2 cost pass-through and windfall profits in the power sector". In: *Climate policy* 6.1, pp. 49–72.

Sims, Christopher A (1980). "Macroeconomics and reality". In: *Econometrica: journal of the Econometric Society*, pp. 1–48.

Sjö, Bo (2011). *Testing for Unit Roots and Cointegration-Guide.*

Smyrgała, Dominik (2017). "Fukushima and Energiewende: Impact on structure of power generation". In: *Energy Sources, Part B: Economics, Planning, and Policy* 12.4, pp. 332–337.

Sturm, Bodo (2008). "Market power in emissions trading markets ruled by a multiple unit double auction: further experimental evidence". In: *Environmental and Resource Economics* 40.4, pp. 467–487.

Thoenes, Stefan (2014). "Understanding the determinants of electricity prices and the impact of the German Nuclear Moratorium in 2011". In: *The Energy Journal* 35.4.

Trotignon, Raphaël and Anais Delbosc (2008). "Allowance trading patterns during the EU ETS trial period: What does the CITL reveal". In: *Climate report* 13, pp. 1–36.

Tsay, Ruey S (2005). *Analysis of financial time series.* Vol. 543. John wiley & sons.

Varian, Hal R (2014). *Intermediate Microeconomics: A Modern Approach: Ninth International Student Edition*. WW Norton & Company.

Venmans, Frank Maarten Jan (2016). "The effect of allocation above emissions and price uncertainty on abatement investments under the EU ETS". In: *Journal of Cleaner Production* 126, pp. 595–606.

Walker, Sébastien EJ (2008). "The EU Emissions Trading Scheme: assessment and outlook". In: *Oxonomics* 3.1, pp. 40–44.

Woerdman, Edwin (2004). *The institutional economics of market-based climate policy*. Elsevier.

Woerdman, Edwin, Oscar Couwenberg, and Andries Nentjes (2009). "Energy prices and emissions trading: windfall profits from grandfathering?" In: *European Journal of Law and Economics* 28.2, pp. 185–202.

Yu, Jongmin and Mindy L Mallory (2014). "Exchange rate effect on carbon credit price via energy markets". In: *Journal of International Money and Finance* 47, pp. 145–161.

13 Appendix

ACF plots for model residuals with systems with Peak and Off-Peak as electricity prices

Figure 14: ACF plots for model with Peak Elec. - Phase 2

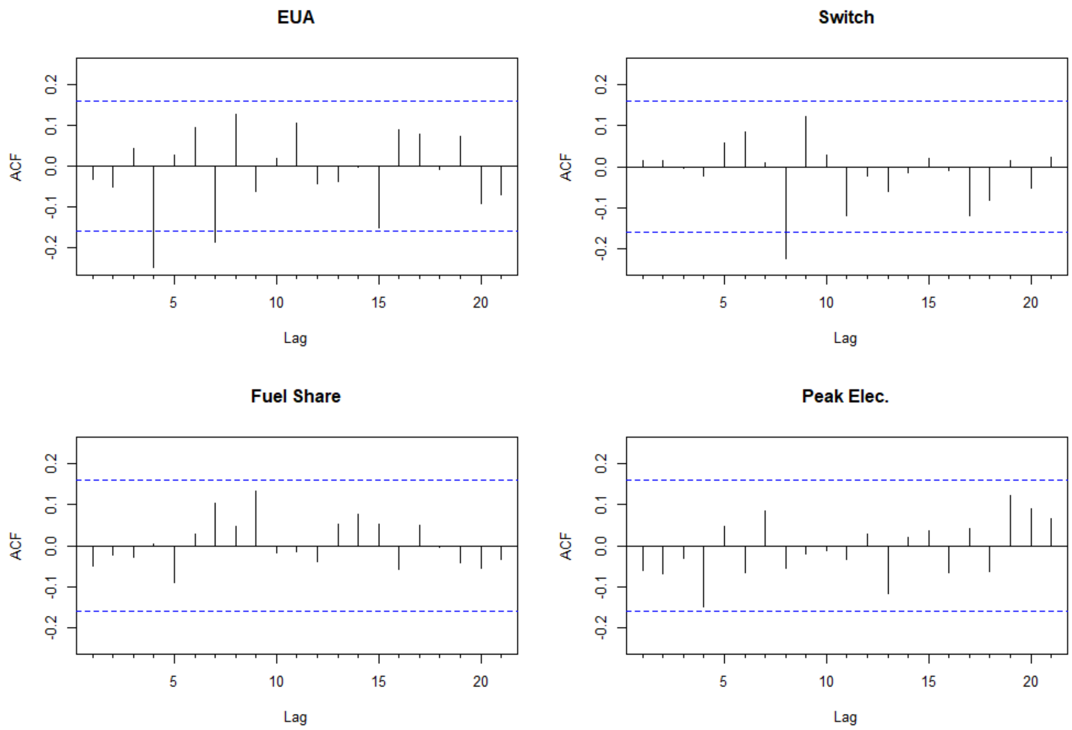


Figure 15: ACF plots for model with Off-Peak Elec. - Phase 2

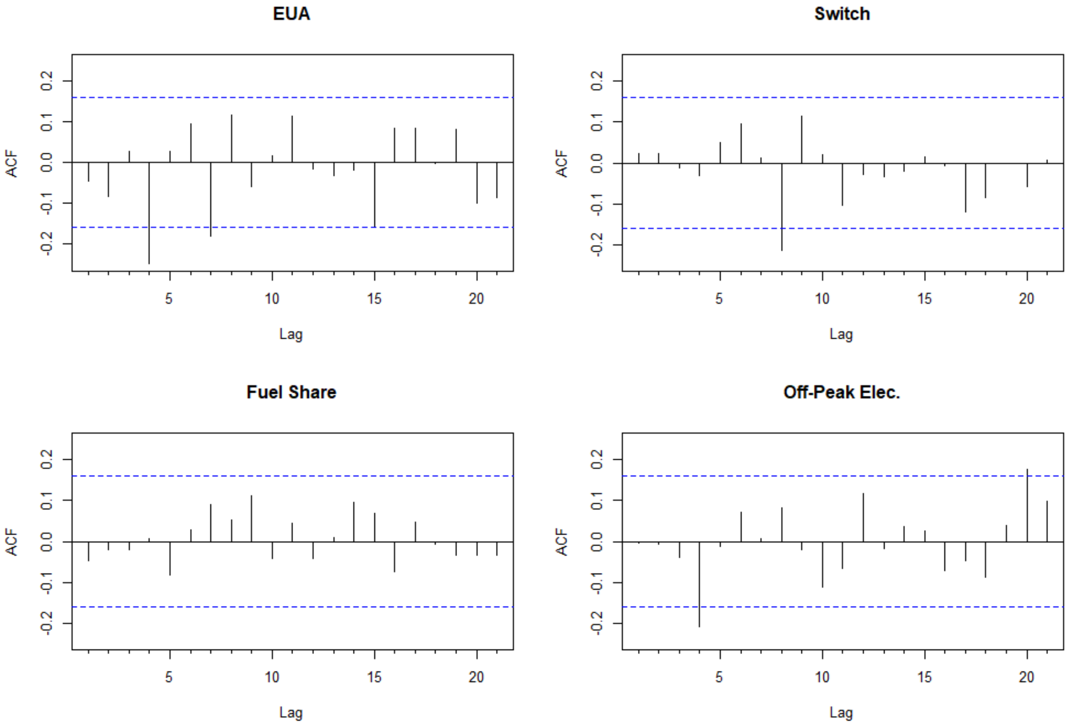


Figure 16: ACF plots for model with Peak Elec. - Phase 3

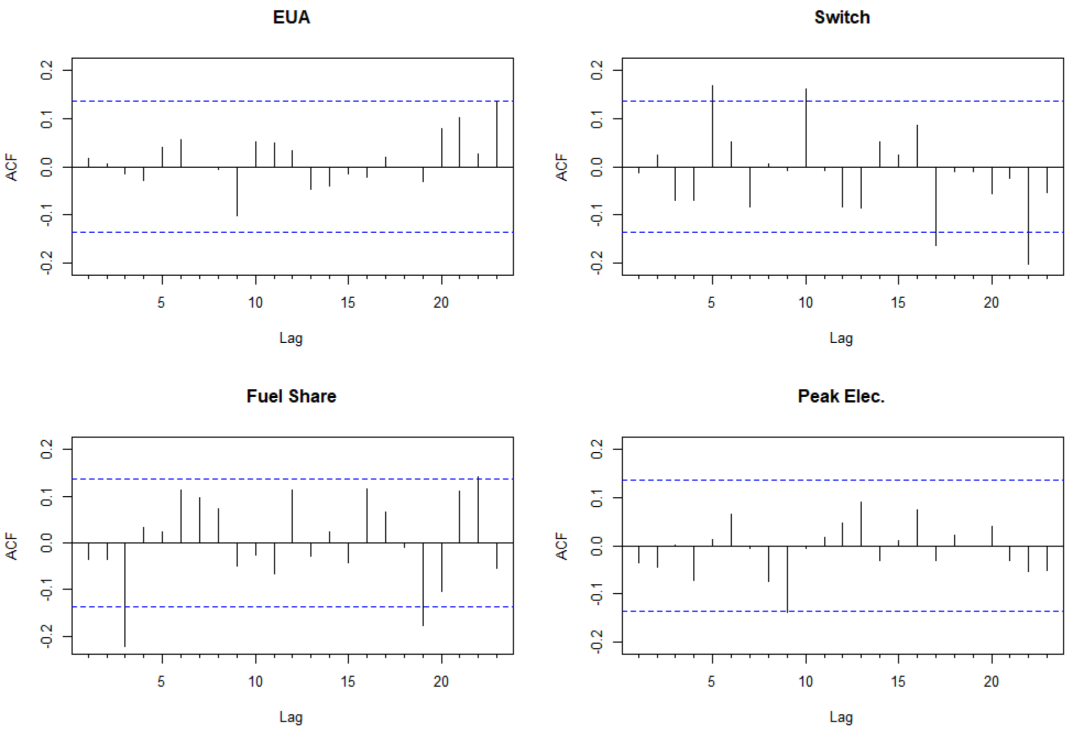
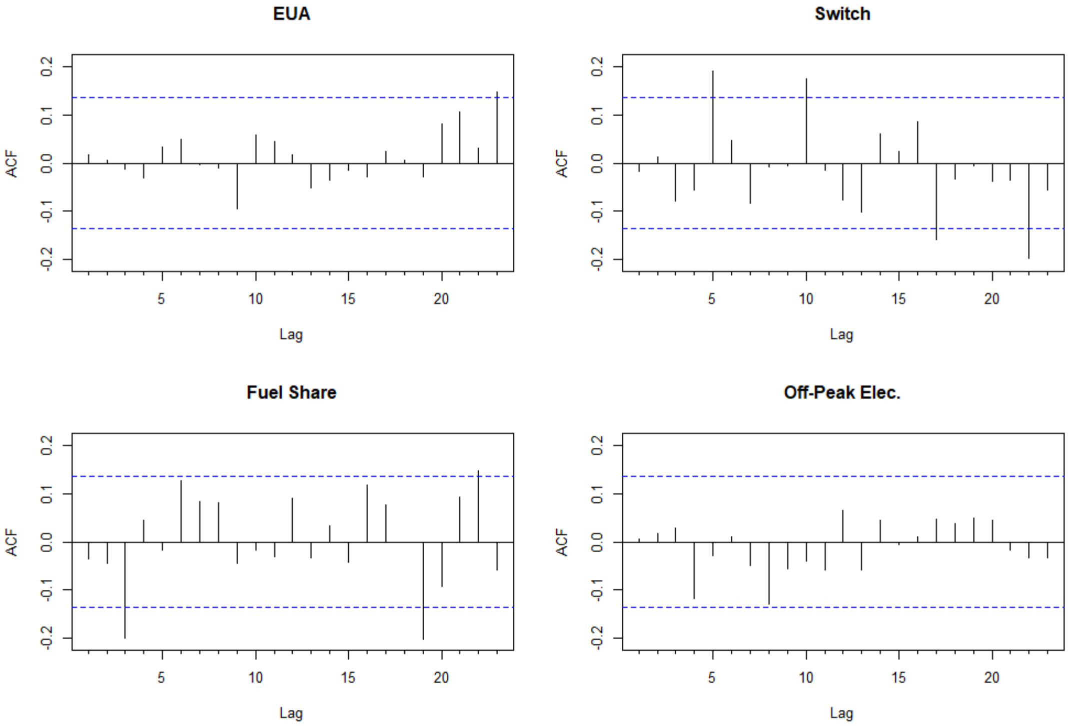


Figure 17: ACF plots for model with Off-Peak Elec. - Phase 3



Unit Root tests for first differenced data

Table 19: KPSS Test for First Differenced Data

KPSS Test	
Phase 2 and 3	
	p-values
EUA	> 0.1
Switch	> 0.1
Avg. Elec.	> 0.1
Peak Elec.	> 0.1
Off-Peak Elec.	> 0.1
Fuel Ratio	> 0.1
Phase 2	
	p-values
EUA	> 0.1
Switch	> 0.1
Avg. Elec.	> 0.1
Peak Elec.	> 0.1
Off-Peak Elec.	> 0.1
Fuel Ratio	> 0.1
Phase 3	
	p-values
EUA	0.097
Switch	> 0.1
Avg. Elec.	> 0.1
Peak Elec.	> 0.1
Off-Peak Elec.	> 0.1
Fuel Ratio	> 0.1

*The KPSS test results are obtained with the short lag version. However test results with long lag version hints towards identical results.

Table 18: Augmented Dickey-Fuller Test Statistics for First-Differenced Data

ADF Test

Phase 2 and 3	
	test statistic
EUA	-5,67**
Switch	-4,91**
Avg. Elec	-6,83**
Peak Elec.	-6,20**
Off-Peak Elec.	-7,38**
Fuel Ratio	-4,94**
Phase 2	
	test statistic
EUA	-3,30*
Switch	-3,47**
Avg. Elec.	-4,20**
Peak Elec.	-4,17**
Off-Peak Elec.	-3,72**
Fuel Ratio	-3,89**
Phase 3	
	test statistic
EUA	-4,22**
Switch	-3,58**
Avg. Elec.	-5,31**
Peak Elec.	-4,86**
Off-Peak Elec.	-6.19**
Fuel Ratio	-3.55**

* Critical values for ADF test are; -2.57 for 10%, -2.87 for 5%, -3.44 for 1%.
** 12 lags are included in ADF tests.
*** Significance codes are 1% $**$, 5%$*$, 10%$^{+}$.

Trace test results with Case 3 specification

Table 20: Johansen Cointegration test results with Case 3 specification

Phase 2 and 3						
	test statistic					
	with Avg.	with Peak	with Off-Peak	%10	%5	%1
r≤3	2.38	2.38	2.32	10.49	12.35	16.26
r≤2	10.36	10.39	10.25	22.76	25.32	30.45
r≤1	43.63	43.42	41.08	39.06	42.44	48.45
r=0	116.30	110.05	122.31	59.14	62.99	70.05
Phase 2						
	test statistic					
	with Avg.	with Peak	with Off-Peak	%10	%5	%1
r≤3	5.65	5.52	5.87	10.49	12.35	16.26
r≤2	12.75	12.48	13.32	22.76	25.32	30.45
r≤1	30.38	29.86	31.36	39.06	42.44	48.45
r=0	76.14	74.65	67.48	59.14	62.99	70.05
Phase 3						
	test statistic					
	with Avg.	with Peak	with Off-Peak	%10	%5	%1
r≤3	4.50	4.50	4.25	10.49	12.35	16.26
r≤2	14.70	14.85	14.38	22.76	25.32	30.45
r≤1	31.76	32.71	30.95	39.06	42.44	48.45
r=0	79.94	82.38	70.87	49.14	62.99	70.05

Impulse Responses Functions

Figure 18: IRF plots for Phase 2 - Average Elec.

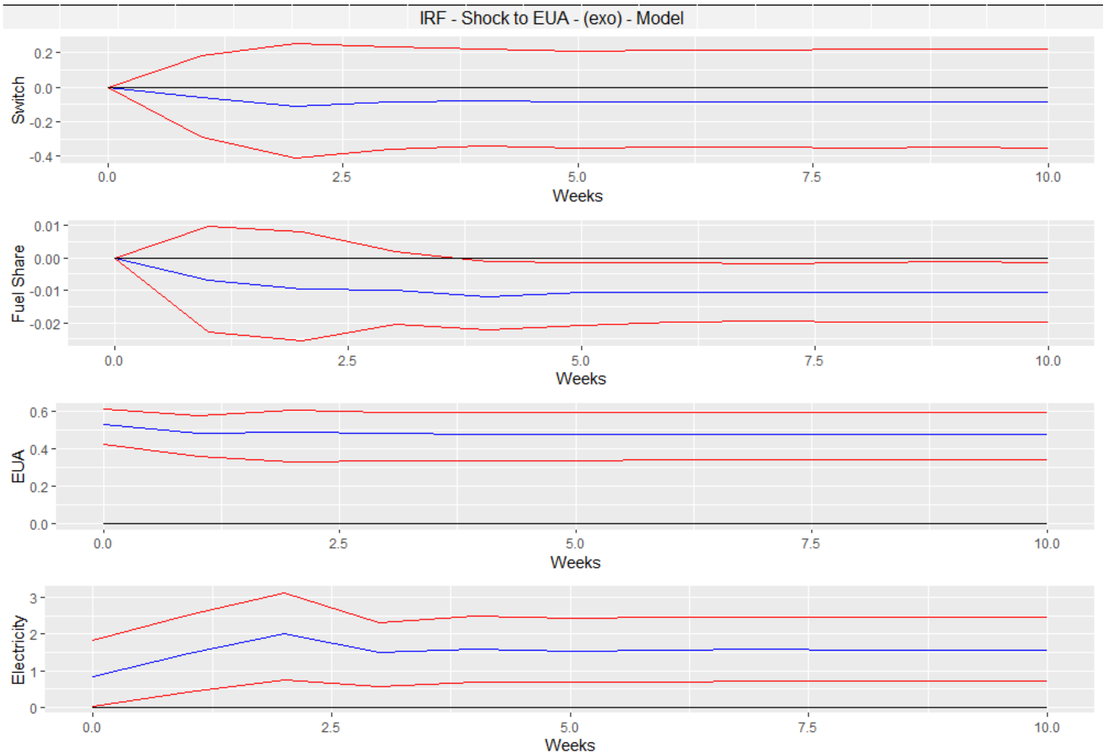


Figure 19: IRF plots for Phase 2 - Peak Elec.

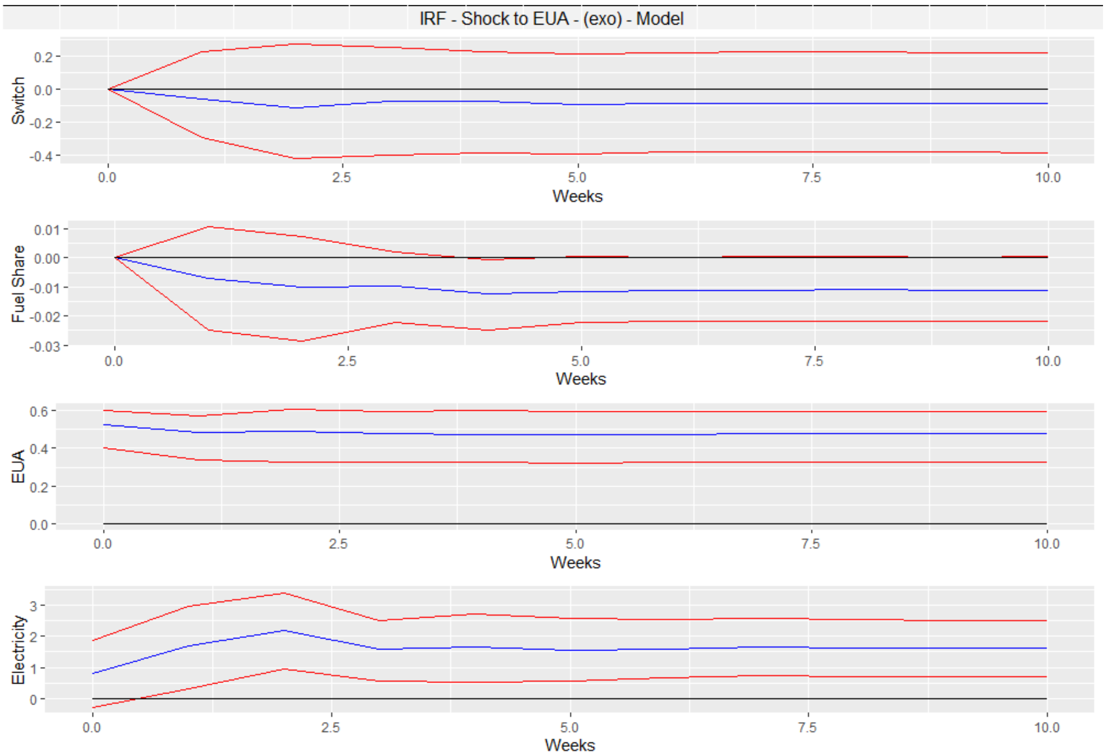


Figure 20: IRF plots for Phase 2 - OffPeak Elec.

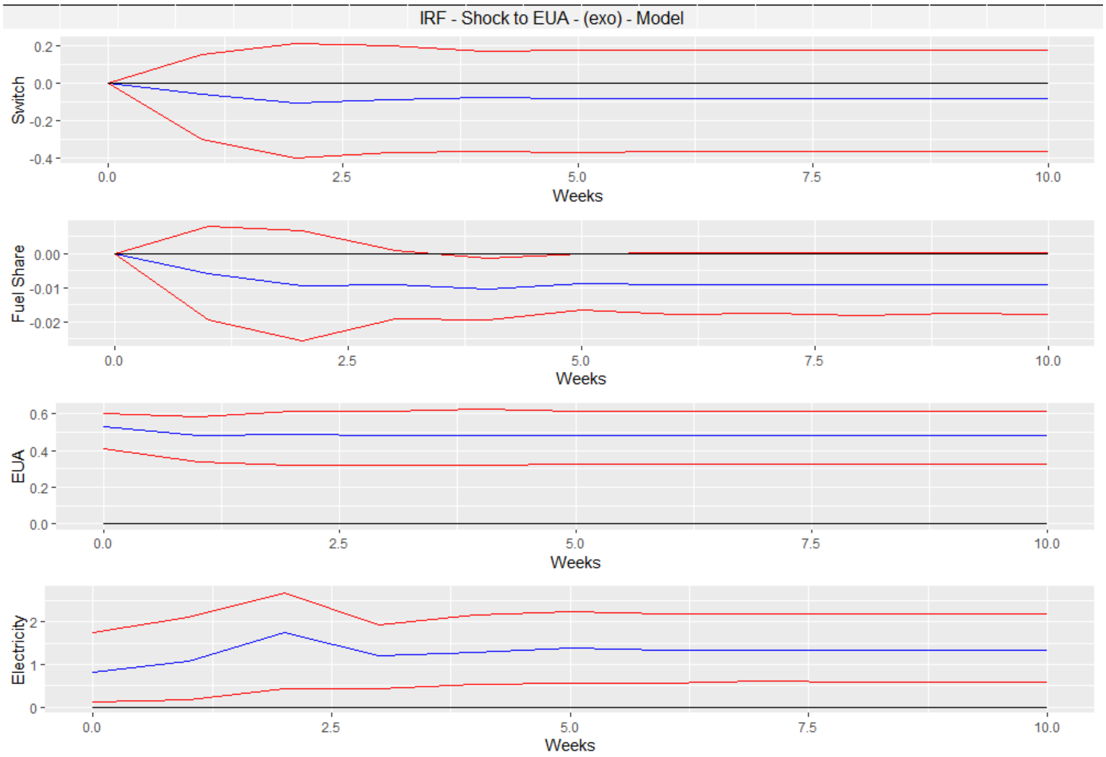


Figure 21: IRF plots for Phase 3 - Average Elec.

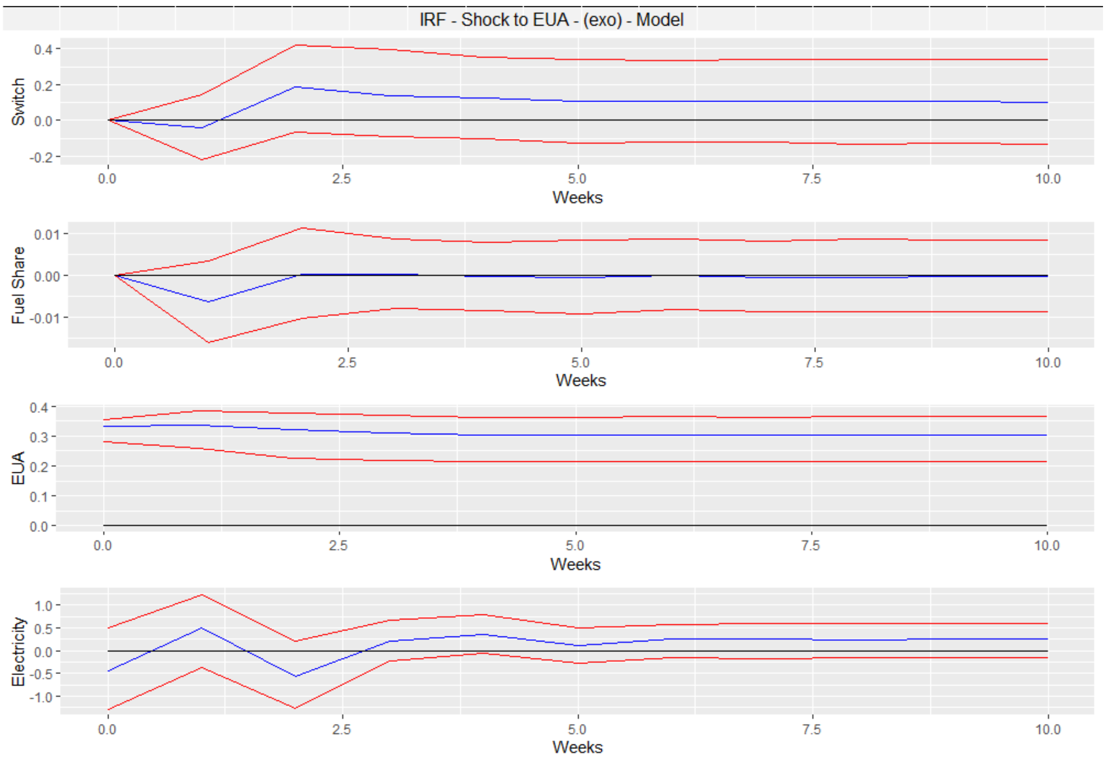


Figure 22: IRF plots for Phase 3 - Peak Elec.

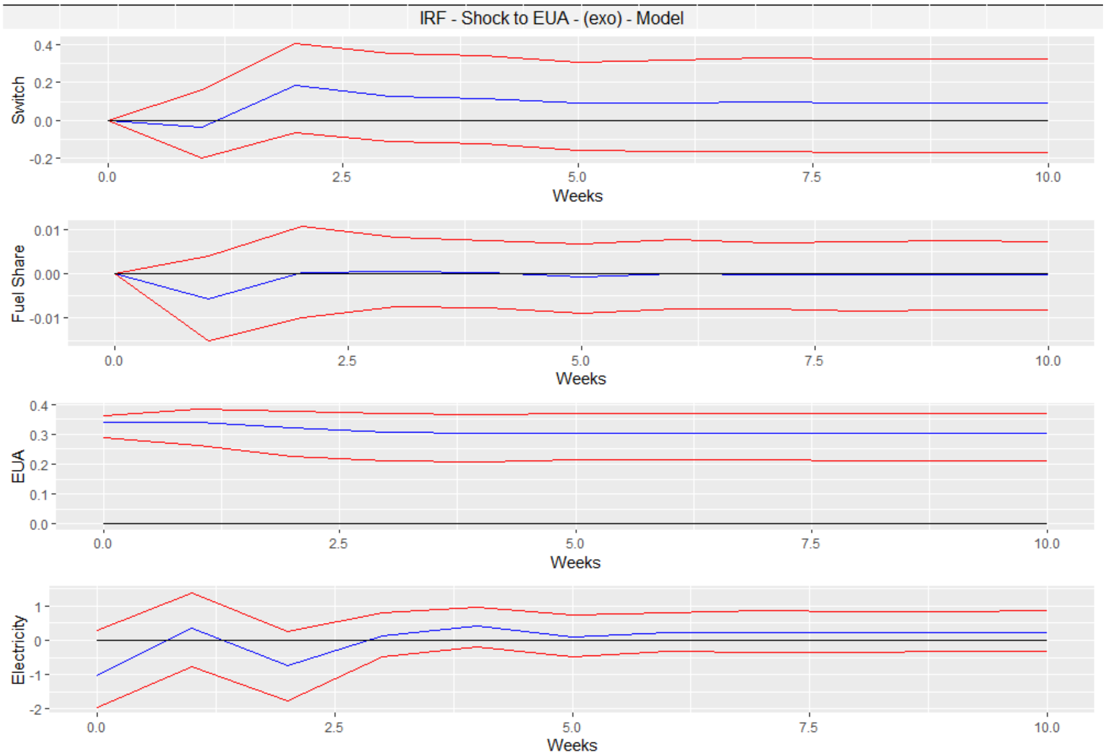


Figure 23: IRF plots for Phase 3 - OffPeak Elec.